

NATIONAL TECHNICAL UNIVERSITY OF ATHENS

PHD DISSERTATION

EMG Based Interfaces for Human Robot Interaction in Structured and Dynamic Environments

Author: Minas LIAROKAPIS Advisor: Prof. Kostas Kyriakopoulos

Co-Advisor: Prof. Panagiotis Artemiadis

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

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Control Systems Lab School of Mechanical Engineering

July, 2014

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Μ' αρέσει να βλέπω την άσπρη γραμμή που αφήνουνε πίσω τα αμάξια όταν τρέχουν, να φτάνω σε πόλεις που μόλις να έχουν ανάψει τα φώτα χαι μια μουσιχή, να φωτίζει απαλά τις ψυχές των ανθρώπων μες στη ματιά τους να βλέπω νερό, να ρωτάω πως λέγεται η πόλη χαι όλοι να λένε δεν ξέρω, δεν είμαι από εδώ...

Παύλος Παυλίδης

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NATIONAL TECHNICAL UNIVERSITY OF ATHENS

Abstract

School of Mechanical Engineering

Doctor of Philosophy

EMG Based Interfaces for Human Robot Interaction in Structured and Dynamic Environments

by Minas LIAROKAPIS

In this PhD thesis we focus on EMG based interfaces that can be efficiently used for Human Robot Interaction (HRI) applications in structured and dynamic environments. Initially, we present a series of advanced learning schemes for EMG based interfaces that take advantage of both a classifier and a regressor, in order to split the task-space and provide better human motion estimation accuracy with task specific models.

Regarding HRI applications, we mainly focus on anthropomorphism of robot artifacts. At first we distinguish between the different notions of anthropomorphism and we introduce Functional Anthropomorphism for mapping human to anthropomorphic robot motion, respecting at the same time specific human imposed functional constraints.

Then we propose a methodology for quantifying anthropomorphism of robot hands, based on set theory and computational geometry methods. This latter methodology concludes to a comprehensive score of anthropomorphism that ranges between 0 (nonhumanlike) and 1 (human identical) and can be used for various robot artifacts.

Subsequently, we develop a series of open-source, modular, intrinsically-compliant, lowcost, light-weight, underactuated robot hands that can be easily reproduced with offthe-self materials. The proposed hands, efficiently grasp a plethora of everyday life objects, under object pose and/or shape uncertainties and can be used for various HRI applications or even as affordable myoelectric prostheses.

In order to prove the efficiency of the proposed methods, we have conducted numerous experiments involving different robot artifacts, operating in both structured and dynamic environments.

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Εθνικό Μετσόβιο Πολυτεχνείο

Περίληψη

Σχολή Μηχανολόγων Μηχανικών

Διδακτορική Διατριβή

Διεπαφές Ηλεκτρομυογραφικών Σημάτων για την Αλληλεπίδραση Ανθρώπου Ρομποτικών Συστημάτων σε Δομημένα και Δυναμικά Περιβάλλοντα

Μηνάς Λιαροκάπης

Σε αυτή την διδακτορική διατριβή επικεντρωνόμαστε σε διεπαφές ηλεκτρομυογραφικών σημάτων οι οποίες μπορούν να χρησιμοποιηθούν για εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων, τόσο σε δομημένα όσο και σε δυναμικά περιβάλλοντα.

Αρχικά παρουσιάζουμε μια σειρά από προηγμένα σχήματα μηχανικής μάθησης για διεπαφές ηλεκτρομυογραφικών σημάτων, τα οποία συνδυάζουν έναν ταξινομητή με έναν παλινδρομητή, προκειμένου να κατακερματίσουν τον χώρο δράσης του ρομπότ, προσφέροντας καλύτερα αποτελέσματα αποκωδικοποίησης της ανθρώπινης κίνησης με μοντέλα εκπαιδευμένα για συγκεκριμένες διεργασίες.

Όσον αφορά τις εφαρμογές αλληλεπίδρασης ανθρώπου ρομπότ, επικεντρωνόμαστε κυρίως στη έννοια και τις διαφορετικές χρήσεις του ανθρωπομορφισμού των ρομποτικών συστημάτων. Αρχικά διακρίνουμε τις διαφορετικές έννοιες του ανθρωπομορφισμού και εισάγουμε την έννοια του λειτουργικού ανθρωπομορφισμού για σχήματα αντιστοίχησης της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση, τηρώντας παράλληλα συγκεκριμένους περιορισμούς που θέτει ο χρήστης.

Στην συνέχεια προτείνουμε μια ολοκληρωμένη μεθοδολογία για την ποσοτικοποίηση του ανθρωπομορφισμού των ρομποτικών χεριών, βασισμένη σε μεθόδους θεωρίας συνόλων και υπολογιστικής γεωμετρίας. Η συγκεκριμένη μεθοδολογία παρέχει ένα κατανοητό μετρικό του ανθρωπομορφισμού το οποίο κυμαίνεται από 0 (μηανθρωπομορφικά ρομποτικά συστήματα) σε 1 (ανθρωπομορφικά ρομποτικά συστήματα) και μπορεί να χρησιμοποιηθεί για διαφορετικά είδη ρομπότ.

Τέλος, αναπτύσσουμε μια σειρά από ρομποτικά χέρια, ανοιχτού υλικού και κώδικα, τα οποία είναι ελαφριά, χαμηλού κόστους, εύκολα συναρμολογούμενα, υποϋπενεργούμενα και εγγενώς υποχωρητικά. Τα συγχεχριμένα χέρια μπορούν να χρησιμοποιηθούν τόσο για μελέτες ηλεχτρομυογραφικού ελέγχου (αχόμη και για οιχονομικά μυσηλεχτρικά προσθετικά χέρια), όσο και για εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων (για μελέτες τηλεχειρισμού ρομποτικών συστημάτων βραχίονα – χεριού), για την αρπαγή πληθώρας καθημερινών αντικειμένων σε δυναμικά περιβάλλοντα (αχόμη και υπό συνθήκες αβεβαιότητας σχετικά με τη θέση και το σχήμα των αντικειμένων).

Προχειμένου να αποδείξουμε την αποδοτικότητα και λειτουργικότητα των προτεινόμενων μεθοδολογιών, εχτελέσαμε σειρά πειραμάτων με διαφορετικά ρομποτικά συστήματα, τόσο σε δυναμικά όσο και σε δομημένα περιβάλλοντα.

Preface

Over the last decades, the cross-disciplinary field of electromyography (EMG) based interfaces has received increased attention. The possible applications range from EMG based teleoperation of robot artifacts in remote and/or dangerous environments, EMG control of prosthetic/robotic limbs, EMG control of exoskeletons (for rehabilitation) and development of muscle computer interfaces (for human computer interaction). This PhD thesis, focuses on how these EMG based interfaces can be efficiently used for Human Robot Interaction (HRI) applications.

A series of advanced learning schemes are proposed, that can be used to efficiently decode the human intention and/or motion from EMG signals. Three different task features are discriminated: subspace to move towards, object to be grasped and task to be executed (with the object). Based on these three task features, appropriate classifiers can be used to decode user's intention and decide on the task to be executed, using myoelectric activations of the human muscles.

The proposed learning schemes take advantage of both a classifier and a regressor (using sophisticated machine learning techniques), that cooperate advantageously in order to split the task-space and achieve better estimation accuracy, with task-specific models. Task-specific models outperform - in terms of motion estimation accuracy - general models trained for the whole task-space. The proposed learning schemes can be used for a variety of EMG-based interfaces. These interfaces can be employed for various HRI applications as well as in rehabilitation robots and prosthetic devices, helping patients and amputees respectively regain part of their lost mobility/dexterity.

Regarding HRI applications, this PhD thesis mainly focuses on anthropomorphism of robot artifacts. At first, a distinction between the different notions of anthropomorphism (Functional and Structural Anthropomorphism) is proposed and then a series of metrics for the quantification of anthropomorphism of robotic devices, are introduced. The final score of anthropomorphism uses a set of weighting factors that can be adjusted according to the specifications of each study, providing always a normalized score between 0 (nonanthropomorphic) and 1 (human identical).

The proposed methodology can be used for example to grade the human-likeness of existing and new robotic hands, as well as to provide specifications for the design of the next generation of anthropomorphic hands. Such humanlike robot hands can be used for numerous HRI applications, for humanoid robots or even for the creation of advanced humanlike myoelectric prostheses. Moreover a complete methodology for mapping human to anthropomorphic robot motion using the notion of Functional Anthropomorphism, is introduced. This latter methodology provides mapping schemes that achieve humanlike robot motion for robot artifacts with arbitrary kinematics (even for the case of hyper-redundant robot arm hand systems), "respecting" specific human imposed functional constraints (e.g., same position and orientation for human and robot end-effectors).

Humanlikeness of robot motion increases safety in HRI applications (anthropomorphic motion can more easily be perceived by humans, who can comply their motion avoiding possible injuries), and human and robot social connection through robot likeability. The proposed schemes can be used for teleoperation or autonomous operation applications, where anthropomorphism is required and skill transfer between humans and robots must be achieved in a learn by demonstration manner.

Finally, a series of affordable, modular, light-weight, intrinsically-compliant, underactuated robot hands and prosthetic devices that can be easily reproduced using off-the-shelf materials, are presented. The design of the proposed robot hands has been coordinated by a robot hands taxonomy that distinguishes and discusses functional and structural aspects for the creation of non-humanlike and human-like robot grippers and hands. The proposed taxonomy follows an order of increased complexity in presenting the different categories (of robot hand designs) and then based on their attributes, the choices made for our design, are appropriately justified.

The proposed robot hands, efficiently grasp a series of everyday life objects and are considered to be general purpose. Moreover, owing to their inherent compliance the proposed robot hands can efficiently grasp a wide range of everyday life objects in humancentric and dynamic environments, under object pose and shape uncertainties.

The possible applications of the proposed hands, range from autonomous grasping and teleoperation/telemanipulation studies (as parts of robot arm hand systems) to humanoids, mobile and aerial vehicle platforms (which can be modified to be grasping capable), educational robotics (provide a low-cost solution for highly intriguing robotics lessons), or even for affordable myoelectric prostheses, assisting amputees in everyday life tasks and helping them regain part of their lost dexterity.

For validating the efficiency of the proposed methods, numerous experiments have been conducted in both structured and dynamic environments, with robot artifacts such as: the Mitsubishi PA10 7DoF robot manipulator, the DLR/HIT II five fingered robot hand and a series of underactuated robot hands developed for that purpose. More details and videos of the experiments, can be found in the "videos" section of my website:

The OpenBionics (http://www.openbionics.org) and the HandCorpus (http://www.handcorpus.org) initiatives (created within the context of this PhD thesis), as well as a list of the research papers published during my PhD studies (e.g., papers in international conferences, journals and workshops, book chapters, technical reports etc.), are presented at the appendices of this PhD thesis.

Athens, July 2014

Minas Liarokapis

Εκτενής Ελληνική Περίληψη

Εισαγωγή και Περιγραφή Προβλήματος

1. Εισαγωγή

Τις τελευταίες δεκαετίες τα διεπιστημονικά πεδία των διεπαφών ηλεκτρομυογραφικών σημάτων (EMG - Electromyography Based Interfaces) και της αλληλεπίδρασης ανθρώπου - ρομποτικών συστημάτων (HRI - Human Robot Interaction), έχουν αποτελέσει αντικείμενο αυξημένου ενδιαφέροντος, εξαιτίας των ποικίλων εφαρμογών τους στην καθημερινότητα, σε δυναμικά αλλά και ανθρωποκεντρικά περιβάλλοντα.

Τυπικές εφαρμογές ηλεκτρομυογραφικών σημάτων είναι ο βασισμένος σε ηλεκτρομυογραφικά σήματα τηλεχειρισμός ρομποτικών βραχιόνων σε απόμερα ή και επικίνδυνα περιβάλλοντα [1], [2], ο χειρισμός προηγμένων προσθετικών μελών με βάση το ηλεκτρομυογράφημα [3], ο ηλεκτρομυογραφικός χειρισμός εξωσκελετών [4] και η ανάπτυξη διεπαφών μυών – υπολογιστή για την αλληλεπίδραση ανθρώπου – υπολογιστή [5], [6]. Από την άλλη πλευρά, μερικές ενδεικτικές εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων, είναι, ανθρωποειδή που αλληλεπίδρούν με παιδιά [7], βιομηχανικά ρομπότ που συνεργάζονται με ανθρώπους [8] με ασφαλή τρόπο [9], ο διαισθητικός τηλεχειρισμός ρομπότ με πλεονάζοντες βαθμούς ελευθερίας [10] και οικιακά ρομπότ που βοηθούν τους ανθρώπους σε καθημερινές εργασίες [11--13].

Στο πλαίσια της συγκεκριμένης διδακτορικής διατριβής, προτείνουμε εξελιγμένα σχήματα μάθησης για ηλεκτρομυογραφικές διεπαφές, τα οποία εκμεταλλεύονται τόσο έναν ταξινομητή όσο και έναν παλινδρομητή, οι οποίοι και συνεργάζονται ώστε να διαιρέσουν/κατακερματίσουν το χώρο δράσης και να παρέχουν καλύτερη ακρίβεια εκτίμησης των ανθρώπινων κινήσεων με μοντέλα εκπαιδευμένα για συγκεκριμένες διεργασίες. Τα συγκεκριμένα συστήματα μπορούν να χρησιμοποιηθούν για ένα μεγάλο εύρος εφαρμογών αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων.

Σχετικά με τις HRI εφαρμογές, επικεντρωνόμαστε κυρίως στον ανθρωπομορφισμό των ρομποτικών τεχνουργημάτων, προτείνοντας μεθόδους που μπορούν να χρησιμοποιηθούν για τη μέτρηση του βαθμού ομοιότητάς τους με τον άνθρωπο και την αποδοτική αντιστοίχιση της ανθρώπινης σε ανθρωπομορφική ρομποτική κίνηση.

Τέλος, προτείνουμε μία σειρά ελαφριών, χαμηλού κόστους, εύκολα συναρμολογούμενων, υποϋπενεργούμενων και εγγενώς υποχωρητικών ρομποτικών χεριών, ανοιχτού κώδικα και υλικού, τα οποία μπορούν να χρησιμοποιηθούν τόσο για μελέτες ηλεκτρομυογραφικού ελέγχου (ακόμη και ως οικονομικές μυσηλεκτρικές προσθέσεις), όσο και για HRI εφαρμογές (για μελέτες τηλεχειρισμού ρομποτικών συστημάτων βραχίονα – χεριού), για την αρπαγή ενός ευρέως φάσματος καθημερινών αντικειμένων σε δυναμικά περιβάλλοντα, λόγο της έμφυτης τους υποχωρητικότητας.

Οι συνεισφορές της συγκεκριμένης διδακτορικής διατριβής επεξηγούνται λεπτομερώς στις ακόλουθες ενότητες, δίνοντας έμφαση στα ακόλουθα τέσσερα πεδία:

- Διεπαφές ηλεκτρομυογραφικών σημάτων.
- Ανθρωπομορφισμός ρομποτικών συστημάτων.
- Αντιστοίχιση ανθρώπινης σε ρομποτική κίνηση.
- Ρομπότ που λειτουργούν σε δομημένα και δυναμικά περιβάλλοντα.

1.1 Ηλεκτρομυογραφικές διεπαφές

Παρόλο που οι διεπαφές ηλεκτρομυογραφικών σημάτων είναι πολλά υποσχόμενες και μπορεί να έχουν καθοριστικό ρόλο στην αλληλεπίδραση ανθρώπου – ρομπότ/υπολογιστή στα επερχόμενα χρόνια, έχουν επίσης συγκεκριμένα προβλήματα τα οποία έχουν εντοπιστεί και συζητηθεί σε πολλές μελέτες στο παρελθόν.

Κάποια από αυτά τα προβλήματα είναι η πολυπλοκότητα και υψηλή διαστατικότητα του ανθρώπινου μυοσκελετικού συστήματος, η μη γραμμική σχέση μεταξύ της ανθρώπινης μυοηλεκτρικής δραστηριότητας και της κίνησης ή της δύναμης που τίθεται προς εκτίμηση, η μυϊκή κόπωση, ο θόρυβος των σημάτων που προκαλείται από τις διαταραχές στην θέση των ηλεκτροδίων, οι μυϊκές συσπάσεις, ο ιδρώτας κλπ.

Προχειμένου να αντιμετωπιστεί το πρόβλημα της υψηλής διαστατικότητας, στο παρελθόν χρησιμοποιήθηκε η μέθοδος Ανάλυσης Κυρίων Συνιστωσών (PCA - Principal Components Analysis) για να ερευνηθούν τόσο η κινηματική του ανθρώπινου χεριού όσο και οι μυϊκές συνέργειες [14--19]. Μία ακόμα δυσκολία την οποία αντιμετωπίζουν οι ερευνητές στο πεδίο των ηλεκτρομυογραφικών διεπαφών, είναι η μη-γραμμική σχέση μεταξύ των μυσηλεκτρικών ενεργοποιήσεων και της ανθρώπινης κίνησης [20]. Για να ξεπεράσουν αυτό το πρόβλημα, η πλειοψηφία των ερευνητών αποφεύγει να αποκωδικοποιεί μία συνεχή αναπαράσταση της ανθρώπινης κίνησης, εστιάζοντας σε μία διακριτή προσέγγιση όπως ο κατευθυντήριος έλεγχος ενός ρομποτικού συστήματος [21], ή ο ηλεκτρομυογραφικός έλεγχος ενός πολυδάκτυλου χεριού σε μία σειρά από διακριτές διαμορφώσεις/θέσεις [22--27].

Σχετικά με τη προσέγγιση του συνεχούς ηλεκτρομυογραφικού ελέγχου, διάφορα μοντέλα έχουν χρησιμοποιηθεί ώστε να παρέχουν εκτιμήσεις για την βασισμένη στις μυοηλεκτρικές ενεργοποιήσεις ανθρώπινη κίνηση. Κάποιες από αυτές είναι, το μυοσκελετικό μοντέλο Hill [28] το οποίο είναι το πιο ευρέως χρησιμοποιούμενο μοντέλο [20, 29--32], τα μοντέλα χώρου κατάστασης [1, 33, 34], Τεχνητά Νευρωνικά Δίκτυα (ANN - Artificial Neural Networks) [35--37] και παλινδρομητές βασισμένοι σε Μηχανές Διανυσματικής Υποστήριξης (SVM - Support Vector Machines) [2, 38].

Συνεισφορά της διδακτορικής διατριβής

Στην συγχεχριμένη διδαχτοριχή διατριβή, διατυπώνουμε ένα ολοχληρωμένο σχήμα μάθησης για διεπαφές ηλεχτρομυογραφιχών σημάτων, το οποίο εχμεταλλεύεται έναν ταξινομητή, ο οποίος και συνδυάζεται με έναν παλινδρομητή (συνδυάζοντάς τη διαχριτή και συνεχή προσέγγιση). Ο ταξινομητής και ο παλινδρομητής συνεργάζονται πλεονασματιχά ώστε να διαιρέσουν/χαταχερματίσουν τον χώρο δράσης και να παρέχουν χαλύτερη αχρίβεια εχτίμησης της ανθρώπινης χίνησης με μοντέλα εχπαιδευμένα για συγχεχριμένες διεργασίες. Το όλο σχήμα είναι βασισμένο στη μεθοδολογία των Δασών Τυχαιότητας (RF - Random Forests) τόσο για την ταξινόμηση όσο χαι για την παλινδρόμηση.

Ηλεκτρομυογραφικά σήματα χρησιμοποιούνται ώστε να διακριθούν κινήσεις προσέγγισης για αρπαγή αντικειμένων στον τρισδιάστατο χώρο. Η ειδικότητα των μοντέλων ώς προς την διεργασία, εισάγεται σε τρία διαφορετικά επίπεδα, υποδηλώνοντας πως η μυοηλεκτρική δραστηριότητα διαφοροποιείται: μεταξύ κινήσεων προσέγγισης για αρπαγή αντικειμένων προς διαφορετικούς υποχώρους, μεταξύ κινήσεων προσέγγισης για αρπαγή προς διαφορετικά αντικείμενα, όπως επίσης και μεταξύ κινήσεων προσέγγισης για αρπαγή προς διαφορετικά αυτικείμενα, όπως επίσης και μεταξύ κινήσεων προσέγγισης για αρπαγή προς ένα συγκεκριμένο αντικείμενο, τοποθετημένο σε συγκεκριμένη θέση αλλά με την πρόθεση να εκτελεσθούν διαφορετικές διεργασίες (με το αρπαγμένο αντικείμενο).

Ο ταξινομητής χρησιμοποιεί την μυσηλεκτρική δραστηριότητα ώστε να διακρίνει μεταξύ αυτών των κινήσεων στον m-διάστατο χώρο των ηλεκτρομυογραφικών σημάτων (m είναι ο αριθμός των καναλιών). Ο παλινδρομητής χρησιμοποιείται πρώτα προκειμένου να εκπαιδεύσει μοντέλα συγκεκριμένων διεργασιών για όλες τις πιθανές διαφορετικές διεργασίες, έτσι ώστε ένα συγκεκριμένο μοντέλο να ενεργοποιείται ανάλογα με την απόφαση της ταξινόμησης.

Η απόφαση ταξινόμησης λαμβάνεται σε συχνότητα 1KHz, επιτρέποντας στο σχήμα μας να προσδιορίζει την εκτελούμενη διεργασία σε πραγματικό χρόνο. Το προτεινόμενο σχήμα μπορεί να παρέχει συνεχείς εκτιμήσεις για την κινηματική ολόκληρου του συστήματος βραχίονα – χεριού (27 μοντελοποιημένων βαθμών ελευθερίας, 7 για τον ανθρώπινο βραχίονα και 20 για το ανθρώπινο χέρι). Αυτές οι εκτιμήσεις μπορούν να χρησιμοποιηθούν από μία σειρά διεπαφών ηλεκτρομυογραφικών σημάτων για διαφορετικές εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων. Περισσότερες πληροφορίες μπορούν να αναζητηθούν στο Κεφάλαιο 3.

Σημαντικές ερωτήσεις για τις διεπαφές ηλεκτρομυογραφικών σημάτων

- Τα μυϊκά μοτίβα συνενεργοποίησης διαφοροποιούνται μεταξύ διαφορετικών διεργασιών;
- Μπορούμε να αποχωδιχοποιήσουμε την ανθρώπινη πρόθεση από μυσηλεχτριχές ενεργοποιήσεις;
- Τι πληροφορίες σχετικά με την εκτελούμενη διεργασία μπορούμε να εξάγουμε από τα ηλεκτρομυογραφικά σήματα;
- Μπορούμε να βελτιώσουμε την αχρίβεια εχτίμησης της χίνησης μέσω των ηλεχτρομυογραφιχών σημάτων;
- Μπορούμε να προσδιορίσουμε ποια ηλεκτρομυογραφικά κανάλια είναι τα πιο σημαντικά;

1.2 Ανθρωπομορφισμός ρομποτικών συστημάτων

Ο ανθρωπομορφισμός η αλλιώς η ομοιότητα της ρομποτικής κίνησης με την ανθρώπινη κίνηση, είναι επίσης πολύ σημαντικός για πληθώρα εφαρμογών αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων.

Σχεδόν 140 χρόνια πριν, ο Κάρολος Δαρβίνος χαρακτήρισε τον ανθρωπομορφισμό ως ένα απαραίτητο εργαλείο για την αποδοτική κατανόηση των μη-ανθρώπινων όντων [39]. Επιπλέον, πρόσφατες έρευνες έδειξαν ότι όσο πιο ανθρωπομορφικό είναι ένα ρομπότ από πλευρά κίνησης, εμφάνισης, εκφράσεων και αντιληπτής νοημοσύνης, τόσο πιο εύκολα μπορεί να καθιερώσει μία σταθερή κοινωνική σχέση με τον άνθρωπο [40--42].

Στο παρελθόν προτάθηκαν διαφορετικοί δείκτες και μονάδες μέτρησης για την αξιολόγηση του ανθρωπομορφισμού ρομποτικών συστημάτων. Οι περισσότεροι από αυτούς επικεντρώθηκαν στον ανθρωπομορφισμό ρομποτικών χεριών.

Στα [43] και [44], ο ανθρωπομορφισμός προκύπτει ως το σταθμισμένο άθροισμα κινηματικής, επιφανειών επαφής και βαθμολογιών μεγέθους, ενώ στα [45] και [46] ο ανθρώπινος και ρομποτικός χώρος εργασίας αναπαραστάθηκαν σε χώρους χαμηλής διάστασης και μετά συγκρίθηκαν. Παρόλο που αυτές οι τελευταίες έρευνες έχουν αρκετό ενδιαφέρον, καμία δεν πρότεινε ένα συστηματικό τρόπο σύγκρισης της κινηματικής των ρομποτικών χεριών με ολόκληρο το κινηματικό μοντέλο του ανθρώπινου χεριού (π.χ., λαμβάνοντας υπόψη την ευκινησία των κοκάλων της παλάμης).

Συνεισφορά της διδακτορικής διατριβής

Σε αυτή τη διδακτορική διατριβή, διακρίνουμε τις διαφορετικές έννοιες του ανθρωπομορφισμού, εισάγοντας τον λειτουργικό ανθρωπομορφισμό και τον αντιληπτό ανθρωπομορφισμό. Περισσότερες πληροφορίες σχετικά με τις διαφορές τους, μπορούν να βρεθούν στο Κεφάλαιο 4.

Επιπλέον, για την μέτρηση του ανθρωπομορφισμού των ρομποτικών χεριών, προτείνουμε μία ολοκληρωμένη μεθοδολογία βασισμένη σε μεθόδους της θεωρίας συνόλων και της υπολογιστικής γεωμετρίας. Πιο συγκεκριμένα, παρουσιάζουμε μία σειρά από μετρήσεις βασισμένες στην ανάλυση του χώρου δράσης των δακτύλων, αξιολογώντας τις σχετικές καλύψεις των ανθρώπινων και ρομποτικών χώρων δράσης των φαλαγγών καθώς και των ανθρώπινων και ρομποτικών χώρων δράσης των πλαισίων των βάσεων των δακτύλων. Ένα σταθμισμένο άθροισμα των προτεινόμενων κριτηρίων, τα οποία μπορούν να προσαρμοστούν κατάλληλα ανάλογα και με τις προδιαγραφές της κάθε έρευνας, καταλήγει σε έναν μετρικό ανθρωπομορφισμού το οποίο κυμαίνεται μεταξύ 0 (μη ανθρωπομορφικά ρομποτικά χέρια) και 1 (ρομποτικά χέρια πανομοιότυπα με αυτά του ανθρώπου).

Τρία διαφορετικά ρομποτικά χέρια εξετάζονται ώστε να δοκιμαστεί η αποδοτικότητα της προτεινόμενης μεθόδου και παρέχεται μία σειρά από προσομοιωμένα παραδείγματα των διαφορετικών τύπων χώρων δράσης. Λεπτομέρειες σχετικά με την ποσοτικοποίηση του ανθρωπομορφισμού ρομποτικών χεριών, μπορούν να βρεθούν στο Κεφάλαιο 5.

Σημαντικές ερωτήσεις σχετικά με τον ανθρωπομορφισμό

Μερικές σημαντικές ερωτήσεις τις οποίες προσπαθούμε να απαντήσουμε σε αυτή τη διδακτορική διατριβή είναι οι παρακάτω:

- Πώς μπορούμε να ορίσουμε τον ανθρωπομορφισμό ενός ρομποτιχού συστήματος (π.χ. χεριού);
- Ποιες είναι οι διαφορετικές έννοιες του ανθρωπομορφισμού;
- Ποιες εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων απαιτούν τον ανθρωπομορφισμό;
- Είναι δυνατόν να ποσοτιχοποιηθεί ο ανθρωπομορφισμός των ρομποτιχών συστημάτων;
- Μπορούμε να εξάγουμε από το ανθρωπομορφικό μετρικό, προδιαγραφές για το σχεδιασμό ανθρωπομορφικών ρομπότ;

1.3 Αντιστοίχιση της ανθρώπινης χίνησης σε ανθρωπομορφιχή ρομποτιχή χίνηση

Το πρόβλημα αντιστοίχισης της ανθρώπινης σε ρομποτική κίνηση, υπήρξε ένα από τα πιο σημαντικά προβλήματα στο πεδίο της ρομποτικής, τα τελευταία 50 χρόνια.

Στο παρελθόν προτάθηκαν διαφορετικές μεθοδολογίες για την αντιστοίχιση της ανθρώπινης κίνησης σε ρομποτική κίνηση: αντιστοίχιση των θέσεων των δακτυλικών άκρων (fingertips mapping) [47, 48], αντιστοίχιση άρθρωσης σε άρθρωση (joint-tojoint mapping) [49], λειτουργική αντιστοίχιση στάσεων/διαμορφώσεων (functional pose mapping) [50] και αντιστοίχιση για συγκεκριμένα αντικείμενα (object specific mapping) [51]. Επιπλέον, ακόμη και οι ανθρώπινες συνέργειες αρπαγής αντικειμένων, αντιστοιχήθηκαν σε συνέργειες ρομποτικών χεριών [52, 53].

Σχετικά με την αντιστοίχιση της κίνησης του ανθρώπινου βραχίονα σε κίνηση του ρομποτικού βραχίονα, οι περισσότερες προηγούμενες έρευνες επικεντρώθηκαν σε μία προσέγγιση ευθείας και αντίστροφης κινηματικής, ώστε να επιτευχθεί ίδια θέση και προσανατολισμός για τα ανθρώπινα και ρομποτικά τελικά σημεία δράσης (endeffectors) [54, 55]. Σε ορισμένες μελέτες προτάθηκαν συγκεκριμένες μεθοδολογίες, ώστε να περιγραφούν και να μοντελοποιηθούν οι εξαρτήσεις μεταξύ των γωνιών των ανθρώπινων αρθρώσεων, επιτυγχάνοντας έτσι ανθρωπομορφική ρομποτική κίνηση [56]. Στην γενική περίπτωση ρομποτικών συστημάτων με πολλαπλούς/πλεονάζοντες βαθμούς ελευθερίας, το πρόβλημα της αντιστοίχισης της ανθρώπινης κίνησης σε ρομποτική κίνηση, διατυπώνεται ως ένα μη γραμμικό πρόβλημα βελτιστοποίησης με περιορισμούς [24, 56, 57].

Όσον αφορά την αντιστοίχιση της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση, μερικές πρόσφατες έρευνες επικεντρώθηκαν στην απόσπαση ανθρωπομορφικών διατάξεων στόχων για ρομποτικά συστήματα [58--60], χωρίς όμως να προτείνουν μία συστηματική μέθοδο για την εξαγωγή ανθρωπομορφικής ρομποτικής κίνησης ακόμα και για ρομποτικά τεχνουργήματα με μη-τετριμμένα κινηματικά στοιχεία (π.χ., συστήματα βραχίονα - χεριού με υπερπλεονάζοντες βαθμούς ελευθερίας).

Συνεισφορά διδακτορικής διατριβής

Σε αυτή τη διδακτορική διατριβή προτείνουμε διάφορα σχήματα αντιστοίχισης της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση, για διαφορετικές εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων. Διαφορετικά κριτήρια του ανθρωπομορφισμού εισάγονται και χρησιμοποιούνται ώστε να επιτευχθεί ανθρωπομορφική ρομποτική κίνηση. Για τα ρομποτικά συστήματα βραχίονα – χεριού με επιλύσιμη αντίστροφη κινηματική (ΙΚ - Inverse Kinematics), οι λύσεις υπολογίζονται αναλυτικά και η πιο ανθρωπομορφική λύση επιλέγεται με τη χρήση συγκεκριμένων κριτηρίων λειτουργικού ανθρωπομορφισμού.

Για τη γενική περίπτωση των ρομποτικών βραχιόνων και χεριών με μη τυπικά κινηματικά χαρακτηριστικά (π.χ., m αριθμό δακτύλων και πλεονάζοντες βαθμούς ελευθερίας), η αντιστοίχιση της ανθρώπινης κίνησης σε ρομποτική, μπορεί να διατυπωθεί ως ένα πρόβλημα βελτιστοποίησης, το οποίο επιλύει στόχους αντίστροφης κινηματικής κάτω από συγκεκριμένες συνθήκες θέσης και προσανατολισμού (επιβαλλόμενοι από τον άνθρωπο λειτουργικοί περιορισμοί), αντιμετωπίζοντας παράλληλα την πλεονασματικότητα των λύσεων με συγκεκριμένα κριτήρια ανθρωπομορφισμού.

Πιο συγχεχριμένα, η αντιστοίχιση διατυπώνεται ως ένα σύνθετο πρόβλημα βελτιστοποίησης για ολόχληρο το σύστημα βραχίονα-χεριού, όπου τα αχροδάχτυλα του ρομποτιχού χεριού θεωρούνται ως τα τελιχά σημεία δράσης αντί για τον ρομποτιχό χαρπό. Επιπλέον, για την περίπτωση των ρομποτιχών χεριών με m αριθμό δαχτύλων, προσδιορίζουμε την θέση του άχρου του ανθρώπινου αντίχειρα ως ένα στόχο θέσης για ένα από τα ρομποτιχά δάχτυλα χαι χρησιμοποιούμε Splines για να υπολογίσουμε τις υπόλοιπες θέσεις των ρομποτιχών δαχτυλιχών άχρων, με παρεμβολή μεταξύ των υπόλοιπων τεσσάρων θέσεων των αχροδαχτύλων του ανθρώπινου χεριού.

Περισσότερες λεπτομέρειες σχετικά με τα σχήματα αντιστοίχισης, μπορούν να βρεθούν στο Κεφάλαιο 6. Λεπτομέρειες σχετικά με τις πιθανές εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων καθώς και πειράματα που διεξάχθηκαν προκειμένου να επικυρωθεί η αποδοτικότητα των προτεινόμενων μεθόδων, μπορούν να βρεθούν στο Κεφάλαιο 7.

Σημαντικές ερωτήσεις σχετικά με τα σχήματα αντιστοίχισης της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση

- Είναι δυνατόν να μεταφερθούν ανθρώπινες δεξιότητες σε ρομποτικά συστήματα; Πως;
- Είναι δυνατόν να αντιστοιχηθεί η ανθρώπινη χίνηση σε ρομποτιχή χίνηση με έναν ανθρωπομορφιχό τρόπο;
- Είναι δυνατόν να αντιστοιχηθεί η ανθρώπινη χίνηση σε ανθρωπομορφιχή ρομποτιχή χίνηση για συστήματα με μη τυπιχά χινηματιχά στοιχεία;
- Είναι δυνατόν να επιτευχθεί ο τηλεχειρισμός ρομποτικών συστημάτων βραχίονα - χεριού με ανθρωπομορφικό τρόπο;

1.4 Λειτουργία και αλληλεπίδραση των ρομπότ σε δομημένα και δυναμικά περιβάλλοντα

Στις μέρες μας είναι σύνηθες τα ρομποτικά συστήματα να λειτουργούν και να αλληλεπιδρούν όχι μόνο μέσα σε προκαθορισμένα, προτέρων γνωστά και δομημένα περιβάλλοντα, αλλά και σε καθημερινά, δυναμικά περιβάλλοντα. Ο όρος αλληλεπίδραση χρησιμοποιείται ως επί το πλείστον για ρομποτικούς τελικούς επενεργητές, οι οποίοι είναι συνήθως ρομποτικά χέρια (τυπικά μέρη ρομποτικών συστημάτων βραχίονα-χεριού). Κατα τη διάρκεια των τελευταίων πενήντα χρόνων, οι ερευνητές του κλάδου της ρομποτικής, έχουν εμπνευστεί και προσπαθήσει να κατανοήσουν τον πιο ευέλικτο και επιδέξιο τελικό επενεργητή της φύσης, το ανθρώπινο χέρι. Τα πρώτα ρομποτικά χέρια ήταν στην πραγματικότητα ρομποτικές λαβίδες, ικανές να πιάνουν ένα περιορισμένο εύρος αντικειμένων με απλή γεωμετρία, τα οποία ήταν τοποθετημένα σε εκ των προτέρων γνωστά περιβάλλοντα. Σήμερα, εξαιτίας της χαμηλής πολυπλοκότητας και του χαμηλού κόστους τους, οι ρομποτικές λαβίδες εξακολουθούν να αποτελούν τη πιο συνηθισμένη εναλλακτική [61, 62].

Όμως το state-of-the-art των ρομποτικών χεριών ακολουθεί το δρόμο της αυξημένης απόδοσης, πολυπλοκότητας, κόστους και ανθρωπομορφισμού [63]. Τέτοια ρομποτικά χέρια έχουν πολλαπλούς βαθμούς ελευθερίας, είναι πλήρως επενεργούμενα, άκαμπτα και εξοπλισμένα με εκλεπτυσμένους ενεργοποιητές και αισθητήρια στοιχεία, προκειμένου να αντιλαμβάνονται το περιβάλλον. Για παράδειγμα είναι κρίσιμο για ένα άκαμπτο ρομποτικό χέρι να διαθέτει αισθητήρες αφής στα ακροδάκτυλα του, προκειμένου οι δυνάμεις αλληλεπίδρασης (π.χ., με ένα πιασμένο αντικείμενο) να μετρηθούν και να εφαρμοστούν οι κατάλληλες πολιτικές ελέγχου δυνάμεων.

Συγκεκριμένα σχήματα ελέγχου δυνάμεων, μπορούν να εξασφαλίσουν αποτελεσματικό πιάσιμο καθημερινών αντικειμένων, αποφεύγοντας πιθανές ζημιές τόσο στο ρομπότ όσο και στο περιβάλλον (π.χ., ώστε να αποφευχθεί η καταστροφή ενός εύθραυστου αντικειμένου). Όμως αυτά τα χέρια είναι επίσης δαπανηρά και βαριά, και επομένως μη προσιτά για πολλά ερευνητικά κέντρα παγκοσμίως και ακατάλληλα για διάφορες εφαρμογές ηλεκτρομυογραφικού ελέγχου, όπως η ανάπτυξη μυσηλεκτρικών προσθετικών μελών.

Πρόσφατα, αρχετές έρευνες επικεντρώθηκαν σε ρομποτικά χέρια χαμηλού κόστους, βασισμένα σε ελαστομερή υλικά ή ελαστικούς συνδέσμους [64--66]. Τέτοια χέρια, παρά την υποεπενεργούμενη σχεδίασή τους, είναι ικανά να εκτελέσουν απλές διεργασίες χειρισμού αντικειμένων [67], και έχουν γίνει εμπορικώς διαθέσιμα σε σημαντικά χαμηλότερες τιμές [68]. Σήμερα, η ελάχιστη τιμή ενός ρομποτικού χεριού είναι 400 USD και το ελάχιστο βάρος είναι 400 gr (0.88 lbs) [64].

Συνεισφορά της διδακτορικής διατριβής

Σε αυτή τη διδακτορική διατριβή, προτείνουμε μία νέα προσέγγιση σχεδιασμού για τη δημιουργία προσιτών (κοστίζουν λιγότερο από 100 USD), ελαφρών (ζυγίζουν λιγότερο από 200 gr | 0.44 lbs), αρθρωτών, εγγενώς υποχωρητικών, υποϋπενεργούμενων ρομποτικών χεριών τα οποία μπορούν να παραχθούν με καθημερινά υλικά και να συναρμολογηθούν εύκολα.

Τα προαναφερθέντα ρομποτικά χέρια μπορούν να χρησιμοποιηθούν για έρευνες τηλεχειρισμού, για να δημιουργηθούν ρομποτικές πλατφόρμες ικανές για αρπαγή αντικειμένων (π.χ., πλατφόρμες εδάφους και εναέρια οχήματα, για τα οποία ο ελαφρύς σχεδιασμός είναι προαπαιτούμενος), για την δημιουργία ρομπότ για εκπαιδευτικούς σκοπούς ή ακόμα και για την δημιουργία προσιτών, μυσηλεκτρικών προσθετικών συστημάτων.

Στα πλαίσια της συγκεκριμένης διατριβής παρέχονται εκτεταμένα πειραματικά μοντέλα, προκειμένου να επικυρωθεί η απόδοση των προτεινόμενων χεριών. Τα πειράματα περιλαμβάνουν δοκιμές αρπαγής πολυάριθμων καθημερινών αντικειμένων, μυοηλεκτρικό έλεγχο ρομποτικών χεριών, κάποια αρχικά συμπεράσματα από την ενσωμάτωση ενός χεριού σε εναέριο όχημα (ArDrone quadrotor) με ικανότητες αρπαγής αντικειμένων, και την δημιουργία αυτόνομων σχημάτων αρπαγής αντικειμένων ακόμη και υπο αβεβαιότητες σχετικά με τη θέση και το σχήμα του αντικειμένου. Λεπτομέρειες για όλα τα πειράματα μπορούν να βρεθούν στο κεφάλαιο 9.

Σημαντικές ερωτήσεις σχετικά με την αλληλεπίδραση των ρομπότ με δυναμικά περιβάλλοντα

- Μπορούμε να απλοποιήσουμε το σχέδιο των υφιστάμενων ρομποτιχών χεριών;
- Πώς μπορούμε να μειώσουμε το κόστος και το βάρος των ρομποτικών χεριών;
- Πώς μπορούμε να μειώσουμε την πολυπλοκότητα των σχημάτων ελέγχου;
- Μπορούμε να σχεδιάσουμε ρομποτικά χέρια που λειτουργούν αποδοτικά σε δυναμικά περιβάλλοντα;
- Είναι δυνατό να δημιουργηθούν ρομποτικά χέρια χαμηλού κόστους και βάρους
 τα οποία να είναι και ικανά για αρπαγή πληθώρας καθημερινών αντικειμένων;
- Θα είναι αυτά τα χέρια ικανά για αρπαγή αντικειμένου, ακόμα και υπο συνθήκες αβεβαιότητας της θέσης και του σχήματος του;

2. Πειραματική Διάταξη

Στην συγκεκριμένη ενότητα παρουσιάζουμε την πειραματική διάταξη που χρησιμοποιήσαμε στην συγκεκριμένη διδακτορική διατριβή. Πιο συγκεκριμένα:

- Τα συστήματα καταγραφής της ανθρώπινης κίνησης.
- Τον βιοενισχυτή που καταγράφει τις ανθρώπινες μυοηλεκτρικές ενεργοποιήσεις.
- Τους αισθητήρες που χρησιμοποιήσαμε για να καταγράψουμε στοιχεία του περιβάλλοντος (π.χ., θέσεις και γεωμετρίες αντικειμένων).
- Τα ρομπότ που χρησιμοποιήσαμε για διαφορετικές εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων.
- Τα υπολογιστικά συστήματα που χρησιμοποιήθησαν και τα πρωτόκολλα επικοινωνίας.

2.1 Ρομπότ

Το Mitsubishi PA-10 είναι ένας ρομποτικός βραχίονας 7 βαθμών ελευθερίας οι οποίοι είναι διατεταγμένοι κατά ανθρωπομορφικό τρόπο: 3 για τον ώμο, 2 για τον αγκώνα και 2 για τον καρπό. Ο σερβοελεγκτής του ρομπότ επικοινωνεί με τον υπολογιστή-/ελεγκτή του ρομπότ μέσω του ARCNET πρωτόκολλου. Περισσότερες πληροφορίες μπορούν να αναζητηθούν στην σχετική δημοσίευση [69].



Ο ρομποτικός βραχίονας Mitsubishi PA10.

Το DLR/HIT II είναι ένα πενταδάκτυλο ρομποτικό χέρι με 15 βαθμούς ελευθερίας. Το DLR/HIT II αναπτύχθηκε από το DLR (Γερμανική Διαστημική Υπηρεσία) και το HIT (Harbin Institute of Technology). Το συγκεκριμένο ρομποτικό χέρι είναι εφοδιασμένο με 5 πανομοιότυπα ρομποτικά δάκτυλα με 3 βαθμούς ελευθερίας. Οι τελευταίες δυο φάλαγγες είναι συζευγμένες με ατσάλινο σύρμα και λόγο γωνιών αρθρώσεων ένα προς ένα. Οι διαστάσεις του μπορούν να χαρακτηριστούν ως ανθρωπομορφικές και το συνολικό βάρος είναι αρκετά χαμηλό 1.6 κιλά. Περισσότερες πληροφορίες μπορούν να βρεθούν στο [70].



Το πενταδάκτυλο DLR/HIT ΙΙ ρομποτικό χέρι.

2.2 Επικοινωνίες

Ένας προσωπικός υπολογιστής (Ubuntu Linux OS 12.04) χρησιμοποιήθηκε για την καταγραφή των ανθρώπινων κινηματικών στοιχείων και των ανθρώπινων μυοηλεκτρικών ενεργοποιήσεων. Κατάλληλες συναρτήσεις αναπτύχθηκαν σε C/C++ για να διευκολύνουν την συλλογή δεδομένων.

Ο ίδιος προσωπικός υπολογιστής ήταν υπεύθυνος και για τον σχεδιασμό πορείας και αρπαγής αντικειμένων. Το συγκεκριμένο PC, εγκαθιδρούσε επικοινωνία βασισμένη σε TCP με τον υπολογιστή/ελεγκτή του Mitsubishi PA10 ρομποτικού βραχίονα (Gentoo Linux soft real-time OS) και UDP επικοινωνία με τον υπολογιστή/ελεγκτή του DLR/HIT II ρομποτικού χεριού (QNX hard real-time OS).



Τα συστήματα καταγραφής της ανθρώπινης κίνησης και ο βιοενισχυτής που χρησιμοποιήθηκε για την καταγραφή των ηλεκτρομυογραφικών σημάτων, απεικονίζονται στο συγκεκριμένο σχήμα.

Διεπαφές Ηλεκτρομυογραφικών Σημάτων

Ένα Σχήμα Μηχανικής Μάθησης για Διεπαφές Ηλεκτρομυογραφικών Σημάτων

Στην συγκεκριμένη ενότητα παρουσιάζουμε ένα σχήμα μηχανικής μάθησης, το οποίο μπορεί να χρησιμοποιηθεί για την αποκωδικοποίηση της ανθρώπινης πρόθεσης και της ανθρώπινης κίνησης, από τις μυοηλεκτρικές ενεργοποιήσεις των μυών του ανθρώπινου άνω άκρου. Το προτεινόμενο σχήμα μηχανικής μάθησης χρησιμοποιεί ένα ταξινομητή ο οποίος συνεργάζεται με έναν παλινδρομητή για τον κατακερματισμό του χώρου δράσης και την επίτευξη καλύτερης αποκωδικοποίησης της ανθρώπινης κίνησης με μοντέλα εκπαιδευμένα για συγκεκριμένες διεργασίες.

Τρία χαρακτηριστικά των διαφορετικών διεργασιών έχουν διακριθεί:

- Υποχώρος εργασίας.
- Αντικείμενο προς αρπαγή.
- Διεργασία προς εκτέλεση με το αρπαχθέν αντικείμενο.

Για την εκπαίδευση τόσο των ταξινομητών όσο και των παλινδρομητών, χρησιμοποιήθηκε η μέθοδος των Δασών Τυχαιότητας (Random Forests). Η απόφαση του ταξινομητή η οποία λαμβάνεται σε πραγματικό χρόνο ενεργοποιεί ένα μοντέλο αποκωδικοποίησης της ανθρώπινης κίνησης, το οποίο ειναι εκπαιδευμένο για την αναγνωρισθείσα διεργασία.

Τα μοντέλα που εκπαιδεύονται για συγκεκριμένες διεργασίες επιτυγχάνουν καλύτερα αποτελέσματα από τα γενικά μοντέλα που εκπαιδεύονται για όλο τον χώρο. Το συγκεκριμένο σχήμα μηχανικής μάθησης μπορεί να χρησιμοποιηθεί από διεπαφές ηλεκτρομυογραφικών σημάτων για σωρεία εφαρμογών αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων.

3.1 Πειράματα

Διαφορετικοί τύποι πειραμάτων εκτελέστηκαν για την σύνθεση του συγκεκριμένου σχήματος μηχανικής μάθησης. Τα πειράματα εκτελέστηκαν από 5 υποκείμενα (4 άνδρες, 1 γυναίκα) 21, 24, 27, 28 και 40 χρονών. Όλα τα πειράματα εκτελέστηκαν από τα υποκείμενα με το κυρίαρχο χέρι τους. Κατά την διάρκεια των πειραμάτων, τα υποκείμενα εκτέλεσαν επαναλαμβανόμενες κινήσεις προσέγγισης και αρπαγής διαφορετικών αντικειμένων, από διαφορετικούς υποχώρους και προκειμένου να εκτελέσουν ένα πλήθος διαφορετικών διεργασιών.



Μια βιβλιοθήκη που περιέχει 3 διαφορετικά αντικείμενα (έναν μαρκαδόρο, ένα τετράγωνο κουτί και μια κούπα), τοποθετημένα σε 5 διαφορετικές θέσεις σε 3 διαφορετικά ράφια. Η συγκεκριμένη βιβλιοθήκη χρησιμοποιήθηκε για τα εκτελεσθέντα πειράματα.



Παραδείγματα των διαφορετικών διεργασιών που εκτελέστηκαν κατά την διάρκεια των πειραμάτων.

3.2 Μέθοδοι

Μερικές προδιαγραφές που κάθε σχήμα μηχανικής μάθησης για διεπαφές ηλεκτρομυογραφικών σημάτων πρέπει να έχει, είναι οι εξής:

- Να μπορεί να αποχωδιχοποιεί την ανθρώπινη πρόθεση (ταξινόμηση).
- Να μπορεί να αποκωδικοποιεί μια συνεχή εκτίμηση της ανθρώπινης κίνησης (παλινδρόμηση).

- Να μπορεί να χρησιμοποιηθεί από ένα ρομποτικό σύστημα σε πραγματικό χρόνο.
- Να μπορεί εκπαιδευτεί εύκολα και γρήγορα για διαφορετικούς χρήστες.
- Να μπορεί να χρησιμοποιηθεί για δεδομένα υψηλής διαστατικότητας και για μεγάλες βάσεις βιολογικών και κινηματικών δεδομένων.







Σχεδιάγραμμα παλινδρομητή.

Όπως έχουμε ήδη αναφέρει οι ταξινομητές και οι παλινδρομητές που χρησιμοποιούνται στην συγκεκριμένη διδακτορική διατριβή βασίζονται στην μεθοδολογία των Δασών Τυχαιότητας (Random Forests). Το τελικό σχήμα μηχανικής μάθησης περιλαμβάνει τρία κύρια τμήματα. Το τμήμα του ταξινομητή παρέχει την "απόφαση" για την ανθρώπινη πρόθεση, ως προς τον ποιόν υποχώρο θέλει να κινηθεί ο χρήστης, ποιό αντικείμενο θέλει να αρπάξει και ποιά διεργασία να εκτελέσει με το συγκεκριμένο αντικείμενο. Το δεύτερο τμήμα του παλινδρομητή, εξετάζει την απόφαση του ταξινομητή και ενεργοποιεί ένα μοντέλο εκπαιδευμένο για την αναγνωρισθείσα διεργασία (ένα μοντέλο εκπαιδευμένο για τον συγκεκριμένο συνδυασμό υποχώρου, αντικειμένου και διεργασίας). Το τρίτο τμήμα της αντιστοίχησης της ανθρώπινης χίνησης σε ρομποτιχή χίνηση, μετασχηματίζει τη εχτιμώμενη από το μοντέλο αποχωδιχοποίησης ανθρώπινη χίνηση, σε ανθρωπομορφιχή ρομποτιχή χίνηση.



Στο συγκεκριμένο σχήμα απεικονίζεται το τελικό σχεδιάγραμμα του σχήματος μηχανικής μάθησης που υλοποιήσαμε για διεπαφές ηλεκτρομυογραφικών σημάτων. Τρία κύρια τμήματα μπορούν να διακριθούν, το τμήμα του ταξινομητή (Classification Module), το τμήμα του παλινδρομητή (Regressor - Task Specific Motion Decoding Module) και το τμήμα αντιστοίχησης της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση (Mapping Human to Robot Motion Module). Μία πιθανή εφαρμογή του συγκεκριμένου σχήματος είναι ο βασισμένος σε ηλεκτρομυογραφικά σήματα τηλεχειρισμός ενός συστήματος βραχίονα - χεριού.

4. Ο Ρόλος του Ανθρωπομορφισμού



Το ανθρωπομορφικό ρομποτικό σύστημα βραχίονα χεριού του DLR.

Στις μέρες μας ο ανθρωπομορφισμός είναι απαραίτητος για 2 χυρίως λόγους:

- Για ασφάλεια στις διαφορετικές εφαρμογές αλληλεπίδρασης ανθρώπου και ρομποτικών συστημάτων.
- Για την καθιέρωση κοινωνικής σύνδεσης μεταξύ ανθρώπου και ρομπότ, εφόσον τα ρομπότ είναι αρεστά στον άνθρωπο.

Όσον αφορά την ασφάλεια στις εφαρμογές αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων, η ανθρωπομορφική ρομποτική κίνηση μπορεί πιο εύκολα να γίνει κατανοητή και να προβλεφθεί από τους ανθρώπους. Το παραπάνω έχει σαν αποτέλεσμα σε διεργασίες όπου οι χρήστες και τα ρομπότ συνεργάζονται πλεονασματικά, αν τα ρομπότ κινούνται ανθρωπομορφικά ο χρήστης να μπορεί πιο εύκολα να προσαρμόσει την κίνηση του, αποφεύγοντας πιθανούς τραυματισμούς.

Για την περίπτωση της κοινωνικής σύνδεσης, όσο πιο ανθρωπομορφικό είναι ένα ρομπότ σε εμφάνιση (χρήση ανθρωπομορφικών διαστάσεων, τεχνητού δέρματος κτλ.), κίνηση (συνεργιστική κίνηση), εκφράσεις (π.χ., εκφράσεις προσώπου) και αντιλαμβανόμενη ευφυία (πόσο έξυπνο φαίνεται το ρομπότ), τόσο πιο πιθανό είναι να αναπτύξει μια σταθερή κοινωνική σχέση με τους ανθρώπους γύρω του. Εξαίρεση σε αυτό τον κανόνα αποτελεί μόνο το φαινόμενο του uncanny valley, όπως έχει περιγραφεί στα [40] και [41]. Περισσότερες πληροφορίες για τον ανθρωπομορφισμό και τις κοινωνικές του επιπτώσεις μπορούν να βρεθούν στα [42], [71] και [72].



Ένας ρομποτικός βραχίονας βοηθά στην κατασκευή εξαρτημάτων μιας μηχανής σε εργοστάσιο της Volkswagen στην Γερμανία. Για πρώτη φορά οι άνθρωποι συνεργάζονται με τα ρομπότ χωρίς μέτρα προστασίας και φράγματα μεταξύ τους. Credit: Universal Robots (http://www.universal-robots.com).



Το ανθρωποειδές ρομπότ iCub [73]. Credit: Cheney D'souza

4.1 Οι διαφορετικές έννοιες του Ανθρωπομορφισμού

Μια πρώτη προσπάθεια να γίνει διάχριση μεταξύ των διαφορετικών κατηγοριών του ανθρωπομορφισμού επιχειρήθηκε στο [74]. Στην συγκεκριμένη μελέτη, οι συγγραφείς διακρίνουν μεταξύ του λειτουργικού (functional) και του δομικού (structural) ανθρωπομορφισμού για την κατασκευή τεχνουργημάτων που θα υποβοηθούν ασθενείς με κινητικά προβλήματα η αναπηρία. Ο λειτουργικός τρόπος για να αναπτύξεις έναν τέτοιο μηχανισμό, είναι να παρέχεις μια συγκεκριμένη λειτουργία ανεξάρτητα από την δομή της συσκευής, ενώ ο δομικός τρόπος, είναι μιμούμενος επακριβώς κάποια χαρακτηριστικά του ανθρώπινου σώματος. Όπως έχουμε ήδη τονίσει, στην συγκεκριμένη διδακτορική διατριβή επικεντρωνόμαστε κυρίως στις διαφορετικές εφαρμογές που ο ανθρωπομορφισμός μπορεί να έχει, για ρομποτικά συστήματα βραχίονα χεριού. Επομένως, επιλέγουμε να διακρίνουμε μεταξύ Λειτουργικού και Αντιληπτού Αντιλαμβανόμενου Ανθρωπομορφισμού.

Ο Λειτουργικός Ανθρωπομορφισμός αφορά ένα σχήμα αντιστοίχησης της ανθρώπινης κίνησης σε ρομποτική κίνηση το οποίο έχει σαν πρώτη προτεραιότητα την εκτέλεση μιας συγκεκριμένης λειτουργίας στον χώρο δράσης και έπειτα έχοντας επιτύχει τον αρχικό αυτό σκοπό της βελτιστοποίησης του ανθρωπομορφισμού του ρομποτικού συστήματος, ελαχιστοποιεί κάποια απόσταση μεταξύ των διαμορφώσεων του ανθρώπου και του ρομπότ. Προκειμένου να οριστεί αυτή η απόσταση, διαφορετικά μετρικά του ανθρωπομορφισμού έχουν προταθεί, τα οποία οδηγούν με χαμηλή πολυπλοκότητα σε μοναδικές ανθρωπομορφικές λύσεις.

Από την άλλη προτείνουμε τον Αντιληπτό Ανθρωπομορφισμό, σαν την υποκατηγορία εκείνη του ανθρωπομορφισμού που αφορά κίνηση με συναρμογή, την συνεργιστική κίνηση, την συμπεριφορά, τις αποφάσεις και τα συναισθήματα τα οποία μπορούν να γίνουν αντιληπτά σαν ανθρωπομορφικά. Ο Αντιληπτός Ανθρωπομορφισμός μπορεί να χωριστεί περαιτέρω σε Δομικό ή Διαμορφωτικό Ανθρωπομορφισμό (που αφορά την στιγμιαία δομική ομοιότητα και τις συνεργιστικές κινήσεις) και τον Συμπεριφορας από τα ρομπότ (π.χ., χρήση παρόμοιων εκφράσεων προσώπου).

4.2 Εφαρμογές του ανθρωπομορφισμού

Ο ανθρωπομορφισμός μπορεί να χρησιμοποιηθεί για σωρεία εφαρμογών αλληλεπίδρασης ανθρώπου ρομπότ. Στην συγκεκριμένη διδακτορική διατριβή επικεντρωνόμαστε στις ακόλουθες δύο εφαρμογές:

- Ανάπτυξη ανθρωπομορφικών ρομποτικών τεχνουργημάτων.
- Αντιστοίχηση της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση.

Προχειμένου να μπορέσουμε να αναπτύξουμε ανθρωπομορφικά ρομπότ (π.χ., ρομποτικά χέρια), πρέπει πρώτα να μπορέσουμε να ποσοτικοποιήσουμε τον ανθρωπομορφισμό των ρομποτικών τεχνουργημάτων. Στο Κεφάλαιο 5, προτείνουμε μια ολοκληρωμένη μεθοδολογία για την ποσοτικοποίηση του ανθρωπομορφισμού ρομποτικών χεριών. Στην συνέχεια προχειμένου να παράγουμε ανθρωπομορφική ρομποτική κίνηση από την ανθρώπινη κίνηση, χρησιμοποιούμε την έννοια του λειτουργικού ανθρωπομορφισμού προτείνοντας μια σειρά από σχήματα αντιστοίχησης που κάνουν χρήση συγκεκριμένων μετρικών του ανθρωπομορφισμού. Περισσότερες πληροφορίες μπορούν να αναζητηθούν στο Κεφάλαιο 6.

5. Ποσοτικοποιώντας τον Ανθρωπομορφισμό Ρομποτικών Συστημάτων

Στην συγκεκριμένη ενότητα επικεντρωνόμαστε στην σύνθεση μιας μεθοδολογίας βασισμένης σε μεθόδους υπολογιστικής γεωμετρίας και θεωρίας συνόλων, για την ποσοτικοποίηση του ανθρωπομορφισμού διαφορετικών ρομποτικών χεριών. Προκειμένου να ποσοτικοποιήσουμε τον ανθρωπομορφισμό, συγκρίνουμε το ανθρώπινο με διάφορα ρομποτικά χέρια σε δυο διαφορετικά επίπεδα: συγκρίνοντας τους χώρους εργασίας του φαλαγγών των δακτύλων και συγκρίνοντας τους χώρους εργασίας των πλαισίων των βάσεων των δακτύλων (λαμβάνοντας υπόψιν την κινητικότητα των κοκάλων της παλάμης).

Το τελικό μετρικό του ανθρωπομορφισμού, χρησιμοποιεί μια σειρά απο σταθμιστικούς παράγοντες για τα διαφορετικά υπο-μετρικά (οι οποίοι μπορούν να ρυθμιστούν ανάλογα με τις προδιαγραφές της κάθε μελέτης), παρέχοντας ένα τελικό σκορ το οποίο κυμαίνεται από 0 (μη ανθρωπομορφικά ρομποτικά χέρια) έως 1 (πανομοιότυπα με το ανθρώπινο ρομποτικά χέρια).

Τα μοντέλα τριών διαφορετικών ρομποτικών χεριών, έχουν χρησιμοποιηθεί για την ανάλυση μας. Πιο συγκεκριμένα το Barrett Hand, το DLR/HIT II και το Shadow hand, έχουν συγκριθεί με το ανθρώπινο χέρι. Η συγκεκριμένη μεθοδολογία μπορεί να εξάγει σχεδιαστικές παραμέτρους για την βαθμολόγηση της ανθρωπομορφικότητας ρομποτικών χεριών και μυσηλεκτρικών προσθετικών συστημάτων, βάσει της περιγραφής του Κεφαλαίου 9.



Τα ρομποτικά χέρια τα οποία χρησιμοποιήθησαν σε αυτήν την μελέτη.

5.1 Μέθοδοι

Προκειμένου να συγκριθούν οι χώροι εργασίας των φαλαγγών και των πλαισίων των βάσεων των δακτύλων τόσο του ανθρώπινου χεριού όσο και των ρομποτικών χεριών, θα πρέπει αρχικά να μπορέσουμε να τους υπολογίσουμε. Για να επιτύχουμε τον συγκεκριμένο στόχο διακριτοποιούμε ώς προς τα όρια των αρθρώσεων τις τιμές που μπορεί να λάβει κάθε βαθμός ελευθερίας και οδηγούμε τις διαφορετικές φάλλαγες των δακτύλων, σε κάθε πιθανή διαμόρφωση που προκύπτει από τις προαναφερθείσες διακριτοποιημένες τιμές. Στην συνέχεια αποθηκεύουμε τις θέσεις των αρθρώσεων στον τρισδιάστατο χώρο σε συγκεκριμένους πίνακες και υπολογίζουμε τα convex hulls κάθε χώρου εργασίας.

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Εν συνεχεία, ο ανθρωπομορφισμός ορίζεται ώς η σχετική κάλυψη μεταξύ των convex hulls κάθε χωρου εργασίας του ανθρώπινου και κάθε ρομποτικού χεριού. Για να καταλήξουμε σε σαφές μετρικό, χρησιμοποιούμε ένα κλάσμα με αριθμητή την τομή των convex hulls και παρονομαστή τη ένωση των convex hulls. Είναι σαφές ότι ξεκινάμε υπολογίζοντας τα ανθρωπομορφικά υπομετρικά για κάθε φάλαγγα κάθε δακτύλου. Το σταθμισμένο άθροισμα των υπομετρικών των φαλαγγών κάθε δακτύλου δίνει το συνολικό σκόρ του δακτύλου, ενώ το σταθμισμένο άθροισμα των υπομετρικών των δακτύλων και των πλαισίων των βάσεων των δακτύλων, δίνει το συνολικό σκορ για κάθε ρομποτικό χέρι.



Δημιουργία χώρων εργασίας για τον δείκτη του ανθρώπινου χεριού.



Κινηματικά μοντέλα των προς σύγκριση ρομποτικών χεριών και χώροι εργασίας των πλαισίων των βάσεων των δακτύλων.



Σύγκριση των χώρων εργασίας των πλαισίων των βάσεων των δακτύλων μεταξύ του ανθρώπινου και των διαφορετικών ρομποτικών χεριών.
Σκόρ ανθρωπομορφισμού για τα διαφορετικά ρομποτικά χέρια και για ένα υποθετικό ρομποτικό χέρι (HRobot - που ακολουθεί το κινηματικό μοντέλο του ανθρώπινου χεριού και έχεις διαστάσεις ίσες με το 110% του ανθρώπινου χεριού), για κάθε δάκτυλο και φάλαγγα

Barrett					
	Index	Middle	Ring	Pinky	Thumb
Proximal	18.89%	20.80%	-	-	0%
Middle	-	-	-	-	-
Distal	0%	0%	-	-	0%
Total	6.30%	6.93%	-	-	0%
		DLR/H	IT II		
Proximal	46.50%	55.80%	67.74%	28.33%	16.35~%
Middle	40.86%	37.08%	65.60%	16.28%	-
Distal	34.33%	57.48%	76.02%	0.9%	0%
Total	40.56%	50.12%	69.79%	15.17%	8.18%
		Shade	ow		
Proximal	45.27%	43.02%	80.85%	49.18%	15.77%
Middle	40.86%	27.59%	53.43%	47.61%	-
Distal	52.81%	39.19%	70.21%	22.07%	22.72%
Total	46.31%	36.60%	68.16%	39.62%	19.25%
HRobot					
Proximal	75.13%	75.13%	75.13%	75.13%	75.13%
Middle	$8\overline{6.49\%}$	87.09%	$8\overline{6.93\%}$	$\overline{86.87\%}$	-
Distal	$\overline{66.55\%}$	$\overline{61.01\%}$	$5\overline{7.42\%}$	$\overline{68.59\%}$	88.66%
Total	76.06%	74.41%	73.16%	76.86%	81.90%

Σκόρ ανθρωπομορφισμού για τα διαφορετικά ρομποτικά χέρια και για ένα υποθετικό ρομποτικό χέρι (HRobot), για τα πλαίσια των βάσεων των δακτύλων

	Barrett	DLR/HIT II	Shadow	HRobot
Positions	44.21%	16.85%	33.41%	75.13%
Orientations	7.34%	0.4%	60.67%	100%
Total	25.78%	8.62%	47.04%	87.57%

Συνολικό σκόρ ανθρωπομορφισμού για τα διαφορετικά ρομποτικά χέρια και για ένα υποθετικό ρομποτικό χέρι (HRobot)

Barrett	DLR/HIT II	Shadow	HRobot
10.38%	26.61%	39.93%	80.24%



Σύγκριση των χώρων εργασίας των φαλαγγών του ανθρώπινου χεριού (χόκκινα convex hulls και μπλέ κινηματικές αλυσίδες) και των ρομποτικών χεριών (μαύρα convex hulls και κόκκινες κινηματικές αλυσίδες).

6. Αντιστοιχίζοντας την Ανθρώπινη σε Ρομποτική Κίνηση με Λειτουργικό Ανθρωπομορφισμό

Στην συγκεκριμένη ενότητα προτείνουμε μια σειρά από σχήματα αντιστοίχησης της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση, για διαφορετικά ρομποτικά συστήματα βραχίονα χεριού. Για να επιτύχουμε τον συγκεκριμένο σκοπό, προτείνουμε συγκεκριμένα κριτήρια/μετρικά του λειτουργικού ανθρωπομορφισμού.

Για την περίπτωση του Mitsubishi PA10 DLR/HIT II ρομποτικού βραχίονα, ένα σχήμα αντιστοίχησης βασισμένο στην αναλυτική επίλυση της ευθείας και αντίστροφης κινηματικής, μπορεί να χρησιμοποιηθεί. Η αντίστροφη κινηματική υπολογίζεται κάνοντας χρήση του IKFast αλγόριθμου του OpenRAVE [75] και η πλεονασματικότητα των λύσεων αντιμετωπίζεται με την διαλογή της πιο ανθρωπομορφικής λύσης που ελαχιστοποιεί κάποιο κριτήριο ανθρωπομορφισμού.

Για την γενική περίπτωση των ρομποτικών συστημάτων με μη τυπικά κινηματικά στοιχεία (με πλεονάζοντες βαθμούς ελευθερίας), το σχήματα αντιστοίχησης υλοποιείται και επιλύεται σαν ένα πρόβλημα μη γραμμικής βελτιστοποίησης με περιορισμούς, όπου ένα συγκεκριμένο κριτήριο λειτουργικού ανθρωπομορφισμού εισάγεται στην αντικειμενική συνάρτηση.

Προκειμένου να αποδείξουμε την αποδοτικότητα των συγκεκριμένων μεθοδολογιών, εκτελέσαμε πολλαπλά πειράματα προσομοίωσης καθώς και πειράματα με πραγματικά ρομποτικά συστήματα, τα οποία επεξηγούνται στο Κεφάλαιο 7.

6.1 Μετρικά Ανθρωπομορφισμού

Προχειμένου να επιτύχουμε ανθρωπομορφική ρομποτική κίνηση, πρέπει να επιστρατεύσουμε συγχεκριμένα μετρικά του λειτουργικού ανθρωπομορφισμού. Τέτοια μετρικά είναι τα ακόλουθα, τα οποία επιτυγχάνουν ανθρωπομορφική κίνηση όταν ελαχιστοποιούνται:

- Ο όγχος του convex hull που δημιουργείται από τις θέσεις των ανθρώπινων και ρομποτικών αρθρώσεων.
- Το άθροισμα των αποστάσεων μεταξύ των ανθρώπινων και των ρομποτικών θέσεων των αρθρώσεων.
- Το άθροισμα των εμβαδών των τριγώνων που δημιουργούνται από τις θέσεις των ανθρώπινων και ρομποτικών αρθρώσεων.

6.2 Σχήμα αντιστοίχησης για το Mitsubishi PA10 DLR/HIT ΙΙ σύστημα βραχίονα χεριού

Προκειμένου να αντιστοιχήσουμε την ανθρώπινη κίνηση σε ανθρωπομορφική ρομποτική κίνηση για το Mitsubishi PA10 DLR/HIT II ρομποτικό σύστημα βραχίονα χεριού, ενεργούμε ως εξής:

- Καταγράφουμε τις θέσεις του ανθρώπινου χαρπού χαι του αγχώνα, με το Isotrak II.
- Καταγράφουμε τις γωνίες των ανθρώπινων δακτύλων με το Cyberglove II.
- Υπολογίζουμε τις θέσεις των ρομποτικών ακροδακτύλων λύνοντας την ευθεία κινηματική τους.
- Για την επιθυμητή θέση και τον επιθυμητό προσανατολισμό του καρπού λύνουμε αναλυτικά την αντίστροφη κινηματική του βραχίονα.
- Αντιμετωπίζουμε την πλεονασματικότητα των λύσεων διαλέγοντας την λύση που είναι η πιο ανθρωπομορφική και μεγιστοποιεί το manipulability measure.
- Εισάγουμε ένα αντιστάθισμα στην θέση του ρομποτιχού χαρπού, για να εξαλείψουμε τις διαστασιαχές διαφορές με το ανθρώπινο χέρι.
- Υπολογίζουμε τις πιο ανθρωπομορφικές λύσεις από όλες τις λύσεις της αντίστροφης κινηματικής για τα ρομποτικά δάκτυλα.
- Αντιμετωπίζουμε την πλεονασματικότητα των λύσεων για το ρομποτικό χέρι με τον προαναφερθέντα - για την περίπτωση του ρομποτικού βραχίονα - τρόπο.

6.3 Σχήμα αντιστοίχησης για την γενική περίπτωση συστημάτων βραχίονα χεριού με υπερπλεονάζοντες βαθμούς ελευθερίας

$$F_{RAH}(\mathbf{q}_{RAH}) = \sum_{i=1}^{m} w_{RAHx_i} \|x_{RAH_i} - x_{RAHgoal_i}\|^2 + \sum_{i=1}^{m} w_{RAHo_i} d_{RAHo_i}(\mathbf{h}_c, \mathbf{h}_g) + w_D \sum_{j=1}^{n} \|s_j - s_{elbow}\|^2$$
(1)

όπου w_{RAHx} , w_{RAHo} και w_D είναι τα βάρη που ορίζουν την σχετική σημαντικότητα των στόχων θέσης, προσανατολισμού και ανθρωπομορφισμού αντίστοιχα, $s_{elbow} \in R^3$ είναι η θέση του ανθρώπινου αγκώνα και το s_j περιέχει τις θέσεις των ρομποτικών αρθρώσεων.



Στιγμιότυπα των πειραμάτων προσομοίωσης, για σχήματα αντιστοίχησης της ανθρώπινης χίνησης σε ανθρωπομορφική ρομποτική χίνηση για βραχίονα 18 βαθμών ελευθερίας, ένα τετραδάχτυλο χέρι χαι ένα ρομποτικό σύστημα βραχίονα χεριού με 44 βαθμούς ελευθερίας για τον βραχίονα χαι 5 δάχτυλα για το χέρι.

Experiment 1 Teleoperation of Mitsubishi PA10 DLR/HIT II model



Experiment 2 Teleoperation of 21 DoFs Robot Arm and DLR/HIT II Robot Hand models



Πειράματα αντιστοίχησης της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση, χρησιμοποιώντας το OpenRAVE simulation environment.

Αλληλεπίδραση Ανθρώπου Ρομπότ: Εφαρμογές, Πειράματα και Προδιαγραφές Σχεδιασμού

7. Τηλεχειρισμός Ρομποτικών Συστημάτων Βραχίονα Χεριού

Στην συγκεκριμένη ενότητα χρησιμοποιούμε τα σχήματα αντιστοίχησης της ανθρώπινης κίνησης σε ανθρωπομορφική ρομποτική κίνηση που προτάθηκαν στο Κεφάλαιο 6, για εφαρμογές τηλεχειρισμού με το Mitsubishi PA10 ρομποτικό βραχίονα και επιδέξιου τηλεχειρισμού με το DLR/HIT II ρομποτικό χέρι.

Προκειμένου να τηλεχειριστούμε το Mitsubishi PA-10 ρομποτικό βραχίονα χρησιμοποιούμε ένα σύστημα καταγραφής της θέσης του ανθρώπινου καρπού και του αγκώνα και υλοποιούμε την αναλυτική προσέγγιση που περιγράψαμε στην προηγούμενη ενότητα.

Για να εκτελέσουμε επιδέξιο τηλεχειρισμό αντικειμένων (μιας μικρής μπάλας και ενός κουτιού πορτοκαλάδας) με το DLR/HIT II ρομποτικό χέρι, χρησιμοποιούμε το άρθρωση προς άρθρωση (joint-to-joint mapping) σχήμα αντιστοίχησης καθώς και μια συσκευή χαμηλού κόστους που παρέχει ανάδραση δύναμης χρησιμοποιώντας RGB LEDs και μοτέρ δόνησης, ώστε να μπορεί ο χρήστης να αντιλαμβάνεται τις ασκούμενες από τα ρομποτικά δάκτυλα δυνάμεις.



Index, Middle Flexion



Thumb Flexion



Index Flexion



Middle Flexion



Parallel Fingers



Abducting Fingers

Διαφορετικά στιγμιότυπα από το πείραμα του τηλεχειρισμού που εκτελέστηκε με το ρομποτικό χέρι DLR/HIT II.



Small Ball Manipulation (Squeezing and Rotation)

Rectangle Manipulation (Squeezing and Slight Rotation)





Στιγμιότυπο από το πείραμα, που αφορούσε τον τηλεχειρισμό του Mitsubishi PA10 ρομποτικού βραχίονα.

To URL του video που περιέχει το πείραμα τηλεχειρισμού του ρομποτιχού βραχίονα Mitsubishi PA10, μπορεί να βρεθεί στο [76].

To URL του video που περιέχει τα πειράματα τηλεχειρισμού και επιδέξιου χειρισμού αντικειμένων με το DLR/HIT ΙΙ ρομποτικό χέρι, μπορεί να βρεθεί στο [77].

8. Κλειστού-Βρόχου Ανθρωπομορφικός Σχεδιασμός Αρπαγής Αντικειμένων Βασισμένος σε Συναρτήσεις Πλοήγησης

Στην συγκεκριμένη ενότητα περιγράφουμε ένα ολοκληρωμένο σχήμα κλειστού βρόχου για ανθρωπομορφικό σχεδιασμό αρπαγής αντικειμένων, βασισμένο σε συναρτήσεις πλοήγησης (Navigation Functions). Το προτεινόμενο σχήμα μπορεί να χρησιμοποιηθεί ώστε το Mitsubishi PA10 DLR/HIT II ρομποτικό σύστημα βραχίονα χεριού, να προσεγγίζει και να αρπάζει με ανθρωπομορφικό τρόπο, πληθώρα καθημερινών αντικειμένων.

Προκειμένου να πετύχουμε τον συγκεκριμένο στόχο, χρησιμοποιούμε δεδομένα ανθρώπινης κίνησης ώστε να μεταφέρουμε δεξιότητες από τον άνθρωπο στο ρομπότ. Πιο συγκεκριμένα χρησιμοποιούμε τα σχήματα αντιστοίχησης κίνησης που προτάθηκαν στο Κεφάλαιο 6, ώστε να παράγουμε από την ανθρώπινη κίνηση, ανθρωπομορφική ρομποτική κίνηση για ολόκληρο το σύστημα βραχίονα χεριού. Στην συνέχεια βασισμένα σε συναρτήσεις πλοήγησεις μοντέλα εκπαιδεύονται, ώστε να μαθαίνουν "πλασματικά" εμπόδια στον χώρο χαμηλής διάστασης των ανθρωπομορφικών ρομποτικών κινηματικών δεδομένων. Αυτά τα εμπόδια τα βοηθούν ώστε να παράγουν νέες ανθρωπομορφικές τροχιές και διαμορφώσεις, εγγυώμενα πάντα σύγκλιση στον επιθυμητό στόχο.

Πρέπει να τονιστεί ότι τα συγκεκριμένα μοντέλα εκπαιδεύονται για συγκεκριμένες διεργασίες ακριβώς όπως στην περίπτωση των διεπαφών ηλεκτρομυογραφικών σημάτων, χρησιμοποιώντας μόνο 2 χαρακτηριστικά των διεργασιών, τον υποχώρο προς τον οποίο πρέπει να κινηθούν και το αντικείμενο που πρέπει να πιάσουν. Το τελικό σχήμα παράγει προσαρμοστική συμπεριφορά παρόμοια με των ανθρώπων, ενεργοποιώντας μοντέλα εκπαιδευμένα για συγκεκριμένες διεργασίες βασισμένο στην απόφαση που παίρνει ένα σύστημα τεχνητής όρασης (σχετικά με τον υποχώρο που βρίσκεται ένα αντικείμενο και το είδος του αντικειμένου).



Εκπαίδευση των μοντέλων για συγκεκριμένες διεργασίες.



Σχεδιάγραμμα του τελιχού σχήματος με το σύστημα τεχνητής όρασης.

Αποτελέσματα από ένα πρώτο πείραμα που αφορούσε την προσέγγιση και αρπαγή ενός αντικειμένου τοποθετημένου σε τυχαία θέση και προσανατολισμό στον τρισδιάστατο χώρο, μπορούν να βρεθούν στο video στο [78].



Το Mitsubishi PA10 DLR/HIT ΙΙ ρομποτικό σύστημα βραχίονα χεριού, απεικονίζεται να αρπάζει ένα τετράγωνο αντικείμενο από τυχαία θέση και προσανατολισμό, με ανθρωπομορφικό τρόπο.

Ένα video από ένα δεύτερο πείραμα, όπου το Mitsubishi PA10 DLR/HIT II σύστημα βραχίονα χεριού, προσεγγίζει και αρπάζει ανθρωπομορφικά ένα κουτί από χυμό πεταμένο σε τυχαία θέση και προσανατολισμό πάνω σε μία επιφάνεια, μπορεί να βρεθεί στο [79].

Closed-Loop Humanlike Grasp Planning with Mitsubishi PA10 DLR/HIT II



Στιγμιότυπα του δεύτερου πειράματος.

9. Ανοιχτού Κώδικα και Υλικού, Χαμηλού Κόστους και Βάρους, Αρθρωτά, Υποεπενεργούμενα Ρομποτικά Χέρια

Στην συγκεκριμένη ενότητα προτείνουμε μια νέα σχεδιαστική προσέγγιση για την δημιουργία, υποεπενεργούμενων ρομποτικών χεριών, τα οποία είναι χαμηλού κόστους (κοστίζουν λιγότερο από 100 USD), χαμηλού βάρους (ζυγίζουν λιγότερο 200 gr | 0.44 lb), είναι εγγενώς υποχωρητικά, αρθρωτά και μπορούν να κατασκευασθούν με φθηνά και εύκολα - στο να τα προμηθευτείς - υλικά. Τα συγκεκριμένα ρομποτικά χέρια μπορούν να χαρακτηριστούν ώς γενικού σκοπού, καθώς μπορούν να χρησιμοποιηθούν από αμέτρητες εφαρμογές αλληλεπίδρασης ανθρώπου ρομπότ.

Η σχεδίαση των συγκεκριμένων ρομποτικών χεριών βασίζεται σε μια απλή αλλά αποτελεσματική ιδέα: του να χρησιμοποιηθούν αγωνιστικές και ανταγωνιστικές δυνάμεις ώστε να υλοποιηθεί η κάμψη και η έκταση των δακτύλων. Σταθερά ελαστομερή υλικά χρησιμοποιούνται ως αντικαταστάτες των ανθρώπινων εκτατικών τενόντων και δυνατά νήματα τα οποία δρομολογούνται μέσα από κυλίνδρους χαμηλής τριβής, χρησιμοποιούνται για να υλοποιήσουν τους καμπτικούς τένοντες.



Η δομή του ρομποτικού δακτύλου.

Two Fingers	Three Fingers	Four Fingers v1	Four Fingers v2
			1
	EE		
A CONTRACTOR OF			
•			

Διαφορετικοί τύποι χεριών (με διαφορετικό αριθμό δακτύλων) που μπορούν να δημιουργηθούν εξαιτίας της αρθρωτής βάσης των δακτύλων με τις 5 θέσεις.

9.1 Ένας διαφορικός μηχανισμός με σχήμα δίσκου

Ο διαφορικός μηχανισμός σε σχήμα δίσκου ενώνει τα διαφορετικά δάκτυλα του ρομποτικού χεριού με τον κινητήρα και εξασφαλίζει ότι ακόμη και αν κάποιο η κάποια δάκτυλα έρθουν σε επαφή με την επιφάνεια ενός αντικειμένου, τα υπόλοιπα δάκτυλα θα συνεχίσουν να κλείνουν/κινούνται εως ότου αποκτήσουν και αυτά επαφή με το αντικείμενο. Ο συγκεκριμένος διαφορικός μηχανισμός είναι μια παραλλαγή του whiffle tree (η seesaw) μηχανισμού [80]. Ένας παρόμοιος διαφορικός μηχανισμός σε σχήμα τριγώνου είχε προταθεί στο παρελθόν στο [81].



Ο διαφορικός μηχανισμός με την μορφή δίσκου.

9.2 Απλά υλικά, χαμηλού κόστους

Τα συγκεκριμένα ρομποτικά χέρια μπορούν να κατασκευαστούν με απλά υλικά, χαμηλού κόστους. Για παράδειγμα οι κύλινδροι χαμηλής τριβής μπορούν να δημιουργηθούν απο μπατονέτες καθαρισμού των αυτιών. Το Plexiglas επιλέχθηκε ώς το κύριο υλικό για τα συγκεκριμένα ρομποτικά χέρια, λόγω του χαμηλού κόστους και των σχετικά καλών ιδιοτήτων, αλλά οποιοσδήποτε μπορεί να επιλέξει διαφορετικό τύπο πλαστικού. Πρέπει επίσης να τονιστεί ότι το συγκεκριμένο design είναι 2D με αποτέλεσμα να μπορεί ένα ρομποτικό χέρι να κατασκευαστεί με ένα απλό laser printer (χωρίς να προυποθέτει ύπαρξη 3D printer).

9.3 Video και Ιστότοπος

Ένα video (σε HD ποιότητα) όπου τα ρομποτικά χέρια χρησιμοποιούνται για διαφορετικές εφαρμογές, μπορεί να βρεθεί στο [82].

Πρέπει τέλος να σημειωθεί ότι ένας ιστότοπος έχει δημιουργηθεί, ώστε να παρέχει πληροφορίες και οδηγίες κατασκευής των προτεινόμενων ρομποτικών χεριών:

http://www.openbionics.org



Τα διαφορετικά κομμάτια που χρησιμοποιούνται για την κατασκευή των ρομποτικών χεριών.



Διαφορετικά μοντέλα και πρωτότυπα ρομποτικών χεριών.

Συμπεράσματα και Μελλοντικές Κατευθύνσεις

10. Συμπεράσματα

Στην συγκεκριμένη διδακτορική διατριβή παρουσιάσαμε σχήματα μηχανικής μάθησης για διεπαφές ηλεκτρομυογραφικών σημάτων, που μπορούν να χρησιμοποιηθούν σε σωρεία εφαρμογών αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων. Τα συγκεκριμένα σχήματα μπορούν να αποκωδικοποιήσουν τόσο την ανθρώπινη πρόθεση όσο και την ανθρώπινη κίνηση, βασισμένα στις μυσηλεκτρικές δραστηριότητες των μυών του ανθρώπινου άνω άκρου. Επιπλέον συνδυάζουν έναν ταξινομητή μαζί με έναν παλινδρομητή, ώστε να κατακερματίσουν τον χώρο δράσης και να προσφέρουν καλύτερη ακρίβεια εκτίμησης της ανθρώπινης κίνησης, με μοντέλα εκπαιδευμένα για συγκεκριμένες διεργασίες.

Όσον αφορά τις εφαρμογές αλληλεπίδρασης ανθρώπου ρομπότ, εστιάσαμε στον ανθρωπομορφισμό των διαφορετικών ρομποτικών τεχνουργημάτων. Πιο συγκεκριμένα διακρίναμε μεταξύ των διαφορετικών εννοιών του ανθρωπομορφισμού, εισάγωντας τις έννοιες του Λειτουργικού και Αντιληπτού Ανθρωπομορφισμού. Επιπλέον, προτείναμε μια ολοκληρωμένη μεθοδολογία για την ποσοτικοποίηση του ανθρωπομορφισμού των ρομποτικών χεριών και συνθέσαμε διαφορετικά σχήματα αντιστοίχησης της ανθρώπινης σε ανθρωπομορφική ρομποτική κίνηση.

Τέλος, προτείναμε μια νέα προσέγγιση για την κατασκευή υποεπενεργούμενων ρομποτικών χεριών, τα οποία είναι ανοιχτού κώδικα και υλικού, χαμηλού κόστους και βάρους, αρθρωτά και εγγενώς υποχωρητικά. Τα συγκεκριμένα ρομποτικά χέρια μπορούν να χρησιμοποιηθούν για πολλαπλούς σκοπούς και εφαρμογές. Προκειμένου να αποδείξουμε την αποδοτικότητα των συγκεκριμένων μεθοδολογιών και των δημιουργηθέντων ρομποτικών χεριών, εκτελέσαμε πληθώρα πειραμάτων που αφορούσαν διαφορετικές εφαρμογές αλληλεπίδρασης ανθρώπου και ρομπότ.

10.1 Κύριες συνεισφορές

Συνοψίζοντας, οι χύριες συνεισφορές της συγχεχριμένης διδαχτοριχής διατριβής, είναι οι αχόλουθες:

Προτείναμε ένα πλήρες σχήμα μηχανικής μάθησης για διεπαφές ηλεκτρομυογραφικών σημάτων, το οποίο:

- Χρησιμοποιεί συνεργατικά έναν ταξινομητή και έναν παλινδρομητή.
- Καταχερματίζει τον χώρο δράσης, διαχρίνοντας τρια χαραχτηριστικά των διαφορετικών διεργασιών: συγκεχριμένο υποχώρο, αντικείμενο προς αρπαγή, διεργασία προς εκτέλεση.

- Μπορεί να αποχωδιχοποιήσει τόσο την ανθρώπινη πρόθεση όσο χαι την ανθρώπινη χίνηση από ηλεχτρομυογραφιχά σήματα.
- Προσφέρει καλύτερη εκτίμηση της ανθρώπινης κίνησης με μοντέλα εκπαιδευμένα για συγκεκριμένες διεργασίες.

Προτείναμε μια μεθοδολογία βασισμένη σε μεθόδους θεωρίας συνόλων και υπολογιστικής γεωμετρίας για την ποσοτικοποίηση του ανθρωπομορφισμού ρομποτικών χεριών:

- Προχειμένου να βαθμολογήσουμε την ανθρωπομορφικότητα υφιστάμενων και νέων ρομποτικών χεριών.
- Για να εξάγουμε προδιαγραφές σχεδίασης, για μια νέα γενιά ανθρωπομορφιχών ρομποτιχών χεριών χαι μυοηλεκτριχών προσθετιχών συστημάτων.

Προτείναμε μια σειρά σχημάτων αντιστοίχησης της ανθρώπινης χίνησης σε ανθρωπομορφιχή ρομποτιχή χίνηση, τα οποία:

- Εγγυώνται τον ανθρωπομορφισμό της ρομποτικής κίνησης εκτελώντας με ακρίβεια συγκεκριμένες διεργασίες (τηρώντας συγκεκριμένους περιορισμούς που έχουν τεθεί από τον χρήστη).
- Προσφέρουν ανθρωπομορφική ρομποτική κίνηση, ακόμη και για ρομποτικά συστήματα βραχίονα χεριού με μη τυπικά κινηματικά χαρακτηριστικά (με πλεονάζοντες βαθμούς ελευθερίας).
- Μπορούν να χρησιμοποιηθούν σε σωρεία εφαρμογών αλληλεπίδρασης ανθρώπου ρομποτικών συστημάτων.

Σχεδιάσαμε και κατασκευάσαμε μια σειρά από υποεπενεργούμενα ρομποτικά χέρια, τα οποία είναι ανοιχτού κώδικα και υλικού, χαμηλού βάρους και κόστους, εγγενώς υποχωρητικά, αρθρωτά και τα οποία:

- Μπορούν να εκτελέσουν αρπαγές πληθώρας καθημερινών αντικειμένων.
- Είναι εξαιρετικά αποδοτικά ακόμη και υπο αβεβαιότητες σχετικά με την θέση και την γεωμετρία των πρός αρπαγή αντικειμένων, εξαιτίας της έμφυτης υποχωρητικότητας τους.
- Μπορούν θεωρηθούν ως ρομποτικά χέρια γενικής χρήσης, καθώς ειναι χρήσιμα για μια σειρά από εφαρμογές αλληλεπίδρασης ανθρώπου ρομπότ.

10.2 Μελλοντικές Κατευθύνσεις

- Διατύπωση ημιαυτόνομων σχημάτων για τον βασισμένο σε ηλεκτρομυογραφικά σήματα έλεγχο ρομποτικών τεχνουργημάτων (κυρίως προσθετικών μελών).
- Σχεδιασμός και κατασκευή υποεπενεργούμενων ρομποτικών χεριών και προσθετικών συστημάτων, τα οποία θα είναι ανοιχτού κώδικα και υλικού, χαμηλού κόστους και βάρους και θα κατασκευάζονται για συγκεκριμένες διεργασίες.
- Σχεδιασμός και κατασκευή υποεπενεργούμενων ρομποτικών χεριών για επιδέξιο χειρισμό καθημερινών αντικειμένων.

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Dedicated to my grandfather Stefanos M. Filos.

Part I - Introduction and Problem Statement
Chapter 1

Introduction

Over the last decades the cross disciplinary fields of ElectroMyoGraphy (EMG) based interfaces and Human Robot Interaction (HRI) have received increased attention, due to their numerous applications in everyday life, dynamic and human-centric environments. Typical EMG based applications are, EMG based teleoperation of robot artifacts in remote and/or dangerous environments [1], [2], EMG based control of advanced prostheses [3], EMG control of exoskeletons [4] and development of muscle computer interfaces for human computer interaction [5] and [6], while some indicative HRI applications are, humanoids that interact with children [7], industrial robots that cooperate advantageously with humans [8] in a safe manner [9], intuitive teleoperation of redundant robots [10] and household robots that assist humans in everyday life tasks [11–13].

In this Ph.D. thesis we propose advance learning schemes for EMG based interfaces, that take advantage of both a classifier and a regressor, that cooperate advantageously in order to split the task-space and provide better human motion estimation accuracy with task-specific models. These schemes can be used for numerous HRI applications.

Regarding HRI applications, we mainly focus on anthropomorphism of robot artifacts, proposing methods that can be used to quantify human-likeness or robot artifacts and efficiently map human to anthropomorphic robot motion.

Finally we propose a series of open-source, light-weight, low-cost, modular, under-actuated, intrinsically-compliant robot hands that can be used for both EMG control studies (even as affordable myoelectric prostheses) and HRI applications (for teleoperation/telemanipulation studies as end-effectors of robot arm hand systems), grasping a wide range of everyday life objects in dynamic environments (even under object position and shape uncertainties), owing to their inherent compliance.

The scope of this Ph.D. thesis and our contributions, are discussed in detail at the following sections, focusing on four different fields:

- EMG based interfaces.
- Anthropomorphism of robot artifacts.
- Mapping human to anthropomorphic robot motion.
- Robots operating in structured and dynamic environments.

1.1 EMG based interfaces

Although EMG based interfaces are very promising and may have a vital role in human robot/computer interaction applications for the years to come, they also have certain problems that have been identified and discussed in many studies in the past. Some of these problems are, the high-dimensionality and complexity of the human musculoskeletal system, the non-linear relationship between the human myoelectric activity and the motion or force to be estimated, the muscular fatigue, the signal noise caused by electrode perturbations, muscles switching, sweat etc.

In order to address the problem of the high-dimensionality, Principal Components Analysis (PCA) has been used in several studies in the past, to investigate both human hand kinematics and muscular synergies [14–19].

Another major difficulty that researchers face in the field of EMG based interfaces, is the highly nonlinear relationship between the myoelectric activations and the human motion [20]. To overcome this problem the majority of the researchers avoid to decode a continuous representation of human kinematics, focusing on a discrete approach like the directional control of a robotic artifact [21] or the EMG based control of a multifingered robot hand to a series of discrete postures [22–27].

Regarding the continuous EMG based control approach, various models have been used to provide human motion estimates based on human myoelectric activations. Some of them are, the Hill-based musculoskeletal model [28] which is the most commonly used model [20, 29–32], the state-space models [1, 33, 34], Artificial Neural Networks (ANN) [35–37] and Support Vector Machines (SVM) based regressors [2, 38].

Ph.D. Thesis Contribution

In this Ph.D. thesis we formulate a complete learning scheme for EMG based interfaces, that takes advantage of a classifier which is combined with a regressor (combining the discrete and continuous approaches). The classifier and the regressor cooperate advantageously in order to split the task space and provide better estimation accuracy, with task specific models. The whole scheme is based on the random forests methodology for classification and regression.

EMG signals are used to discriminate different reach to grasp movements in 3D space. Task specificity is introduced in three different levels, suggesting that the myoelectric activity differentiates; between reach to grasp movements towards different subspaces, between reach to grasp movements towards a specific object placed at a specific position, but with the intention to perform different tasks (with the grasped object). The classifier uses the human myoelectric activity, to discriminate between those different reach to grasp movements in the *m*-dimensional space of the EMG signals (*m* is the number of channels). The regressor is first used to train task-specific models for all possible tasks, so as for a task-specific model to be triggered, based on the classification decision.

Classification decision is taken at a frequency of 1kHz, enabling our scheme to identify the task in real time. The proposed scheme can provide continuous estimates of the full human arm hand system kinematics (27 DoFs modeled, 7 for the human arm and 20 for the human hand). Those estimates can be used by a series of EMG based interfaces for different HRI applications. More details can be found in Chapter 3.

Important Questions for EMG Based Interfaces

Some important/motivating questions that we are trying to address in this Ph.D. thesis, are the following:

- Do muscular co-activation patterns differentiate between different tasks?
- Can we decode human intention from myoelectric activations?
- What task information can be extracted from EMG signals?
- Can we improve EMG based motion estimation accuracy?
- Can we define which EMG channels are the most important?

1.2 Anthropomorphism of Robot Artifacts

Anthropomorphism or else humanlikeness of robot motion is also very important, for a variety of HRI applications. Almost 140 years ago Charles Darwin suggested anthropomorphism as a necessary tool for efficiently understanding nonhuman agents [39]. Moreover, recent studies showed that the more human-like a robot is in terms of motion, appearance, expressions and perceived intelligence, then the more easily will manage to establish a solid social connection with human beings [40–42].

Different indexes/metrics of anthropomorphism have been proposed over the past, for assessing humanlikeness of robot artifacts. Most of them focused on anthropomorphism of robot hands. In [43] and [44], anthropomorphism is derived as the weighted sum of kinematics, contact surfaces and size scores, while in [45] and [46], the human and robot hand workspaces were represented in low-dimensional manifolds and then compared. Although, these latter studies are quite interesting, none of them proposed a systematic way of comparing the robot hand kinematics with the full human hand kinematic model (e.g., taking into account the mobility of the palm bones).

Ph.D. Thesis Contribution

In this Ph.D. thesis, we discriminate between the different notions of Anthropomorphism, introducing Functional Anthropomorphism and Perceptional Anthropomorphism. More details regarding their differences can be found in Chapter 4.

Moreover, we propose a complete methodology based on set theory and computational geometry methods, for quantifying anthropomorphism of robot hands. More specifically we introduce a series of metrics based on finger workspace analysis, assessing the relative coverages of human and robot finger phalanges workspaces, as well as human and robot finger base frames workspaces. A weighted sum of the proposed metrics, which can be adjusted according to the specifications of each study, results always to a normalized score of anthropomorphism (i.e. human-likeness) that ranges between 0 (non-humanlike robot hands) and 1 (human-identical robot hands). Three different robotic hands are examined, in order to test the efficacy of the proposed methodology and a series of simulated paradigms of the different types of workspaces are provided. Details on the quantification of anthropomorphism of robot hands, can be found in Chapter 5.

Important Questions Regarding Anthropomorphism

Some important questions that we are trying to address in this Ph.D. thesis, are the following:

- How can we define anthropomorphism of robot artifacts?
- What are the different notions of anthropomorphism?
- What HRI applications require anthropomorphism?
- Is it possible to quantify anthropomorphism of robot artifacts?
- Can we extract design specifications for the creation of humanlike robots?

1.3 Mapping Human to Anthropomorphic Robot Motion

The problem of mapping human to robot motion, has been one of the most challenging problems of the Robotics field, over the last 50 years.

Various human to robot hand motion mapping methodologies, have been proposed in the past: fingertips mapping [47, 48], joint-to-joint mapping [49], functional pose mapping [50] and object specific mapping [51]. Moreover, human grasping synergies have also been mapped to robot hand synergies [52, 53].

Regarding human to robot arm motion mapping, most previous studies focused on a forward-inverse kinematics approach, to achieve same position and orientation for the human and robot end-effectors [54, 55]. Some of them proposed also methodologies to describe and model the dependencies among the human joint angles, acquiring anthropomorphic robot motion [83]. For the general case of highly articulated figures and multi-DoF robot artifacts the human to robot motion mapping problem is typically formulated as constrained non-linear optimization problem [24, 56, 57].

Regarding anthropomorphism of human to robot motion mapping schemes, some recent studies have focused on the extraction of human-like goal configurations for robotic artifacts [58–60], but there is no systematic method for deriving anthropomorphic robot motion even for robot artifacts with non-trivial kinematics (e.g., hyper-redundant robot arm hand systems).

Ph.D. Thesis Contribution

In this Ph.D. thesis, we propose various human to robot motion mapping schemes, for different HRI applications. Different criteria of anthropomorphism are introduced and they are used in order to achieve humanlike robot motion.

For robot arm hand systems with solvable Inverse Kinematics (IK), the IK solutions are computed analytically and the most anthropomorphic solution is chosen using specific criteria/metrics of functional anthropomorphism.

For the general case of redundant or even hyper-redundant robot arms and m-fingered hands, the human to robot motion mapping can be formulated as an optimization problem, that solves inverse kinematics under position and orientation goals (human imposed functional constraints¹) and handles redundancies with specific criteria of anthropomorphism. More specifically, mapping is formulated as a composite optimization problem for the whole arm hand system, where the fingertips of the robot hand are considered to be the end-effectors instead of the robot wrist. Moreover for the case of m-fingered hands we assign human thumb fingertip position as a position goal for one of the robot fingers and we use splines to calculate the rest robot fingertip positions, interpolating between the rest four (index - pinky) fingertip positions of the human hand.

More details regarding the mapping schemes, can be found in Chapter 6. Details regarding the possible HRI applications and experiments conducted in order to validate the efficiency of the proposed methods, can be found in Chapter 7.

Important Questions Regarding Human to Anthropomorphic Robot Motion Mapping Schemes

Some important questions that we are trying to address in this Ph.D. thesis, are the following:

- Is it possible to transfer human skills to robot artifacts? How?
- Is it possible to map human to robot motion, in a humanlike manner?
- Is it possible to map human to anthropomorphic robot motion, for artifacts with arbitrary kinematics?
- Is it possible to perform teleoperation and telemanipulation with robot arm hand systems in a humanlike manner?

¹These are tasks constraints not optimization constraints.

1.4 Robots Operating and Interacting with Structured and Dynamic Environments

Nowadays it's quite typical for robot artifacts, to operate and interact not only within predefined, a-priori known, structured environments, but also in everyday life, dynamic environments. The term interaction, is typically used for robot end-effectors, that are most commonly robot hands (e.g., typically parts of robot arm hand systems).

Over the last fifty years, roboticists have been intrigued to understand and be inspired by nature's most versatile and dexterous end-effector, the human hand. First robot hands, were actually robot grippers, capable of grasping a limited set of objects with simple geometry, located in a-priori known static environments. Nowadays grippers are still the most common alternative for robot grasping [61, 62], owing to their low-complexity and low-cost.

But the state-of-the-art of robot hands follows the road to increased performance, complexity, cost and humanlikeness [63]. Such robot hands are typically fully actuated, rigid and equipped with sophisticated actuators and sensing elements, in order to perceive the environment. For example it's crucial for a rigid robot hand to have tactile sensors attached at the robot fingertips, in order for the interaction forces (e.g., with a grasped object) to be measured and appropriate force control policies to be employed. Force control schemes, can ensure efficient grasping of everyday life objects, avoiding also possible damages to both the robot and the environment (e.g., to avoid breaking a fragile object). But these hands are also quite expensive and heavy, thus non-affordable for numerous research groups around the world and inappropriate for various EMG based applications, like myoelectric prostheses.

Recently, several studies focused on low-cost robot hands based on elastomer materials or elastic hinges [64–66]. Such hands, despite the under-actuated design, can also be capable of performing simple manipulation tasks [67] and have been made commercially available, in significant lower prices [68]. Nowadays the minimum cost for a robot hand is 400 USD and the minimum weight is 400 gr (0.88 lb), as reported in [64].

Ph.D. Thesis Contribution

In this Ph.D. thesis we propose a new design approach, for the creation of affordable (less than 100 USD), light-weight (less than 200 gr | 0.44 lb), modular, intrinsically-compliant, underactuated robot hands, that can be easily reproduced with off-the-shelf materials. These robot hands can be used for teleoperation and telemanipulation studies,

to create grasping capable platforms (e.g., mobile and aerial vehicles, for which lightweight design is a prerequisite), for educational robotics or even as affordable, myoelectric prostheses. Extensive experimental paradigms are provided within the context of this thesis, in order to validate the efficiency of the proposed hands. The experiments, involve grasping trials of numerous everyday life objects, myoelectric (EMG) control of robot hands, some preliminary results on a grasping capable quadrotor (using an aerial gripper) and autonomous grasp planning under object position and shape uncertainties (e.g., as end-effector of a robot arm hand system). Details can be found in Chapter 9.

Important Questions Regarding Robots Interacting with Dynamic Environments

Some important questions that we are trying to address in this Ph.D. thesis, are the following:

- Can we simplify robot hands design?
- How can we minimize robot hands cost and weight?
- How can we minimize control effort?
- Can we design robot hands that operate efficiently in dynamic environments?
- Is it possible to create low-cost and light-weight robot hands that grasp efficiently a series of everyday life object.
- Will these latter hands be able to grasp objects, even under object position and shape uncertainties?

1.5 Concluding Remarks

In this chapter we presented an introduction covering some important aspects, of EMG based interfaces and Human Robot Interaction applications. Then, some well-known problems and open questions of these fields were presented and the motivation for this Ph.D. thesis as well as our contributions were discussed.

Chapter 2

Experimental Setup

In this section we present the experimental setup (motion capture systems, sensors, robots etc.) used in order to conduct the experiments required for this Ph.D. thesis. More precisely we present:

- The Motion Capture Systems (MCS) used to track the human kinematics.
- The bioamplifiers used to capture human myoelectric activations.
- The sensors used to perceive the environment.
- The robots used for the Human Robot Interaction applications.
- The computer systems used and the communication protocols.

2.1 Motion Capture Systems

In order to describe the motion of the human upper limb (arm hand system) in 3-D space we typically use (in some Chapters the kinematic model differs) three rotational DoFs to model the shoulder joint, one rotational DoF for the elbow joint, one rotational DoF for pronation-supination, two rotational DoFs for the wrist and twenty rotational DoFs for the fingers.

Regarding the fingers we use for each of the four kinematically identical fingers (index, middle, ring and pinky) three rotational DoFs for flexion-extension and one rotational DoF for abduction-adduction, while for the thumb we use two rotational DoFs for flexion-extension, one rotational DoF for abduction-adduction and one rotational DoF to model the palm mobility that allows thumb to oppose to other fingers.



FIGURE 2.1: Kinematic model depicting the degrees of freedom (DoFs) of the human hand, while being teleoperated (in Matlab) by the Cyberglove II MCS.

MCS are used in this Ph.D. thesis, for three major applications:

- To facilitate the creation of advanced learning scheme for EMG-based interfaces.
- To map human to robot motion in a humanlike manner.
- For teleoperation and telemanipulation studies.

In order to record the motion of the human arm hand system and to extract the corresponding joint angles (27 modeled DoFs), we use two different magnetic position tracking systems and a dataglove.

Isotrak II, Polhemus

The first magnetic position tracking system is the Isotrak $II^{\textcircled{0}}$ (Polhemus Inc.) which is equipped with two position tracking sensors and a reference system. In order to capture human arm kinematics with the Isotrak II, two sensors are placed on the elbow and wrist respectively, while the reference system is placed on the human shoulder. The position measurements are provided at the frequency of 30 Hz. The Isotrak II provides high accuracy in both position and orientation, 0.1 in and 0.75 deg respectively.



FIGURE 2.2: The Isotrak II (Polhemus Inc.) magnetic MCS is presented.

Liberty, Polhemus

The second magnetic position tracking system is the Liberty[®] (Polhemus Inc.) which is equipped with four position tracking sensors and a reference system. In order to capture human arm kinematics with the Liberty system, three sensors are placed on the human shoulder, the elbow, and the wrist respectively. More details on the computation of the kinematics are included in [83]. The Liberty system provides measurements at the frequency of 240 Hz and higher accuracy in both position and orientation, 0.03 in and 0.15 degrees respectively.



FIGURE 2.3: The Liberty (Polhemus Inc.) magnetic MCS is presented.

Cyberglove II, Cyberglove Systems

In order to measure the rest 22 DoFs of the human hand and the wrist we use the Cyberglove II[®] (Cyberglove Systems). The Cyberglove II has 22 flex sensors capturing all twenty DoFs of the human hand and the two DoFs of the human wrist. More specifically, the abduction-adduction and flexion-extension of the wrist, the flexion-extension of the proximal, metacarpal and distal joints of each finger and the abduction between the fingers, can be measured. The acquisition frequency of the Cyberglove II is 90 Hz and the accuracy is 1 degree.



FIGURE 2.4: The Cyberglove II (Cyberglove Systems) flex sensors based MCS is presented.

2.2 Bioamplifiers

Bagnoli 16, Delsys Inc.

The Bagnoli 16[®] (Delsys Inc.) is an EMG bioamplifier, equipped with 16 single-differential surface EMG electrodes (DE-2.1[®], Delsys Inc.). A signal acquisition board (NI-DAQ 6036E[®], National Instruments), is used for signal digitization and data acquisition, at a frequency of 1 kHz.



FIGURE 2.5: The Bagnoli 16 (Delsys Inc.) bioamplifier, is presented.

2.3 Sensors

RGB-D Camera, Kinect, Microsoft

The Microsoft Kinect features an RGB-D camera (RGB camera plus a depth sensor) and multi-array microphone. It provides full-body 3D motion capture, facial recognition and voice recognition capabilities, but in this Ph.D. thesis was mainly used for object recognition and object pose estimation purposes. For doing so the Point Cloud Library (PCL) [84] was used and appropriate functions were developed.



FIGURE 2.6: The Kinect (Microsoft) RGB-D camera, is presented.

2.4 Robots

Mitsubishi PA10 7DoF Robotic Manipulator

The Mitsubishi PA-10 is a redundant robotic manipulator, which has seven rotational DoFs arranged in an anthropomorphic way: three DoFs at the shoulder, two DoFs at the elbow, and two DoFs at the wrist. The robot servo controller communicates with a personal computer (PC) via the ARCNET protocol. More details regarding the kinematics, parameters and control of the Mitsubishi PA10, can be found in [69].



FIGURE 2.7: The Mitsubishi PA10 7 DoF robot arm, is depicted.

DLR/HIT II Five Fingered Robot Hand

The DLR/HIT II is a five fingered dexterous robot hand with a total of fifteen DoFs. DLR/HIT II was jointly developed by DLR (German Aerospace Center) and HIT (Harbin Institute of Technology). It has five kinematically identical fingers with three DoFs per finger, two DoFs for flexion and extension (corresponding to the proximal interphalangeal and metacarpophalangeal joints of the human hand) and one DoF for abduction-adduction (corresponding to the metacarpophalangeal joint of the human hand). The last joint of each finger (distal interphalangeal equivalent) is coupled with the middle one, using a mechanical coupling based on a steel wire, with transmission ratio 1:1. The dimensions of the robotic hand are considered to be quite human-like and the total weight is quite low, 1.6 kg. More details regarding the kinematics or other specifications of the DLR/HIT II, can be found in [70].



FIGURE 2.8: The DLR/HIT II five fingered robot hand, is presented.

2.5 Data Collection and Communications

Regarding data collection the trajectory and grasp planning PC (running Ubuntu OS 12.04) is used in order to capture both the myoelectric activations and the kinematics of the full human arm hand system. Appropriate functions have been developed in C/C++ to facilitate data collection from all bioamplifiers and MCS.



FIGURE 2.9: The different motion capture systems and bioamplifiers that capture human arm hand system motion and myoelectric activations respectively, are depicted.

Regarding communications the trajectory and grasp planning PC, establishes with the Mitsubishi PA10 PC/Controller (running a Gentoo Linux soft real-time OS) a TCP-based communication, sending position, velocities or torque commands and getting back the full status of the robot arm (joint angles, velocities, torques). A UDP communication is also established between the trajectory and grasp planning PC and the DLR/HIT II PC/controller (running a QNX hard real-time OS).

2.6 Concluding Remarks

In this chapter we presented the experimental setup (motion capture systems, bioamplifier, sensors and robots) that was used to conduct the experiments required for this PhD thesis, in order to validate the efficiency of the proposed methods.

Part II - EMG Based Interfaces

Chapter 3

A Learning Scheme for EMG Based Interfaces

In this chapter, we present a learning scheme for EMG based interfaces, which can be used to decode human intention and estimate human kinematics using the myoelectric activity captured from human upper-arm and forearm muscles. The proposed learning scheme takes advantage of both a classifier and a regressor, that cooperate advantageously in order to split the task space and provide better estimation accuracy with task-specific models.

Three different task features are distinguished:

- subspace to move towards
- object to be grasped
- task to be executed (with the grasped object)

The discrimination between the different reach to grasp movements is accomplished with a random forest classifier. A Random Forests regressor is used to train taskspecific models for all possible tasks. The classification decision triggers a task-specific motion decoding model that outperforms "general" models, providing better estimation accuracy. The proposed scheme can be used for a plethora of EMG-based interfaces focusing on different HRI applications.

3.1 Introduction

EMG based interfaces were first used, for the control of advanced prosthetic devices, 30 years ago [85]. During the last decades, the field has received increased attention, as many applications have emerged. Some of these applications are: EMG based teleoperation [1], [2] of robot artifacts (e.g., in remote or dangerous environments), EMG based control of advanced prosthetic limbs [3] that help patients regain lost dexterity, EMG control of exoskeletons [4] that can be used for rehabilitation purposes and muscle computer interfaces, for human computer interaction [5] and [6].

Thus, EMG based interfaces are definitely very promising and EMG control schemes will probably have a vital role in human robot/computer interaction applications for the years to come, but they also have many problems that have been identified and discussed in many studies in the past. Some of these problems are the high-dimensionality and complexity of the human musculoskeletal system, the non-stationarity of the EMG signals and the non-linear relationship between the human myo-electric activity and the motion or force to be estimated.

In order to overcome the problem of the high-dimensionality of the human musculoskeletal system, standard dimensionality reduction techniques can be employed. Principal components analysis (PCA) has been used by several studies in the past, for the investigation of human hand kinematic and/or muscle synergies. In [14] optical markers were mounted on 23 different points on the human hand and kinematics were captured during an unconstrained haptic exploration task. Authors concluded to a set of hand postures, representative of most naturalistic postures that appear during object manipulation. Santello et al. [15] and Todorov et al. [16] captured the human hand kinematics with datagloves and identified a limited number of postural synergies "representing" most of human grasping variance, for a wide variety of object grasps. In [17] a similar study was conducted, using a camera-based motion capture system. Regarding muscle synergies, glove measurements combined with EMG activity were acquired in [18], from subjects using the American Sign Language (ASL) manual alphabet, revealing temporal synergies across different muscles and different hand movements. Muscle synergies ability to formulate a predictive framework, capable to associate muscular co-activation patterns with new static hand postures, was investigated in [19].

As we have already mentioned some of the main difficulties that researchers face in the field of EMG based interfaces, are the highly nonlinear relationship between the human myoelectric activity and human kinematics as described in [20] and the nonstationarity of the EMG signals. This difficulty forced most researchers to avoid to decode a continuous representation of human kinematics, choosing to focus on a discrete approach, such as the directional control of a robotic wrist [21] or the control of multifingered robot hands to a series of discrete postures [22], [23] and [24–26, 86]. For doing so, machine learning techniques and more specifically classification methods were used. In [22] and [23] classifiers were used to discriminate based on the human myoelectric activity, between independent human hand's digit movements or different hand postures. Castellini et al. [27] used forearm surface EMGs for the feed-forward control of a hand prosthesis, discriminating between three different grip types, in real-time. Brochier et al. [87] used the myoelectric activity of two adult macaque monkeys, to discriminate muscular co-activation patterns associated with different grasping postures. The latter study was conducted for grasping tasks involving 12 objects of different shapes.

Although the discrete EMG based control approach, has been used by many studies in the past and has led to many interesting applications, the use of finite postures may cause severe problems such as the lack of motion smoothness. In fact for most EMG based applications, that require the execution of everyday life tasks, decoding of complete trajectories is of paramount importance. Thus, a specification for any proposed methodology, should be to address the issues of continuous and smooth control.

Regarding the continuous EMG based control approach, various techniques have been used to provide estimates of human kinematics based on human myoelectric activity. Some of them are; the Hill-based musculoskeletal model, the state-space model, artificial neural network based models, support vector regression based models and random forests based models. The Hill-based musculoskeletal model [28] is the most commonly used model, for continuous EMG based control of robotic devices, using human motion decoded from EMG signals. Some application of the Hill-based model can be found in [20] and [29–32]. However the aforementioned Hill model based studies, typically focus on few degrees of freedom (DoFs), because Hill model equations are non-linear and there is a large number of unknown parameters per muscle. State-space models were used by Artemiadis et al. in [33],[1] and [34]. In [33], a state-space model was used to estimate human arm kinematics from the myoelectric activity of the muscles of the upper-arm and the forearm, while emphasis was given to the non-stationarity of the EMG signals and the evolution of signal quality over time (i.e. due to muscle fatigue, sweat etc.). In [1] and [34] authors proposed a methodology that "maps" muscular activations to human arm motion, using a state space models and the low dimensional embeddings of the myoelectric activity (input) and kinematics (output). Artificial neural networks (ANN) were used in [35] to estimate the continuous motion of the human fingers, using the myoelectric activity of forearm muscles (only one degree of freedom per finger was decoded), in [36] to control using EMG signals a robot arm with one degree of freedom and in [37] to decode from EMGs human arm motion, restricting the analyzed movements to single-joint isometric motions.

All the aforementioned studies, addressed the issue of EMG based continuous human motion estimation, but none of them focused on the full human arm-hand system coordination. A Support Vector Machines (SVM) based regressor was used in [2] to decode full arm hand system kinematics. However, only the position and orientation of the human end-effector (wrist) and one DoF for the human grasp, were decoded. Such a choice limits method's applicability to everyday life scenarios, where independent finger motions are of paramount importance. Finally the latter method requires smooth and slow movements from the user.

In [88–90], we proposed learning schemes that combine a classifier with a regressor to perform task-specific EMG-based human motion estimation for reach to grasp movements. Principal Component Analysis (PCA) was applied to extract the low dimensional manifolds of the EMG activity and the human kinematics. These low dimensional spaces, were used to train different task-specific models, formulating a regression problem. The scheme's classifier was used to discriminate first the task to be executed and then trigger a task-specific EMG based motion decoding model, which achieves better estimation results than "general" models. The estimated output was back projected in the high dimensional space (27 DoFs) to provide an accurate estimate of the full human arm-hand system motion. A similar methodology was recently proposed in [38], where classification techniques were used in order to discriminate between reach to grasp movements towards objects of different sizes and weights. Moreover recently we extended the learning scheme proposed in [90], in order to discriminate also the "task to be executed", as well as to perform efficient features selection with random forests [91].

3.2 Apparatus and Experiments

3.2.1 Experimental Protocol

Two different types of experiments were conducted for the formulation of the proposed learning scheme. All experiments were performed by five (4 male, 1 female) healthy subjects 21, 24, 27, 28 and 40 years old. The subjects gave informed consent of the experimental procedure and the experiments were approved by the Institutional Review Board of the National Technical University of Athens. Experiments were performed by all subjects, using their dominant hand (right hand for all subjects involved). During experiments the subjects were instructed to perform different reach to grasp movements in 3D space, to reach and grasp different objects placed at different positions in 3D space, in order to execute different tasks with the grasped objects. The object positions, are depicted in Fig. 3.1.



FIGURE 3.1: A bookcase containing three different objects (a marker, a rectangularshaped object and a mug), placed at five different positions, at three different shelves, is depicted. A superimposed diagram presents the distances between the different object positions. These five positions were used for both types of experiments.

The first type of experiments, involved reach to grasp movements towards different positions (five different positions depicted in Fig. 3.1) and different objects (a mug, a rectangular shaped object and a marker) and was used for EMG-based "subspace discrimination" and "object discrimination". The second type of experiments, involved reach to grasp movements towards specific positions and objects, in order to execute two different tasks (two classes), with the same object. A tall glass, a wine glass, a mug and a mug plate were used for the second type of "task discrimination" experiments. These first type of experiments was used for the initial formulation of the learning framework proposed in [88] and was once again used in [91] together with the second type of experiments, to discriminate between different tasks and compute feature variables importance for different positions, objects and tasks.

The tasks executed for the second type of experiments appear in Fig. 3.2. During the experiments, each subject conducted several trials, for each position, object and task combination. In order to ensure data quality and avoid fatigue, adequate resting time of one minute, was used between consecutive trials.

3.2.2 Motion Data Acquisition

In order to capture efficiently human kinematics - using appropriate motion capture systems - the kinematic models of the human arm and the human hand must be described. The kinematic model of the human arm, that we use in this study, consists of three rotational degrees of freedom (DoFs) to model shoulder joint, one rotational



FIGURE 3.2: Tasks executed for the second type of experiments. The tall glass tasks were: task 1, side grasp (to drink from it) and task 2, front grasp (to transpose it). The wine glass tasks were: task 1, side grasp (to drink from it) and task 2, stem grasp (to drink from it). The mug tasks were: task 1, handle grasp (to drink from it) and task 2, top grasp (to transpose it). Finally the mug plate tasks were: task 1, side grasp (to lift and hold it) and task 2, top grasp (to transpose it).

DoF for elbow joint, one rotational DoF for pronation-supination and two rotational DoFs for wrist flexion/extension and abduction/adduction. The kinematic model of the human hand consists of twenty rotational DoFs, four for each one of the five fingers. Regarding fingers we used for the four kinematically identical fingers (index, middle, ring and pinky) three rotational DoFs to model flexion-extension of the different joints and one rotational DoF for abduction-adduction. Human thumb is modeled, using two rotational DoFs for flexion-extension, one rotational DoF for abduction-adduction and one rotational DoF to describe palm's mobility that allows thumb to oppose to other fingers. The kinematic models of the human arm and hand are presented in Fig. 3.3.

Human Hand	Human Arm
Kinematic Model	Kinematic Model

FIGURE 3.3: Kinematic models depicting the degrees of freedom (DoFs) of the human arm and hand.



FIGURE 3.4: Two position tracking sensors of Isotrak II are used to capture user's shoulder, elbow and wrist position in 3D space, while a dataglove is used to capture the wrist and fingers joint angles. The position tracker reference system is placed on the shoulder. The human arm joint values can be computed through the human arm's inverse kinematics. q_1 and q_2 jointly correspond to shoulder flexion-extension and adduction-abduction, q_3 to shoulder internal-external rotation, q_4 to elbow flexion-extension, q_5 to pronation-supination and q_6 and q_7 jointly correspond to wrist flexion-extension and adduction-abduction.

In order to capture the human arm hand system motion in 3D space, extracting the corresponding joint angles (27 modeled DoFs), we used a dataglove for the human hand and a magnetic position tracking system for the human arm. The Isotrak II[®] (Polhemus Inc.) magnetic motion capture system used, is equipped with two position tracking sensors and a reference system. The two sensors of Isotrak II, were placed on the elbow and the wrist respectively, while the reference system was placed on the user's shoulder.

Having captured the positions of the human shoulder, elbow and wrist, the inverse kinematics of the human arm can be computed, following the directions provided in [83]. Alternatively for human robot interaction applications, a human to robot motion mapping procedure like the one proposed in [92], can be used. Regarding the human hand, the Cyberglove II[®] (Cyberglove Systems), is used to measure the two DoFs of the wrist (flexion-extension and abduction-adduction) and the twenty DoFs of the human fingers. The experimental setup that was used to track human arm hand system kinematics, is depicted in Fig. 3.4.



FIGURE 3.5: The motion capture systems used, are depicted.

3.2.3 Electrode Positioning and EMG Data Acquisition

In total, we recorded the myoelectric activity of sixteen muscles, of the upper arm (eight muscles) and the forearm (eight flexor and extensor muscles). More specifically the chosen muscles are: flexor pollicis longus, flexor digitorum superficialis, flexor carpi ulnaris, flexor carpi radialis, extensor pollicis longus, extensor indicis, extensor carpi ulnaris, extensor carpi radialis, deltoid anterior, deltoid posterior, deltoid middle, trapezius, teres major, brachioradialis, biceps brachii and triceps brachii. The selection of the muscles and the placement of the surface electromyography electrodes, was based on the related literature [22, 93]. In order to achieve easy, portable and fast to use training schemes several researchers have chosen to place the EMG electrodes, in specific regions but in random (not precise) positions [2]. We believe that the next generation of epidermal electronics [94] will make the electrode positioning faster and easier, thus we choose to take advantage of the higher signal to noise ratio, that accurate electrode positioning offers.

EMG signals were acquired and conditioned using an EMG system (Bagnoli-16[®], Delsys Inc.), equipped with single differential surface EMG electrodes (DE-2.1[®], Delsys Inc.). A signal acquisition board (NI-DAQ 6036E[®], National Instruments), was used for signal digitization and data acquisition.

3.2.4 EMG and Motion Data Processing

Regarding data processing, EMG signals were band-pass filtered (20-450 Hz), sampled at 1 kHz, full-wave rectified and low-pass filtered (Butterworth, fourth order, 8 Hz), while for the position measurements, which were provided by the position tracking system at the frequency of 30 Hz, an antialiasing finite-impulse-response filter (low pass, order: 24, cutoff frequency: 100 Hz), was used to resample them at a frequency of 1 kHz (same as the sampling frequency of the EMG signals).

3.2.5 Muscular co-activation patterns extraction

After data collection, all EMG recordings, were pre-processed and epochs of data were created. Those epochs included the different reach-to-grasp movements captured during the experiments. Then, all data were resampled at 100 Hz, where each sample at the new frequency (100 Hz) was calculated as the mean value of ten (10) samples of the original frequency (1kHz). Based on the profiles of the rectified EMG signals at the new frequency, the onset of muscular activations was defined comparing the amplitude of each muscle's myoelectric activation to it's relaxed state. Finally, epochs including only



FIGURE 3.6: Comparison of a Boxplot and a "Boxplot Zone" visualization of muscular co-activation patterns across sixteen (16) muscles of the upper arm and the forearm for one subject (Subject 1), performing reach to grasp movements towards a mug placed at position I.

muscular activations captured during the actual tasks were created, and were used to formulate synergistic profiles, using a novel statistical representation technique, that we introduced and which we call "Boxplot Zones".

A boxplot (alt. box-and-whisker plot) is a method to graphically depict groups of numerical data, through the following five-number summaries: smallest observation (sample minimum), lower quartile (Q1), median (Q2), upper quartile (Q3), and largest observation (sample maximum). Boxplot zones were first defined in [88] to visualize muscular co-activation patterns and are an equivalent of boxplots, while more visually informative representation, suitable for the representation of synergistic profiles. Boxplot zones consist of three different layers. The first layer includes the median line, connecting the medians of all boxplots. The second layer includes the box zone (blue zone), connecting the boxes that contain all the values between the lower and the upper quartile, while the third layer includes the whisker zone (white zone), connecting the whiskers that mark the largest and the smallest observation. A direct comparison of a boxplot and a boxplot zone visualization, can be found in Fig. 3.6.

In Fig. 3.7 we present a "boxplot zones" based visualization of muscular co-activation patterns of sixteen (16) muscles (of the upper arm and the forearm), for one subject (Subject 1) executing reach to grasp movements, towards five (5) different positions in 3D space, to grasp three (3) different objects. The muscular co-activation patterns presented in Fig. 3.7 in terms of synergistic profiles formulated with boxplot zones, depict a significant differentiation between the different reach-to-grasp movements, although the same joints of the arm hand system (human upper arm joints and human hand fingers) are involved, but for a different task. More precisely, if we examine the synergistic profiles (muscular co-activation patterns) across different subspaces (different positions),

we notice that the activity of the muscles of the upper-arm (EMG channels 1-8) reflects most of the differentiation. In contrary if we examine the muscular co-activation patterns across different objects, placed in the same subspace (a specific position), the activity of the muscles of the forearm (EMG channels 9-16) reflects most of the differentiation.



FIGURE 3.7: "Boxplot Zones" visualization of muscular co-activation patterns of sixteen (16) muscles (of the upper arm and the forearm), for one subject (Subject 1) performing reach to grasp movements towards, five different positions $(P_I, P_{II}, P_{III}, P_{IV} \text{ and } P_V)$ in 3D space, to grasp three different objects (a marker, a rectangle and a mug). The sixteen (16) muscles are reported in the following order (1 to 16): deltoid anterior, deltoid middle, deltoid posterior, teres major, trapezius, biceps brachi, brachioradialis, triceps brachii, flexor pollicis longus, flexor digitorum superficialis, flexor carpi ulnaris, flexor carpi radialis, extensor pollicis longus, extensor indicis, extensor carpi ulnaris and extensor carpi radialis.

In Fig. 3.8 we present a "boxplot-zones" based visualization of muscular co-activation patterns differentiation, for 16 muscles of the human upper-arm and forearm, for three different subjects performing different reach to grasp movements, towards five (5) different positions in 3D space, to grasp a specific object (rectangular-shaped object).

As we have already noted there is a significant differentiation between muscular coactivation patterns associated with different reach to grasp movements. Statistical significance of muscular co-activation patterns differentiation, can be assessed using appropriate statistical tests. More precisely the Lilliefors test (adaptation of the Kolmogorov-Smirnov test) was used to test the null hypothesis that the EMG data - containing the myoelectric



FIGURE 3.8: "Boxplot Zones" visualization of different muscular co-activation patterns of sixteen (16) muscles of the upper arm and the forearm, for three (3) different subjects performing reach to grasp movements towards, the aforementioned five (5) positions in 3D space, to grasp a specific object (a rectangle).

activations - come from a normal distribution. The test rejects the null hypothesis at the 5% significance level (p = 0.05), so the data are not normally distributed. Thus, we use non parametric tests such as, the Kruskal-Wallis and the Wilcoxon rank sum test, in order to assess the significance of muscular co-activation patterns differentiation, for different strategies.

The Kruskal-Wallis compares the medians of the myoelectric activity of the selected muscles, for different muscular co-activation patterns, and returns the p value for the null hypothesis that all samples are drawn, from the same population (or from different populations with the same distribution). The Wilcoxon rank sum test, performs a two-sided rank sum test of the null hypothesis that data of myoelectric activations with different muscular co-activation patterns, are independent samples from identical continuous distributions, with equal medians.

More details regarding the statistical procedures used, the reader can find in [95]. All tests were performed to check the differentiation of muscular co-activation patterns for the following three cases:

- For the same reach to grasp movement, between different subjects.
- For reach to grasp movements towards five different positions in 3D space.
- For reach to grasp movements towards three different objects, placed at a specific position in 3D space.

For all sets, confidence levels were set at 95%. All tests null hypotheses for all three cases were rejected, proving that muscular co-activation patterns differentiate, between



FIGURE 3.9: Means and confidence intervals of EMG activity across eight (8) muscles of the upper arm and eight (8) flexor and extensor muscles of the forearm, for one subject (Subject 1) performing reach to grasp movements, towards three (3) different objects, placed at a specific position (Pos 3) in 3D space.



FIGURE 3.10: Means and confidence intervals of EMG activity across eight (8) muscles of the upper arm and eight (8) flexor and extensor muscles of the forearm, for one subject (Subject 1) performing reach to grasp movements, towards a marker, placed at five (5) different positions in 3D space.

different subjects and between different tasks. In Fig. 3.9, we present the means and the confidence intervals of EMG activity across eight muscles of the upper arm and eight muscles of the forearm, for a subject performing reach to grasp movements, towards three (3) different objects. In Fig. 3.10, we present the means and the confidence intervals of EMG activity across eight muscles of the upper arm and eight muscles of the forearm for a subject performing reach to grasp movements, towards a marker, placed at five (5) different positions in 3D space.

Therefore, we conclude that the muscular co-activation patterns vary significantly not only between different subjects, but also between different reach-to-grasp movements of the same subject (towards different subspaces or different objects placed at specific position), and therefore should be considered and analyzed as subject-specific and taskspecific characteristics.

3.3 Methods

In this section we present some typical specifications for EMG based interfaces and we describe the problem formulation and the methods used for discrimination of different muscular co-activation patterns, associated with different reach to grasp movements (classification) and EMG based motion estimation (regression).

3.3.1 Classification and Regression Modules

Some specifications that every learning scheme for EMG based interfaces should have, are the following:

- To be able to "decide" on user's intention (classification part).
- To decode a continuous representation of human motion (regression part).
- To allow its application at a robot control scheme, in real time.
- To be easy and fast to be trained for different users (as musculoskeletal characteristics may vary significantly across subjects).
- To be able to handle multidimensional spaces and large databases of myoelectric and motion data.

In this chapter we present an EMG-based learning scheme, using the Random Forests (RF) technique - which meets the aforementioned specifications - for both classification and regression. Thus, the classifier and the regressor cooperate advantageously, in order to split the task space and confront the non-linear relationship between the EMG signals the motion to be estimated, with task specific models that provide better estimation accuracy than the "general" models (built for all tasks).

In Fig. 3.11 we present a block diagram of a typical random forests based classification procedure. Random forests are used for a multiclass classification problem, where we need to discriminate between reach to grasp movements, towards different positions, different objects (to be grasped) and different tasks (to be executed with the object) in 3D space, using human myoelectric activity (EMG).

In Fig. 3.12 we present the block diagram for a typical random forests based regression procedure. The task specific models trained are used to estimate for new EMG data (not previously seen during training) "new" human arm hand system kinematics.



FIGURE 3.11: Block diagram of the classification procedure.



FIGURE 3.12: Block diagram of the regression procedure.

A complete block diagram of the EMG-based learning scheme proposed, is depicted in Fig. 3.13. Two main modules appear, the classification module and the task specific model selection module. Classification module provides decision for subspace to move towards, object to be grasped and task to be executed (with the object). Task specific model selection module, examines classification decisions and triggers a subspace, object and task specific motion decoding model.



FIGURE 3.13: A block diagram of the proposed EMG-based learning scheme is presented. Two main modules, formulate the "backbone" of the learning scheme, the classification module and the task specific model selection module. Classification module (based on the classifier) provides decision for subspace to move towards, object to be grasped and task to be executed with the object. Task specific model selection module (based on the regressor) examines classification decisions and triggers a subspace, object and task specific motion decoding model (from all possible models trained). The task specific motion decoding model efficiently estimates the full human arm hand system motion (27 joint values), using human myoelectric activity (EMG signals). Finally an EMG-based interface can take advantage of the proposed scheme and the estimated human motion. For example a human to robot motion mapping procedure may take as input the estimated human arm hand system motion, to generate equivalent robot motion, as described in Chapter 6. A possible application of the proposed learning scheme, is the EMG-based teleoperation of a robot arm hand system.

3.3.2 Multiclass Classification in the *m*-Dimensional Space of Myoelectric Activations (*m* - number of EMG channels)

As we have already noted, synergistic profiles depicted in terms of "boxplot zones" in Fig. 3.7 denote that there is a significant differentiation of muscular co-activation patterns for reach to grasp movements towards different positions and different objects placed at the same position. In order to be able to take advantage of this differentiation, we choose to discriminate the different reach to grasp movements in the *m*-dimensional space of the myoelectric activations (where *m* is the number of EMG channels), using the EMG signals to "decide" on the task to be performed (human intention decoding).

In Fig. 3.14 we present a typical classification problem of discriminating based on the myoelectric activity of 16 muscles of the human arm hand system, two different strategies for reaching and grasping a specific object placed in two different positions. Reaching, grasping and return phases are depicted. The top subplot presents the distance between the two classes in the 16-dimensional space (16 EMG channels are used). Such a distance, give us a measure of classes separability (i.e. how easily these classes can be discriminated). The bottom subplot, presents the evolution of classification decision over time. The accumulation of misclassified samples is reasonable for those time periods, when the distance between the two classes is small (i.e. begin and end of experiments, when human end-effector (wrist), is close to its starting position).



FIGURE 3.14: Comparison of two reach to grasp movements towards a marker placed at position I (Strategy I) and a marker placed at position II (Strategy II). First subplot presents the distance of the two strategies in the m-dimensional space (where m=16 the number of the EMG channels). The second subplot focuses on the evolution of classification decision per sample, over time.

In Fig. 3.15 we present the classification problem of discriminating two different different reach to grasp movements, towards a specific object placed at a specific position, but in order to execute two different tasks (with the object). Once again, top subplot presents the distance between the two classes in the 15-dimensional space (15 EMG channels are used), as well as the reaching, grasping and return phases. Bottom subplot presents once again the evolution of the classification decision and there is a similar with Fig. 3.14, accumulation of misclassified samples for the time periods, that the distance between the two tasks is small (i.e. begin and end of the experiment).

3.3.2.1 Random Forests Classifier

The Random Forests technique proposed by Tin Kam Ho of Bell Labs [96] and Leo Breiman [97], can be used for classification creating an ensemble classifier that consists



FIGURE 3.15: Comparison of two reach to grasp movements, towards Position I to grasp a Tall Glass with two different grasps (side grasp and front grasp), to execute two different tasks. First subplot presents the distance of the two tasks in the *m*-dimensional space (where m = 15 the number of the EMG channels). The second subplot focuses on the evolution of classification decision per sample, over time.

of many decision trees. The Random Forests classifier's output, is the class that is the mode of the individual trees class's output. Thus, the classifier consists of a collection of tree structured classifiers $\{h(\mathbf{x}, \Theta_N), N = 1, ...\}$ where $\{\Theta_N\}$ are independent identically distributed random vectors. Each decision tree of the random forest, casts a vote for the most popular class at input \mathbf{x} .

The classification procedure for N trees grown is presented in Fig. 3.16. Some advantages of the random forests technique for classification are:

- Runs efficiently and fast on large databases.
- Provides high accuracy.
- Does not overfit.
- Provides feature variables importance.
- Can handle thousands of input variables without variable deletion.
- Can handle multiclass classification problems.
- Can be used efficiently in multidimensional spaces.



FIGURE 3.16: Random forests based classification procedure for N trees grown. OOB stands for out-of-bag samples.

3.4 Features Selection with Random Forests

In the aforementioned classification examples we used the random forests technique to discriminate, between different reach to grasp movements in the m-dimensional space of the myoelectric activations, using multiple EMG channels (m is 15 or 16). Its quite typical for EMG based interfaces, a limited number of EMG channels to be available (e.g., due to cost or complexity limitations), or EMG electrodes positioning to be not precise (some EMG channels may be more noisy). Thus, a fundamental question is: "Is it possible to select which EMG channels are the most important? How this features selection can be accomplished?". With Random Forests we can perform efficient features selection, using their ability to compute the importance score of each feature variable and consequently access the relative importance for all feature variables (e.g. EMG channels).

More precisely random forests use for the construction of each tree, a different bootstrap sample set from the original data. One-third of the samples are left out of the bootstrap sample set (out-of-bag samples) and are not used in the construction of the Nth tree. Feature variables importance, is computed as follows; in every grown tree in the forest, we put down the out-of-bag samples and count the number of votes cast for the correct class. Then the values of a variable m are randomly permuted in the out-of-bag samples and these samples are put down the tree. Subtracting the number of votes casted for the
correct class in the m-variable permuted out-of-bag data from the previously computed number of votes for the correct class in the untouched out-of-bag data, we get the importance score of a feature variable m for each tree. The raw importance score for each feature variable m is the average importance score for all trees of the random forest. The random forests feature variable importance calculation procedure, is depicted in Fig. 3.17.



FIGURE 3.17: Diagram of the random forests feature variable importance calculation procedure. OOB stands for out-of-bag samples.

In case that we want to reduce the number of EMG channels used (in this study we have already used 15 and 16 EMG channels), random forests can be initially run with all the variables (EMG channels) and then run once again with the most important variables selected during the first run. For example, we can use the random forests classifier with all 15 EMG channels, compute the feature variables importance and re-solve the classification problem, using the most "important" EMG channels. Before doing so, we present the feature variables importance for the problems of discriminating from EMG signals, reach to grasp movements towards, different subspaces, different objects and different tasks.

In Fig. 3.18 we present the importance plots of different feature variables (EMG channels), for two different cases, subspace discrimination and object discrimination. We can notice that for subspace discrimination, the feature variables corresponding to upper-arm muscles (first 8 EMG channels) appear to have increased importance, while for object discrimination the feature variables corresponding to the forearm muscles (last 8 EMG channels), accumulate most of the importance.



FIGURE 3.18: Importance plots of feature variables (EMG channels) - expressed as mean decrease in accuracy - for Subject I, for subspace and object discrimination respectively. For subspace discrimination data involving all objects are used, while for object discrimination, a specific position is used (Pos I). Positions 1 to 5 correspond to positions Pos I to Pos V. Objects 1, 2 and 3 correspond to mug, marker and rectangle respectively.

This latter evidence can also be verified by the fact that for reach to grasp movements towards different subspaces, the muscular co-activation patterns of the upper-arm muscles accumulate most of the differentiation, while for reach to grasp movements towards different objects, the muscular co-activation patterns of the forearm muscles (responsible for grasping), accumulate most of the differentiation.

In Fig. 3.19 we present the importance plots for different feature variables (EMG channels), for task discrimination. Four different barplots are depicted, that contain the importance scores per variable for different objects placed in position I. We can notice that the feature variables corresponding to the forearm muscles (last 8 EMG channels) appear to have once again increased importance (similarly to object discrimination), since the forearm muscles are responsible for hand preshaping, in order to grasp and/or manipulate objects.



FIGURE 3.19: Importance plots of feature variables (EMG channels) for task discrimination. Reach to grasp movements towards all objects placed in Position I were performed, so as to execute two different tasks per object. A list of the tasks executed can be found in Fig. 3.2.

3.4.1 Task Specific Motion Decoding Models

3.4.1.1 Task Specific EMG Based Motion Decoding Models based on Random Forests Regression

The Random Forests technique can also be used for regression, growing trees depending on a random vector Θ such that the tree predictor $h(\mathbf{x}, \Theta)$ takes on numerical values (not class labels used for classification). The random forest predictor, is formed similarly to the classification case, as appeared in Fig. 3.16, by taking instead of the most popular class, the average over the N trees of the forest { $h(\mathbf{x}, \Theta_N)$ }.

Some advantages of the random forests regression are the following:

- Are easily implemented and trained.
- Are very fast in terms of time spent for training and prediction.
- Can be parallelized.
- Can handle thousands of input variables and run efficiently on large databases (similarly to classification).
- Are resistant to outliers.

- Have very good generalization properties.
- Can output more information than just class labels (e.g., sample proximities, visualization of output decision trees etc.).

3.4.1.2 Dimensionality Reduction

In order to formulate the regression problem used in this study, we need the lowdimensional spaces of the myoelectric activations and the human motion. Thus, in order to represent our data in low-d spaces, we used the Principal Components Analysis (PCA), dimensionality reduction method. For the EMG signals recorded, a 4-D space suffices, representing most of the original high-dimensional data variance (more than 92%). Regarding the human arm hand system kinematics, a 4-D space once again suffices to describe adequately the 27-DoF motion of the human arm hand system, representing most (94%) of the original data variance. We chose to use the PCA as a dimensionality reduction technique - in order to take advantage of the underlying covariance of our data - representing also the same variability in a low-d space, without losing important information of the original data. More details regarding the employment of PCA in EMG based interfaces, can be found in [1].

3.5 Results

3.5.1 Classifiers Comparison

In order to validate our hypothesis that random forests based classification is an ideal method for EMG based interfaces, we have applied a wide variety of classification techniques in our dataset, comparing them with random forests, in terms of classification accuracy and time required for training.

More precisely, we performed Support Vector Machines (SVM) based classification (with a Radial Basis Function (RBF) kernel), we constructed a single hidden-layer Neural Network (NN) with ten hidden units (trained with the Levenberg-Marquardt backpropagation algorithm) and we used the k nearest neighbors (kNN) classifier, for the simplest case where k = 3. Finally random forests were grown with ten trees for speed. Random Forests outperformed the classification performance of all other classifiers and performed quite well in terms of speed of execution.

The classification success rate (classification accuracy) is defined, as the percentage of EMG data points classified to the correct reach to grasp movement. It must be noted that

the classification is done for every acquired EMG data point, thus the proposed learning scheme is able to decide in real-time the reach to grasp movement to be performed (for a specific task), and even switch to different tasks online. All classification results presented in this section, are the average values over the five rounds, of the five-fold cross-validation method applied.

The training dataset that was used to compare classifiers in terms of speed of execution, involved Subject 1 data of reach to grasp movements towards different objects, placed at Position I (Class I) and Position II (Class II). Results are reported in Table 3.1. All benchmarks were performed using MATLAB (Mathworks) in a standard PC with Intel(R) Core(TM) I5 CPU 611 @3.33GHz and 4GB RAM (DDR3) memory.

Classifiers	Samples	Training Time
	2 Classes of 1500	0.011 sec
LDA	2 Classes of 15000	$0.058 \sec$
	2 Classes of 1500	0.005 sec
QDA	2 Classes of 15000	0.051 sec
	2 Classes of 1500	0.014 sec
kNN	2 Classes of 15000	$1.65 \sec$
	2 Classes of 1500	1.06 sec
ANN	2 Classes of 15000	16.05 sec
	2 Classes of 1500	$0.34 \sec$
SVM	2 Classes of 15000	$7.09 \sec$
	2 Classes of 1500	0.06 sec
Random Forests	2 Classes of 15000	0.87 sec

TABLE 3.1: Comparison of classifiers in terms of time required for training.

The training dataset that was used to compare classifiers in terms of classification accuracy, involved Subject 1 data of reach to grasp movements towards two objects (two classes), placed across three different positions in 3D space. Results are reported in Table 3.2.

3.5.2 Comparison of different Decoding Methods

In order to validate our hypothesis that random forests based regression is an ideal method for EMG based interfaces, we have applied also a wide variety of regression techniques in our data, comparing them with random forests, in terms of estimation accuracy and time spent for training. More specifically we performed Multiple Linear Regression (MLR), we created a State-Space model as described in [1], we performed SVM regression (with a RBF kernel) and we constructed a single hidden layer Neural Network with ten hidden units (trained with the Levenberg-Marquardt backpropagation

Classifiers	Positions	Mug	Rectangle
	Pos I	96.75%	83.36%
LDA	Pos III	96.50%	90.40%
	Pos V	91.44%	95.00%
	Pos I	95.34%	80.52%
QDA	Pos III	97.30%	91.45%
	Pos V	92.30%	95.60%
	Pos I	96.33%	81.63%
kNN	Pos III	98.20%	94.50%
	Pos V	96.50%	98.68%
	Pos I	94.67%	84.63%
ANN	Pos III	98.50%	94.76%
	Pos V	94.52%	98.87%
	Pos I	97.46%	87.42%
$_{\rm SVM}$	Pos III	98.81%	94.50%
	Pos V	98.00%	96.50%
	Pos I	99.67%	89.02%
Random Forests	Pos III	100%	96.50%
	Pos V	98.87%	99.00%

TABLE 3.2: Comparison of classifiers for discriminating two different reach to grasp movements, towards two objects placed across three different positions in 3D space, for Subject 1.

algorithm). Finally random forests were used as a regression technique, growing ten (10) decision trees, to increase speed of execution and computational efficiency.

The formulated regression problem, was to map the low-d space (4 dimensions) of the myoelectric activity (EMG signals), to the low-d space (4 dimensions) of the human motion. The low-d spaces of human myoelectric activations and human motion were extracted using the PCA method. Then the estimated low-d human motion was backprojected to the high-d space providing an estimate of the full human arm hand system kinematics (27 DoFs). As far as the estimation accuracy is concerned, we compared the methods for different datasets, estimating human motion for reach to grasp movements, towards different positions, as well as different objects placed at the same position. Regarding training time, we chose to compare the different techniques in terms of time required for training, applying the various methods to a separate dataset, that serves as a benchmark. In table 3.3, we can notice that random forests outperform most other techniques, in terms of speed of execution.

Method	Time in sec.
MLR	0.0054 sec
State Space	$8.65 \ sec$
ANN	28.83 sec
SVM	$27.72 \sec$
Random Forests	5.89 sec

TABLE 3.3: Time spend for the training procedure across different methods for a specific dataset (10000 samples) that serves as a benchmark (Average Values).

In Table 3.4 we can notice that random forests outperform also the other regression techniques, such as the Support Vector Machines (SVM) and the Artificial Neural Networks (ANN), in terms of estimation accuracy. In order to compare the different regressors a standard PC with an Intel(R) Core(TM) I5 CPU 611 @3.33GHz, equipped with a 4GB RAM (DDR3) memory, was once again used. The benchmark was performed using MATLAB (Mathworks). More information regarding the regression techniques comparison results, can be found in [89].

TABLE 3.4: Comparison of different methods and estimation results, for specific position (Pos III) and specific object (Marker), for Subject 1. Average values for different validation set splittings.

Method	Arm Joints	Hand Joints
	Similarity (%)	Similarity $(\%)$
MLR	81.60%	84.31%
State Space	82.74%	85.10%
ANN	85.10%	86.92%
SVM	86.01%	88.90%
Random Forests	86.93%	90.42%

3.5.3 Classification Results

In Table 3.5, we present the classification results across different reach to grasp movements, for a specific position and three different objects (three classes) for all subjects, using the random forest method. In Table 3.6 we present the classification accuracy across different reach to grasp movements, for a specific object and five different object positions (five classes), for all subjects, using random forests.

In Table 3.7 we present the classification accuracy of random forest models, across reach to grasp movements towards five different positions (five classes), for all objects and subjects, using the random forest method. In Table 3.8, we present the classification

Positions		Objects (Classes)	
	\mathbf{Mug}	Marker	Rectangle
Pos I	$87.82\% (\pm 4.52)$	$91.15\% (\pm 5.31\%)$	$88.82\% (\pm 4.63\%)$
Pos II	$84.24\% \ (\pm 5.99\%)$	$90.40\% (\pm 4.52\%)$	$91.81\% (\pm 5.41\%)$
Pos III	$84.78\% (\pm 5.78\%)$	$86.72\% (\pm 5.16\%)$	$85.39\% (\pm 4.95\%)$
Pos IV	$83.24.\% (\pm 6.14\%)$	$84.17\% (\pm 6.21\%)$	$86.93\% (\pm 4.83\%)$
Pos V	$86.55\% (\pm 4.39\%)$	$89.32\% (\pm 3.81\%)$	$90.74\% (\pm 3.78\%)$

TABLE 3.5: Classification accuracy across different reach to grasp movements towards a specific position and three different objects (three classes), for all subjects (using random forests)

TABLE 3.6: Classification accuracy across different reach to grasp movements, for a specific object and five different object positions (five classes), for all subjects (using random forests)

Positions		Objects	
(Classes)	Mug	Marker	Rectangle
Pos I	$86.01\% (\pm 4.16\%)$	$89.83\% (\pm 4.01\%)$	$87.01\% \ (\pm 6.57\%)$
Pos II	$83.76\% (\pm 6.24\%)$	87.95% (±4.78%)	$88.43\% \ (\pm 5.51\%)$
Pos III	$89.74\% (\pm 3.41\%)$	$87.23\% (\pm 4.92\%)$	$90.30\% (\pm 4.01\%)$
Pos IV	$91.23\% (\pm 2.39\%)$	$90.05\% (\pm 4.86\%)$	$90.51\%~(\pm 3.92\%)$
Pos V	$91.80\% (\pm 3.45\%)$	$92.34\% \ (\pm 2.69\%)$	$90.90\%~(\pm 3.01\%)$

results achieved, using 15 EMG channels to discriminate between reach to grasp movements, towards specific position and object combinations (for all objects and positions), to execute two different tasks per object (two classes). As it can noticed, classification accuracy is consistently high across different positions, different objects and different tasks. The latter evidence proves the efficiency of the proposed scheme for various reach to grasp movements and tasks.

TABLE 3.7: Classification accuracy across different reach to grasp movements towards different positions, for all objects and subjects. Random Forests classifier was used for data with 16 EMG channels, from all subjects.

		Positions		
Pos I	Pos II	Pos III	Pos IV	Pos V
88.51%	86.29%	87.91%	89.20%	91.02%

In Table 3.8, we reported some interesting classification results for task discrimination, using a lot of EMG channels (15 EMG channels) which typically may not be available, due to hardware, cost or other limitations. Thus in this work we use the random forests technique to compute the feature variables (EMG channels) importance for each position

TABLE 3.8: Classification accuracy across different reach to grasp movements, towards different positions and objects, to execute two different tasks (two classes). Random forests classifier was used for 15 EMG channels, of Subject 1 data.

Tall Glass			
Side Grasp	Front Grasp		
$76.31\% (\pm 7.41\%)$	$78.87\% (\pm 4.72\%)$		
$89.77\% (\pm 5.43\%)$	$87.88\% (\pm 9.42\%)$		
84.86% (±8.27%)	$85.75\% (\pm 2.38\%)$		
$89.69\% (\pm 5.61\%)$	$86.82\% \ (\pm 8.06\%)$		
87.56% (±8.20%)	$90.36\% (\pm 4.77\%)$		
Wine Glas	55		
Side Grasp	Stem Grasp		
84.14% ($\pm 4.15\%$)	$85.20\% \ (\pm 4.59\%)$		
71.23% ($\pm 5.19\%$)	$79.72\%~(\pm 9.31\%)$		
$66.64\% (\pm 8.15\%)$	$77.71\% (\pm 11.47\%)$		
$87.98\% (\pm 5.21\%)$	$89.02\%~(\pm 5.81\%)$		
$66.44\% (\pm 8.66\%)$	$64.28\%~(\pm 7.62\%)$		
Mug			
Handle Grasp	Top Grasp		
$89.33\% \ (\pm 6.66\%)$	$90.74\% \ (\pm 6.78\%)$		
$79.77\% \ (\pm 6.74\%)$	$82.31\% (\pm 7.02\%)$		
$75.98\% \ (\pm 9.63\%)$	$83.52\%~(\pm 7.03\%)$		
$84.91\% (\pm 3.83\%)$	$86.99\%~(\pm 5.20\%)$		
$77.83\% (\pm 5.79\%)$	$77.36\%~(\pm 3.95\%)$		
Mug Plat	e		
Side-Pinch Grasp	Top Grasp		
$84.98\% (\pm 2.52\%)$	$81.76\% (\pm 4.99\%)$		
$89.58\% (\pm 6.11\%)$	$92.76\% (\pm 4.27\%)$		
<i></i>			
$86.73\% (\pm 7.57\%)$	$95.58\% (\pm 1.92\%)$		
$\frac{86.73\% (\pm 7.57\%)}{87.16\% (\pm 6.59\%)}$	$\frac{95.58\% (\pm 1.92\%)}{85.64\% (\pm 9.86\%)}$		
	Side Grasp $76.31\% (\pm 7.41\%)$ $89.77\% (\pm 5.43\%)$ $84.86\% (\pm 8.27\%)$ $89.69\% (\pm 5.61\%)$ $87.56\% (\pm 8.20\%)$ Wine Glass Side Grasp $84.14\% (\pm 4.15\%)$ $71.23\% (\pm 5.19\%)$ $66.64\% (\pm 8.15\%)$ $87.98\% (\pm 5.21\%)$ $66.44\% (\pm 8.66\%)$ Mug Handle Grasp $89.33\% (\pm 6.66\%)$ $79.77\% (\pm 6.74\%)$ $75.98\% (\pm 9.63\%)$ $84.91\% (\pm 3.83\%)$ $77.83\% (\pm 5.79\%)$ Mug Plat Side-Pinch Grasp $84.98\% (\pm 2.52\%)$ $89.58\% (\pm 6.11\%)$		

and object combination and resolve the classification problems for task discrimination, using the 6 most important EMG channels.

Results for task discrimination, using the most important EMG channels, are reported in Table 3.9. We can notice that even for the reduced number of feature variables (EMG channels), classification accuracy remains consistently high and the results are equal or better that the initial results (with the 15 EMG channels).

In the aforementioned results, is evident that the classification accuracy and the overall ability of our scheme to discriminate different reach to grasp movements, towards different tasks (executed with the same object), depends on:

TABLE 3.9: Classification accuracy across different reach to grasp movements, towards different positions and objects, to execute two different tasks (two classes), for Subject 1. Random forests were used with the 6 most important EMG channels selected using the features selection method.

Tasks	Side Grasp	Front Grasp	
Pos I	$81.43\% (\pm 2.64\%)$	79.91% (±7.69%)	
Pos II	89.79% (±7.35%)	90.79% (±7.97%)	
Pos III	82.84% (±9.12%)	88.76% (±3.34%)	
Pos IV	89.82% (±5.89%)	87.71% (±7.97%)	
Pos V	84.66% (±9.98%)	92.85% (±4.14%)	
L	Wine Glas	55	
Tasks	Side Grasp	Stem Grasp	
Pos I	86.77% (±3.72%)	84.30% (±3.77%)	
Pos II	$74.50\% (\pm 9.81\%)$	81.20% (±9.64%)	
Pos III	$72.62\% (\pm 8.66\%)$	79.39% (±13.56%)	
Pos IV	86.90% (±8.40%)	$87.61\% (\pm 5.95\%)$	
Pos V	$63.41\% (\pm 6.88\%)$	$64.24\% \ (\pm 9.72\%)$	
Mug			
Tasks	Handle Grasp	Top Grasp	
Pos I	$87.17\% (\pm 4.67\%)$	$87.85\% (\pm 4.59\%)$	
Pos II	$80.10\% (\pm 7.36\%)$	83.72% (±5.87%)	
Pos III	$77.90\% (\pm 5.40\%)$	$81.43\% \ (\pm 6.98\%)$	
Pos IV	$85.35\% (\pm 4.14\%)$	$84.98\% \ (\pm 6.07\%)$	
Pos V	$81.06\% (\pm 8.29\%)$	$78.95\%~(\pm 9.57\%)$	
Mug Plate			
Tasks	Side-Pinch Grasp	Top Grasp	
Pos I	$84.34\% \ (\pm 5.57\%)$	83.60% (±3.44%)	
Pos II	$90.74\%~(\pm 4.59\%)$	$94.01\% (\pm 3.49\%)$	
Pos III	$85.55\% \ (\pm 12.07\%)$	$95.61\% (\pm 2.89\%)$	
Pos III Pos IV	$\frac{85.55\% (\pm 12.07\%)}{86.74\% (\pm 10.18\%)}$	$\frac{95.61\% (\pm 2.89\%)}{83.79\% (\pm 7.27\%)}$	

Tall Glass

• The "distance" (in the configuration space) between the final postures of the full human arm hand system, that correspond to different tasks.

For example the two tasks of the tall glass, mug and mug plate result to completely different human wrist angles (wrist motion strongly affects forearm muscles). Thus, for these tasks better classification results can be achieved, in contrast to the wine glass tasks that involve mainly finger motions and variations of the aperture (less differentiation of muscular co-activation patterns).

• The position of the object to be grasped, as different positions result to different classification accuracies for the same object and tasks.

For example for positions I and IV the classifier achieves better classification accuracy for wine glass and mug, while positions II and V achieves better results for tall glass and mug plate.

3.5.3.1 Majority Vote Criterion

Given the fact that the classification decision in our scheme is taken at a frequency of 1 kHz, we can use a sliding window of width N, in order for all the N samples to be used for the classification decision. Inside this window, we can use the Majority Vote Criterion (MVC), which classifies all the samples of a set of N samples, in the class that was the most common between them (the class gathering the most votes). The use of the majority vote criterion, can improve the classification results acquired with the proposed methods.

More details regarding the sliding window and the MVC can be found in [88] and [98]. In Table 3.10, we present improved classification results using the majority vote criterion in a sliding window of N = 50 samples, for Subject 1 performing reach to grasp movements, towards a specific object (marker) and varying object position.

TABLE 3.10: Classification accuracy across different reach to grasp movements of Subject 1, towards a specific object (Marker) and varying object position, using random forests and random forests with MVC (in a sliding window of N=50 samples).

Object	Subject1				
Rectangle	Pos I	Pos II	Pos III	Pos IV	$\mathbf{Pos} \ \mathbf{V}$
Random Forests	87.03%	91.61%	90.51%	86.25%	92.61%
RF with MVC	100%	100%	100%	100%	100%

3.5.4 Task Specific Motion Decoding Results

In this section we present the EMG-based motion estimation results, for reach to grasp movements towards three different objects, placed at five different positions in 3D space. Highly accurate estimation results are achieved using task-specific random forest models, triggered from our scheme, taking into account the classification decision on the "task" to be executed.

More specifically in Table 3.11 we present estimation results for five subspace specific models, trained with Subject 1 data, to decode human motion during reach to grasp movements, towards five different positions to grasp a specific object (marker). In Table 3.12 we present estimation results for three object specific models, trained with Subject

1 data, to decode human motion during reach to grasp movements, towards a specific position (Pos I), to grasp three different objects (a marker, a rectangle and a mug).

In Tables 3.11 and 3.12 we can notice, that the models trained for each position or object separately, outperformed the "general" models built for all positions (for a marker) and all objects (placed at specific position, Pos III). With the term "general" models we mean those models trained for all positions in 3D space or all objects placed at a specific position (training of "general" models requires a training set that contains data for all classes of a specific problem).

Position	Arm	Hand
	Similarity (%)	Similarity (%)
Pos I	$83.78\% \pm 4.01\%$	$83.43\% \pm 13.77\%$
Pos II	$88.80\% \pm 3.98\%$	$86.60\% \pm 15.02\%$
Pos III	$86.93\% \pm 3.95\%$	$90.42\% \pm 10.47\%$
Pos IV	$89.47\% \pm 6.25\%$	$83.73\% \pm 16.12\%$
Pos V	$91.53\% \pm 6.57\%$	$89.04\% \pm 10.09\%$
ALL	$80.19\% \pm 7.32\%$	$81.15\% \pm 16.24\%$

 TABLE 3.11: Estimation results for a specific object (a marker) across all five object positions, for Subject 1, using a random forests model.

TABLE 3.12: Estimation results for a specific position (Pos III) and all three different
objects, for Subject 1, using a random forests model.

Object	Arm	Hand
	Similarity (%)	Similarity (%)
Marker	$86.93\% \pm 3.95\%$	$90.42\% \pm 10.47\%$
Rectangle	$87.76\% \pm 4.13\%$	$82.33\% \pm 12.31\%$
Mug	$89.62\% \pm 5.13\%$	$83.52\% \pm 13.57\%$
ALL	$83.26\% \pm 7.2\%$	$80.47\% \pm 11.72\%$

Finally in Table 3.13 its evident, that the estimation results were usually better for the human arm (better estimation accuracy for human arm motion was achieved) than for the case of the human hand (human fingers motion). Such a finding, supports the applicability of our method, since precisely estimating the position of the human arm hand system end-effector (wrist), is far more important than fingers placement.

Similarity between the estimated and the captured human motion is defined as:

$$S = 100(1 - RMS(q_c - q_e)/RMS(q_c))\%$$
(3.1)

Subject	Arm	Hand	
	Similarity (%)	Similarity $(\%)$	
Subject 1	$87.76\% \pm 4.13\%$	$82.33\% \pm 10.47\%$	
Subject 2	$85.91\% \pm 6.21\%$	$81.59\% \pm 11.78\%$	
Subject 3	$89.44\% \pm 4.30\%$	$84.93\% \pm 14.93\%$	
Subject 4	$87.32\% \pm 5.34\%$	$85.28\% \pm 10.16\%$	
Subject 5	$82.11\% \pm 7.79\%$	$80.54\% \pm 16.32\%$	

TABLE 3.13: Estimation results for specific position (Pos III) and specific object (a rectangle), for all subjects using a random forests model.

where RMS is:

$$RMS(q_c - q_e) = \sqrt{\frac{\sum_{i=1}^{n} (q_c - q_e)^2}{n}}$$
(3.2)

where q_c are the captured joint values, q_e the estimated joint values and n the number of samples. In Fig. 3.20 we compare the estimated from the task-specific model, user's wrist position, with the user's wrist position captured using the Isotrak II motion capture system, during the experiments. The data used are part of a validation set, not previously seen during training.



FIGURE 3.20: EMG-based human end-effector (wrist) position estimation (using a taskspecific motion decoding model). Straight lines represent the captured values (during the experiments), while the dashed lines represent the estimated values.

3.6 Concluding Remarks

A complete learning scheme for EMG based interfaces, has been proposed. A regressor and a classifier cooperate advantageously in order to split the task space, and achieve better motion decoding for reach to grasp movements, using task specific models. Thus, the proposed scheme is formulated so as to first discriminate between different reach to grasp movements, providing an appropriate classification decision and then trigger a task-specific EMG based motion decoding model, that achieves better motion estimation, than the "general" models. Principal Component Analysis (PCA) is used to represent in low dimensional manifolds the human myoelectric activity and the human motion. The regression problem is then formulated using these low-dimensional embeddings. The estimated output (human motion) can be back projected in the high dimensional space (27 DoFs), in order to provide an accurate estimate of the full human arm-hand system motion. The proposed scheme can be used by a series of EMG-based interfaces and for applications that range from human computer interaction and human robot interaction, to rehabilitation robotics and prosthetics.

Part III - Anthropomorphism

Chapter 4

The Role of Anthropomorphism



FIGURE 4.1: The DLR Anthropomorphic Arm Hand System.

The essence of anthropomorphism as described in [99], is to imbue the imagined or real behavior of nonhuman agents with humanlike characteristics, motivations, intentions and emotions. Anthropomorphism is derived from the greek word *anthropos* (that means human) and the greek word *morphe* (that means form).

4.1 The Role of Anthropomorphism

Almost 140 years ago Charles Darwin suggested anthropomorphism as a necessary tool for efficiently understanding nonhuman agents [39]. Nowadays, we experience an increasing demand for human robot interaction applications that require anthropomorphism, for two main reasons:

- Safety in human robot interaction.
- Social connection through robot likeability.

Regarding safety in HRI applications, humanlike motion can more easily be interpreted by the humans. Thus, when humans and robots cooperate advantageously in order to execute a series of specific tasks, if robots move anthropomorphically, users can more easily predict robots motion complying accordingly their activity/motion, to avoid possible injuries.

Regarding social connection through robot likeability, the more human-like a robot is in terms of appearance (e.g., humanlike appearance, use of artificial skin etc.), motion (e.g., co-ordinated movements, use of synergies etc.), expressions (e.g., facial expressions) and perceived intelligence (how intelligent the robot "seems" to be), then the more easily will manage to establish a solid social connection with humans. An exception to this rule of thumb, is the well-known uncanny valley, as described by [40] and [41]. More information regarding anthropomorphism and it's social implications, can be found in [42], [71] and [72].



FIGURE 4.2: A robot arm helps make engine components at a Volkswagen factory in Germany. For the first time, robots are working alongside humans without guards or other safety barriers between them. Credit: Universal Robots (http://www.universal-robots.com).



FIGURE 4.3: The iCub humanoid robot [73]. Credit: Cheney D'souza

4.2 Functional and Perceptional Anthropomorphism

A first approach to investigate the different expressions of anthropomorphism can be found in [74]. In this latter study, the authors discriminate between functional and structural anthropomorphism for the development of technical devices that will assist disabled people. The *functional way* to develop such a device, is to provide a human function independently of the structural form, while the *structural way*, is to more or less accurately imitate some part of the human body.

As we have already noted in this Ph.D. thesis, we mainly focus on the different applications of anthropomorphism for robot arm hand systems that can be used with EMG based interfaces, for Human Robot Interaction applications (e.g., EMG based teleoperation, EMG control of anthropomorphic prosthetic devices etc.). Thus, in order to discriminate between the different notions of anthropomorphism, we propose a clear distinction between *Functional* and *Perceptional Anthropomorphism*.

Functional Anthropomorphism concerns a mapping approach that has as first priority to guarantee the execution of a specific functionality in task-space and then having accomplished such a prerequisite to optimize anthropomorphism of structure or form (minimizing some "distance" between the human and robot motion). For defining that "distance", appropriate metrics / criteria of anthropomorphism have to be defined, that will lead with low-complexity in unique anthropomorphic solutions. On the other hand we suggest *Perceptional Anthropomorphism* as the subcategory of anthropomorphism that concerns co-ordinated motion, behavior, decisions or even emotions that can be perceived intuitively as human-like (of human nature). Perceptional anthropomorphism can be further splitted in structural or postural anthropomorphism focusing on instantaneous structural similarity, motion co-ordination and synergistic performance, as well as in behavioral anthropomorphism concerning the imitation of human behavior by robots (e.g., use of similar facial expressions by humanoids, empathetic behavior etc.).

As it can be easily hypothesized the "boundaries" between postural/structural and behavioral anthropomorphism are not clear, as parameters like the velocity profile of a motion may be classified subjectively in both categories. Thus, we propose the generic term perceptional anthropomorphism to examine all those cases where the "pursuit" of anthropomorphism is not constrained by having as a prerequisite the execution of a specific functionality in task-space.

4.3 Applications of Anthropomorphism

Anthropomorphism may be used for various Human Robot Interaction applications. In this Ph.D. thesis we focus on the following two:

- Development of human-like robotic artifacts.
- Mapping human to humanlike robot motion.

In order to develop human-like robots (e.g., human-like robot hands), we need first to be able to measure anthropomorphism/humanlikeness of robot artifacts. Thus, in Chapter 5, we propose a complete methodology for quantifying anthropomorphism of robot hands, comparing them with nature's most dexterous end-effector, the human hand.

Then, in order to map human to anthropomorphic robot motion we use the notion of Functional Anthropomorphism, proposing a series of mapping schemes, that take advantage of specific criteria of anthropomorphism. These criteria, lead to the minimization of structural dissimilarity between human and robot arm hand systems configurations. More information can be found in Chapter 6.

4.4 Concluding Remarks

In this Chapter we presented a brief introduction on the definition of anthropomorphism of robot artifacts, we discussed the importance of humanlikeness, we introduced the notions of Functional and Perceptional Anthropomorphism and we presented some possible applications.

Chapter 5

Quantifying Anthropomorphism of Robot Artifacts

In this chapter we propose a methodology based on set theory and computational geometry methods, for the quantification of anthropomorphism of robot hands. In order to quantify anthropomorphism we choose to compare human and robot hands in two different levels: comparing finger phalanges workspaces and comparing workspaces of the finger base frames. A series of metrics are introduced that assess robot's ability to mimic the human hand. The final score of anthropomorphism uses a set of weighting factors for the different metrics (that can be adjusted according to the specifications of each study), providing always an overall normalized score that ranges between 0 (non-anthropomorphic) and 1 (human-identical). The models of three different robot hands have been used for our analysis, the Barrett Hand, the DLR/HIT II and the Shadow hand. The proposed methodology can be used to grade the humanlikeness and to provide specifications for the design of the next generation of anthropomorphic robot hands and myoelectric prostheses, as described in Chapter 9.

5.1 Introduction

During the last decades, the field of robot hands design has received an increased attention, as robot hands can be used for a plethora of everyday life applications, that range from lightweight prostheses that can help amputees regain lost dexterity [100] and teleoperation/telemanipulation studies [101], to autonomous anthropomorphic grasp planning [102]. Nowadays, anthropomorphic characteristics (e.g. appearance, links lengths etc.), use of light-weight, low-cost and flexible materials and synergistic actuation are the prevailing trends for robot hands design.

Despite the increased interest and the numerous robot hand designs proposed, there is still a lack of insight regarding anthropomorphism of robot hands. How can we define "anthropomorphism"? Is it possible to discriminate if a robot hand is more anthropomorphic that another? How can anthropomorphism be helpful? Why do we need anthropomorphism in the first place? These are some of the fundamental questions that will be raised and addressed in this chapter.

As we have already noted in Chapter 4, anthropomorphism becomes a necessity for two main reasons; safety and social connection through robot likeability. Moreover, for the case of robot hands, we must take into consideration the fact that everyday life objects are designed to be manipulated by the human hand. Thus, the pursue of humanlike design becomes a necessity not only to increase dexterity of the robotic artifacts and to mimic the human hand in terms of appearance, but also in order to incorporate in the robotic hand design some human specifications, according to which the objects surrounding us have been crafted.

Regarding previous attempts to analyze anthropomorphism of robotic hands, an index of anthropomorphism was proposed in [43] and [44], as the weighted sum of kinematics, contact surfaces and size scores. These studies take many robot attributes into consideration, but they don't provide a comparative analysis of the workspaces of human and robot fingers and they don't take into consideration the mobility of finger base frames, for the computation of the score of anthropomorphism. In [103] a review of the performance characteristics of many commercial prosthetic and anthropomorphic robotic hands is conducted, but the approach is strictly qualitative. Recent quantitative studies [45] and [46], use Gaussian Process - Latent Variable Models (GP-LVM) to represent in lowdimensional manifolds the human and robot hand workspaces and compare them. Only the fingertip positions are included in their analysis, without taking into account the configurations, the phalanges lengths, or the mobility of the human finger base frames.

Regarding workspaces analysis, in [58] a comparison is performed between a haptic interface (based on two DLR-KUKA LWR arms) and the reachable workspace of the human arm, using the reachability map proposed in [104]. Such an analysis focuses on the position of the tool center point (TCP) in 3D space, discriminating not only the reachable and the dexterous workspaces as defined in [105] but also a capability map for the whole space. Regarding human hand workspace analysis, in [106] the authors propose a methodology that can be used to quantify the functional workspace of the precision thumb - finger grasp, defined as the range of all possible positions in which thumb fingertip and each fingertip can simultaneously contact each other.

5.2 Kinematics Models

This section focuses on the 25 Degrees of Freedom (DoFs) kinematic model of the human hand that we use in this Chapter and presents also the three robot hands, that will be studied.

5.2.1 Kinematic Model of the Human Hand

The kinematic model of the human hand that we use consists of 25 DoFs, five DoFs for the thumb, four DoFs for index and middle fingers and six DoFs for each one of the ring and pinky fingers. We use 6 DoFs for the ring and pinky fingers of the human hand model, in order to take into account the mobility of the carpometacarpal bones of the palm, that results to varying positions for the fingers base frames. Although human hand digit lengths, are quite easy to be measured, expressing the base of each finger relatively to the base of the wrist is a difficult problem, which requires advance techniques such as fMRI [107]. In this work we use the parametric models for each human digit (derived from hand anthropometry studies) [108], [109] and [110], in order to define the lengths for all phalanges of the human hand. Moreover we incorporate the kinematics of the carpometacarpal bones as defined in [111], in the proposed human hand model in order to be able to compute the workspace of the human fingers base frames. The parametric models depend on specific parameters of the human hand that are the hand length (HL) and the hand breadth (HB). In this study we set both the HL and the HB parameters, to the mean value of the men and women 50th percentiles, according to the hand anthropometry study conducted in [112].

5.2.2 Robot Hands

Three quite different robot hands are examined in this study (due to space constraints). The five fingered DLR/HIT II (DLR - German Aerospace Center) [70], the Shadow Robot Hand (Shadow) [113] and the Barrett Hand (Barrett Technology Inc.) [114], that appear in Fig. 9.11.



FIGURE 5.1: The robot hands examined in this study.

5.2.3 Defining the Correspondences between Human and Robot Hands Components

In this study, we consider each human and robot finger as a typical finger with two or three joints and three or four DoFs respectively (one for abduction/adduction and two or three for flexion/extension). In case that a robot finger has more degrees of freedom we consider that these DoFs contribute to the positioning of its base frame and we include them in the analysis during human and robot fingers base frames workspaces comparison. Thus human thumb is used for finger phalanges workspaces analysis, as a finger with two joints and three DoFs (one for abduction/adduction and two for flexion/extension) and the rest human fingers are used as fingers with three joints and four DoFs (one for abduction/adduction and three for flexion/extension). If a robot hand has fingers with more than four DoFs (e.g. the pinky finger of Shadow hand [113]), we consider the rest as DoFs of the palm that contribute to the positioning of its fingers base frames. In order to compare human and robot fingers phalanges workspaces we must first define the correspondences between human and robot components. For example it's quite typical for a robot hand to have less than five fingers or less than three phalanges per finger [114]. To handle such situations we propose to map human to robot fingers with an order of significance starting from thumb and index, to middle, ring and pinky. Such a choice is justified by the fact that thumb, index and middle are the most important fingers participating in the various grasp types according to grasp taxonomy studies [115], [116], while ring and pinky appear to be subsidiary. Regarding the robot to human phalanges correspondence we follow a similar approach, assigning first the distal, then the proximal and finally the middle phalanx. In case that we have to find the correspondences for a robot hand with more than five fingers, we use the combination of consequent fingers that gives the highest score of anthropomorphism and if we have to find correspondences for a robot finger with more than three phalanges, we keep some joints fixed to zero, formulating those virtual phalanges that give once again the highest score of anthropomorphism.

5.3 Methods

5.3.1 Convex Hulls

The convex hull of a set of points S in three dimensions is the intersection of all convex sets containing S. For N points $s_1, s_2, ..., s_N$, the convex hull C is given by the expression:

$$C \equiv \left\{ \sum_{k=1}^{N} a_k s_k : a_k \ge 0 \text{ for all } k \text{ and } \sum_{k=1}^{N} a_k = 1 \right\}$$
(5.1)

The convex hull of a finite point set $S \in \mathbb{R}^n$ forms a convex polytope in \mathbb{R}^n . Each $s \in S$ such that $s \notin Conv(S \setminus \{s\})$ is called a vertex of Conv(S). In fact, a convex polytope in \mathbb{R}^n is the convex hull of its vertices. When $S \in \mathbb{R}^3$ as in our case, the convex hull is in general the minimal convex polyhedron $S \subseteq \mathbb{R}^3$ that contains all the points in the set and which is the set of solutions to a finite system of linear inequalities:

$$P = \left\{ \mathbf{s} \in R^3 : \mathbf{As} \le \mathbf{b} \right\}$$
(5.2)

where m is the number of half-spaces defining the polytope, **A** is an mxn matrix, **s** is an nx1 column vector of variables, and **b** is an mx1 column vector of constants. To compute the exact volume of a polytope P, it must be decomposed into simplices, following the simplex volume formula:

$$Vol(\Delta(s_1, ..., s_n)) = \frac{|\det(s_2 - s_1, ..., s_n - s_1)|}{n!}$$
(5.3)

where $\Delta(s_1, ..., s_n)$ denotes the simplex in \mathbb{R}^n with vertices $s_1, ..., s_n \in \mathbb{R}^n$. Moreover, when the triangulation method is used to decompose the polytope into simplices, then the volume of P is simply the sum of simplices volumes:

$$Vol(P) = \sum_{i=1}^{N} Vol(\Delta(i))$$
(5.4)

There are plenty of methods available to compute the convex hull of a set S of points. In this study we choose to use the well known quickhull algorithm for convex hulls, that has been proposed in [117].

5.3.2 Quantifying Anthropomorphism of Robot Hands

In order to quantify anthropomorphism of robot hands, we must first answer the question What are those characteristics that make the human hand the most dexterous and versatile end-effector known? One main advantage of the human hand, is its ability to move the fingers base frames, using the mobility of the carpometacarpal bones. More specifically, a series of power - prehensile grasps, such as the circular grasp or the lateral pinch, are typical examples, where the mobility of the human fingers base frames is of outmost importance. Thus, we choose to compare human and robot hands in two different levels: comparing finger phalanges workspaces and comparing human and robot fingers base frames workspaces.

5.3.2.1 Workspaces Computation

In order to quantify robot fingers anthropomorphism, we choose to perform a one-to-one comparison between the workspaces of human and robot fingers. For doing so, we need three sets of points $S_D, S_M, S_P \in \mathbb{R}^3$ for each human and robot finger, that contain the boundary points of the workspaces of the distal, middle (i.e. intermediate) and proximal phalanges respectively. Human thumb doesn't have a middle phalanx, so the S_M point set is excluded, while thumb's workspace computation follows the same procedure. In order to conclude to these sets, we set some DoFs fixed to zero and we compute the forward kinematics of each finger while exploring the joint space of the moving DoFs. More specifically to compute set S_P we keep DoFs 3 and 4 fixed to zero, to compute set S_M we keep DoFs 2 and 4 fixed to zero and to compute S_D we keep DoFs 2 and 3 fixed to zero. DoF 1 (abduction/adduction) is always active, as it contributes to the workspaces of all phalanges. To proceed to workspace computation we discretize the joint space of active DoFs using a step of $\frac{R}{n}$, where usually n=20 degrees and R is the range of motion. Then we compute the forward kinematics for all n^2 possible configurations (where 2 is always the number of the active DoFs). S_P is the set containing all possible joint 2 positions as well as joint 1 static position, S_M is the set containing all possible joint 2 and joint 3 positions, while finally S_D is the set containing all possible joint 3 and fingertip positions. Then, the computed sets of points S_P , S_M and S_D are used to create the convex hulls of the phalanges workspaces, as depicted in Fig. 5.2.

Regarding the computation of robot fingers base frames anthropomorphism, we choose to perform a one-to-one comparison between human and robot fingers base frames workspaces. Base frames may differ not only in positions but also in orientations (relatively to the global reference frame at the center of the wrist), so in order to compute anthropomorphism of robot fingers base frames, we choose to compare human and robot finger bases frames positions and orientations workspaces. For doing so, we need a set of points S_{BFP} containing the boundary points of positions workspaces and a set S_{BFO} containing the boundary points of orientations workspaces (in S_{BFO} points are represented in euler angles). Once again, the workspaces are created using the palm forward kinematics and discretizing the joint space with a step of $\frac{R}{n}$ (usually n=20) degrees, where R



FIGURE 5.2: Workspace creation per phalanx for index finger of human hand.

is the range of motion. Such workspaces will be computed using the robot forward kinematics, only if the robot hand has at least one DoF contributing to the mobility of the fingers base frames. If robot base frames are fixed [70] then the fingers base frames positions "workspace" will be computed as the convex hull created by the five static robot fingers base frames positions, while the orientations "workspace" will be computed as the convex hull created by the five static robot fingers base frames orientations. Finally regarding forward kinematics, we use a simple and systematic approach to assign the DH parameters, as described in [118].

5.3.2.2 Finger Phalanges Workspaces Comparison

Let S_{HID} be the set of points of the human index distal phalanx (HID) and S_{RID} the set of points of the robot index distal (RID) phalanx. We compute the convex hull of the human index distal phalanx workspace C_{HID} , and the convex hull of the robot index distal phalanx workspace C_{RID} . In order to quantify anthropomorphism of each robot finger, we propose to compare the workspaces of its phalanges with the workspaces of the equivalent human finger phalanges. Thus for index finger, we compute the intersection and the union of the human and robot workspaces for each phalanx. Let $C_{DI} = C_{RID} \cap C_{HID}$, be the intersection of the human and robot index distal phalanges workspaces and $C_{DU} = C_{RID} \cup C_{HID}$ be the union of the human and robot index distal phalanges. (A_{ID}) is computed as follows:¹

$$A_{ID} = \frac{Vol(C_{DI})}{Vol(C_{DU})} 100 \ (\%) \tag{5.5}$$

Equivalently for index finger, we quantify anthropomorphism for middle phalanx (A_{IM}) and proximal phalanx (A_{IP}) .

5.3.2.3 Fingers Total Score

In order to conclude to the anthropomorphic score for the whole index finger (A_I) , we use a weighted sum of the scores of its phalanges:

$$A_{I} = \frac{w_{ID}A_{ID} + w_{IM}A_{IM} + w_{IP}A_{IP}}{w_{ID} + w_{IM} + w_{IP}} \ (\%)$$
(5.6)

where $w_{ID} + w_{IM} + w_{IP} = 1$, $w_{ID}, w_{IM}, w_{IP} \ge 0$ are the weights for each phalanx and can be set subjectively according to the specifications of each study. The same procedure can be used to quantify anthropomorphism of robot middle (A_M) , robot ring (A_R) , robot pinky (A_P) and robot thumb (A_T) .

5.3.2.4 Fingers Base Frames Positions Comparison

In order to compute the level of anthropomorphism of the robot fingers base frames positions, we choose to compare the human and robot fingers base frames positions workspaces. For doing so, we use the convex hulls created by the human fingers base frames positions and the robot fingers base frames positions. Then, we compute the intersection of the human and robot fingers base frames positions convex hulls:

$$C_{BFPI} = C_{RBFP} \cap C_{HBFP} \tag{5.7}$$

where C_{RBFP} is the convex hull of the robot fingers base frames positions, C_{HBFP} is the convex hull of the human fingers base frames positions and C_{BFPI} is the convex hull of their intersection. The union of these convex hulls (C_{BFPU}), can be defined as:

$$C_{BFPU} = C_{HBFP} \cup C_{RBFP} \tag{5.8}$$

¹In this work we use a series of fractions with numerator always the volume of the intersection of the human and robot workspaces and denominator the volume of their union. So in order not to penalize the case a robot hand to be more dexterous than the human hand, if a robot hand has a joint with joint limits greater than human, we change them in order to be equal with the human limits.

In order to compute the level of anthropomorphism of robot fingers base frames positions (A_{BFP}) , we proceed as follows:

$$A_{BFP} = \frac{vol(C_{BFPI})}{vol(C_{BFPU})} 100 \ (\%) \tag{5.9}$$

5.3.2.5 Fingers Base Frames Orientations Comparison

In order to compute the level of anthropomorphism of the robot fingers base frames orientations workspace, we choose to compare the convex hulls created by the human fingers base frames orientations and the robot fingers base frames orientations. More specifically we compute the intersection of the human and robot convex hulls:

$$C_{BFOI} = C_{RBFO} \cap C_{HBFO} \tag{5.10}$$

where C_{RBFO} is the robot fingers base frames orientations convex hull, C_{HBFO} is the human fingers base frames orientations convex hull and C_{BFOI} is the convex hull of their intersection. The union of human and the robot fingers base frames orientations convex hulls (C_{BFOU}), can be defined as:

$$C_{BFOU} = C_{HBFO} \cup C_{RBFO} \tag{5.11}$$

To compute the level of anthropomorphism of robot fingers base frames orientations (A_{BFO}) , we proceed as follows:

$$A_{BFO} = \frac{vol(C_{BFOI})}{vol(C_{BFOU})} 100 \ (\%) \tag{5.12}$$

5.3.2.6 Fingers Base Frames Total Score

In order to conclude to the fingers base frames total score, we use a weighted sum of the base frames positions score and the base frames orientations score, as follows:

$$A_{BF} = \frac{w_{BFP}A_{BFP} + w_{BFO}A_{BFO}}{w_{BFP} + w_{BFO}} \ (\%) \tag{5.13}$$

 w_{BFP} , w_{BFO} are the base frames positions and orientations scores weights, where $w_{BFP} + w_{BFO} = 1$ and $w_{BFP}, w_{BFO} \ge 0$.

5.3.2.7 Total Score of Anthropomorphism

In order to compute the total score of anthropomorphism for each robot hand (A_R) , we use a weighted sum of the computed scores for the robot fingers and the robot fingers base frames, as follows:

$$A_{R} = \frac{w_{I}A_{I} + w_{M}A_{M} + w_{R}A_{R} + w_{P}A_{P} + w_{T}A_{T} + w_{BF}A_{BF}}{w_{I} + w_{M} + w_{R} + w_{P} + w_{T} + w_{BF}} \tag{\%}$$
(5.14)

where $w_I + w_M + w_R + w_P + w_T + w_{BF} = 1$, $w_I, w_M, w_R, w_P, w_T, w_{BF} \ge 0$ are the weights for the robot fingers scores and the robot fingers base frames score respectively and can be also set subjectively according to the specifications of each study. Weights must be chosen according to the relative importance of each part of the hand. For example, the index, the middle and the thumb fingers can be considered more important that the ring and the pinky, while the fingers base frames weight must be quite high, because the ability of fingers base frames to move is a key factor of human hand's dexterity.

5.4 Results and Simulations

In order to compute and visualize the convex hulls as well as their unions and intersections we used the multiparametric toolbox (MPT) [119], together with the ninth version of Robotics Toolbox developed and distributed by Peter Corke [120]. In Fig. 5.3 the kinematic models of the human hand and the three robot hands are presented together with the convex hulls of their fingers base frames positions workspaces.



FIGURE 5.3: Human hand and robot hands kinematic models and fingers base frames positions convex hulls.

Fig. 5.4 and Fig. 5.5 present comparisons between the fingers base frames positions workspaces and the fingers base frames orientations workspaces for human and robot hands, while Table 5.1 presents the score of anthropomorphism for each phalanx of each finger and the total score per finger.

Results in Table 5.1 are reported for all three robot hands and a hypothetical robot hand that "follows" human hand specifications, but with size equal to the 110% of the human hand (like DLR/HIT II). The fingers phalanges weights were set to $\frac{1}{3}$, except thumb phalanges weights that were set to $\frac{1}{2}$.



FIGURE 5.4: Comparison of human hand (red) and robot hands (black) fingers base frames positions convex hulls. Results can be found in Table 5.2.



FIGURE 5.5: Comparison of human hand (red) and robot hands (black) fingers base frames orientations convex hulls. Results can be found in Table 5.2.

 TABLE 5.1: Score of Anthropomorphism for all Robot Hands and Hypothetical Robot Hand (HRobot), for Each Finger and Each Phalanx

$\mathbf{Barrett}$							
	Index	Thumb					
Proximal	18.89%	20.80%	-	-	0%		
Middle	-	-	-	-	-		
Distal	0%	0%	-	-	0%		
Total	6.30%	6.93%	-	-	0%		
DLR/HIT II							
Proximal	46.50%	55.80%	67.74%	28.33%	16.35~%		
Middle	40.86%	37.08%	65.60%	16.28%	-		
Distal	34.33%	57.48%	76.02%	0.9%	0%		
Total	40.56%	50.12%	69.79%	15.17%	8.18%		
Shadow							
Proximal	mal 45.27% 43.02% 80.85% 49.18% 15.77						
Middle	40.86%	27.59%	53.43%	47.61%	-		
Distal	52.81%	39.19%	70.21%	22.07%	22.72%		
Total	46.31%	36.60%	68.16%	39.62%	19.25%		
HRobot							
Proximal	75.13%	75.13%	75.13%	75.13%	75.13%		
Middle	86.49%	87.09%	86.93%	86.87%	-		
Distal	$\overline{66.55\%}$	$\overline{61.01\%}$	$5\overline{7.42\%}$	$\overline{68.59\%}$	88.66%		
Total	76.06%	74.41%	73.16%	76.86%	81.90%		

Table 5.2 presents the score of anthropomorphism of the palm's mobility quantified via the comparison of human and robot fingers base frames positions workspaces and fingers base frames orientations workspaces, for all five robot hands using weights: $w_{BFP} = \frac{1}{2}$ and $w_{BFO} = \frac{1}{2}$.

Table 5.3, presents the overall score of anthropomorphism for each robot hand, as the weighted sum of the aforementioned metrics, using weights: $w_I = 0.2, w_M = 0.2, w_R = 0.05, w_P = 0.05, w_T = 0.2, w_{BF} = 0.3$.

Shadow hand is reported to be the most anthropomorphic of the robot hands compared, mainly because of the mobility of the thumb and pinky fingers base frames. The high score of the hypothetical robot hand remains a goal for robot hand designers. Table 5.4 assesses the effect of the workspace sampling resolution (expressed as the discretization of the range of motion R), on the score of anthropomorphism.

 TABLE 5.2: Score of Anthropomorphism of Fingers Base Frames for all Robot Hands and Hypothetical Robot Hand (HRobot)

	Barrett	DLR/HIT II	Shadow	HRobot
Positions	44.21%	16.85%	33.41%	75.13%
Orientations	7.34%	0.4%	60.67%	100%
Total	25.78%	8.62%	47.04%	87.57%

 TABLE 5.3: Total Score of Anthropomorphism for all Robot Hands and Hypothetical

 Robot Hand (HRobot)

Barrett	DLR/HIT II	Shadow	HRobot
10.38%	26.61%	39.93%	80.24%

TABLE 5.4: Effect of Workspace Sampling Resolution on Anthropomorphic Index Comparing Human vs Shadow Hand for all Index Finger Phalanges (R = Range of Motion)

Resolution	R/5	R/10	R/15	R/20	R/25	R/30
Score	46.564	46.331	46.300	46.288	46.284	46.282

Finally in Fig. 5.6, we present a comparison between the finger phalanges workspaces for the human hand and the three robot hands.

5.5 Concluding Remarks

In this chapter we proposed a systematic approach to quantify anthropomorphism of robot hands. The proposed methodology is based on computational geometry and set theory methods and takes into account those specifications that make human hand the most dexterous end-effector known (e.g. opposable thumb, palm mobility etc.).



FIGURE 5.6: Phalanges workspaces comparison for human hand (red convex hulls and blue kinematics chains) and robot hands (black convex hulls and red kinematic chains). The comparisons scores can be found in Table 5.1.

More specifically we choose to compare human and robot hands in two different levels; comparing finger phalanges workspaces and the workspaces of the fingers base frames. The efficacy of our method is validated, comparing three different robot hands against the human hand. The proposed methodology can be used to provide specifications, for the design of a new generation of anthropomorphic robot hands and prosthetic devices.
Chapter 6

Mapping Human to Robot Motion with Functional Anthropomorphism

In this chapter, we propose a series of schemes for mapping human to robot motion with functional anthropomorphism, for the case of different robot arm hand systems. For doing so, we first propose various criteria of functional anthropomorphism that can be incorporated in our mapping schemes.

For the case of Mitsubishi PA10 DLR/HIT II robot arm hand system, a forward/inverse kinematics mapping is used for both the robot arm and the robot hand. Inverse Kinematics (IK) of Mitsubishi PA10 are computed analytically using the IKFast algorithm of OpenRAVE [75] and redundancy handling is performed, selecting the most anthropomorphic solution, derived from a specific criterion of anthropomorphism (solution that minimizes also structural dissimilarity between human and robot artifacts).

For the general case of hyper-redundant robot arms and m-fingered robot hands, we address the mapping as an optimization problem, using a criterion of functional anthropomorphism incorporated in a composite objective function. The role of the proposed function is twofold: a) to guarantee the execution of specific human-imposed functional constraints by the robotic artifacts (i.e. same position and orientation for human and robot endeffectors) and b) to handle redundancies presented at the solution spaces of the robotic artifacts.

In order to prove the efficiency of the proposed methods, we experimentally validate our results, using extensive simulated paradigms as well as real experiments presented for teleoperation and telemanipulation studies in Chapter 7.

6.1 Introduction

Over the last 50 years mapping human to robot motion has been one of the most challenging problems in robotics, with numerous applications varying from teleoperation, to human robot interaction and learn by demonstration. Nowadays anthropomorphism of robot motion is very important, for certain Human Robot Interaction (HRI) applications. Humanoids are used to interact with children, industrial robots must cooperate advantageously with humans, hyper-redundant robots must be teleoperated intuitively in remote and dangerous environments and a new generation of prosthetic or assistive devices must be developed to help patients or amputees regain lost dexterity.

But how anthropomorphism affects the problem of mapping human to robot motion? The answer is that anthropomorphism reformulates the mapping, as a two step procedure that will first guarantee specific human imposed functional constraints and will then "seek" a relationship between the human and the robotic artifact, that will ensure human-likeness of robot motion. In Chapter 4 and in [92], we proposed a clear distinction between *Functional* and *Perceptional Anthropomorphism* for human to robot motion mapping.

As we have already mentioned, *Functional Anthropomorphism* concerns a mapping approach that has as first priority to guarantee the execution of a specific functionality in taskspace and then, having accomplished that, to optimize anthropomorphism of structure or form, minimizing a "distance" between the human and robot motion. The idea of a functional constraint is more evident in case of robot arm hand systems, where a typical prerequisite is the human and the robot end-effectors to achieve same position and orientation in 3D space. Moreover anthropomorphism can also be used to handle redundancy of robotic artifacts, so in this chapter we choose to address the problem of human to robot motion mapping, not only for robot artifacts with common kinematics, but also for the general case of highly redundant robotic arm hand systems.

Regarding hand motion mapping, four major methodologies have been proposed in the past: fingertips mapping, joint-to-joint mapping, functional pose mapping and object specific mapping. Fingertips mapping appears in [47, 48, 121–124] and is based on the computation of forward kinematics (FK) and inverse kinematics (IK) for each human and robot finger, in order to achieve same fingertip positions in 3D space. The linear joint-to-joint mapping is a one-to-one, joint-to-joint angle mapping, where the joint angle values of the human hand are mapped to the corresponding joints of the robot hands [49, 125, 126]. In joint-to-joint mapping, the replicated by the robot postures are identical to the human hand postures, as human and robot finger links attain same orientations. Functional Pose Mapping [50] places both the human and the robot hand in a number

of similar functional poses and then a relationship between each human and robot joint is found (e.g., using the least squares fit method). Finally, the object-specific mapping, which was originally proposed in [51], provides a mapping between different human and robot hand configurations for the case of a specific object. More specifically, the object based scheme, assumes that a virtual sphere is held between the human thumb and index fingers. The parameters of the virtual object (size, position and orientation) are scaled independently and non-linearly, to create a corresponding virtual object in the robot hand workspace, that is then used to compute the robot fingertip locations.

A first approach to map human grasping synergies to a robot, was proposed in [52], where the authors trained a neural network, to predict from object features (i.e., length, width, height and pose), the coefficients of the synergies (hand approaching vector, hand posture). In [53] and [127] authors extended the aforementioned object based approach, to map synergies from human to robot hands with dissimilar kinematics. An optimization-based approach for calculating the hand and finger pose, for a given grasp (e.g., precision and pinch grasps), was proposed in [128]. A task-space framework was formulated in [129] for gesture based telemanipulation with a five fingered robot hand. The authors utilized a library of task specific gesture commands, which replaces the conventional mapping between the human and the robot hands and provide extensive experimental paradigms involving a series of manipulation tasks. Finally, a hybrid mapping approach was proposed in [130], where the authors combined some of the best features of the aforementioned mapping methodologies and experimentally validated their approach, with telemanipulation tasks performed using the Schunk Anthropomorphic Hand (SAH).

Regarding arm motion mapping, previous studies focused on a forward-inverse kinematics approach, to achieve same position and orientation for the end-effectors of the human and the robot arm. In [54] and [55] analytical computation of inverse kinematics for seven Degrees of Freedom (DoFs) redundant arms was performed respecting joint limits. A biomimetic approach for the inverse kinematics of a seven DoFs redundant robotic arm (Mitsubishi PA10), has been presented in [83]. Authors used captured human arm kinematics, to describe and model the dependencies among the human joint angles via a Bayesian Network. Then an objective function was built employing the extracted model and was used in a closed loop iterative inverse kinematics algorithm.

Regarding hyper redundant robot arms, in [131] a redundancy resolution method was proposed based on a backbone curve model. In [56] authors used a control approach for hyper-redundant arms based on constrained optimization. In [57] the process of manipulating the pose of an articulated figure, was approached as a non-linear optimization problem. Finally, in [24] authors proposed to handle the inverse kinematics problem of highly articulated figures with nonlinear programming, formulating the problem as a constrained minimization of a nonlinear function. Despite the fact that nonlinear programming algorithms may terminate at local minima, authors presented significant results that have inspired numerous studies over the years.

Regarding anthropomorphism of robot motion, a recent study [58] focused on the extraction of human-like goal configurations for robotic arm hand systems using a criterion from ergonomics [132], that yields a discrete score of posture's ergonomical quality. In [59] a combination of bio-inspired optimization principles - like minimization of hand jerk - are incorporated in an optimization problem to compute robot reaching motion trajectories similar to human behavior. The latter methodology was experimentally validated using the iCUB for which "strong anatomical human-robot similarities can be appreciated on the shoulder and elbow joint", thus it didn't take into account anthropomorphism as part of the mapping procedure. In [60] authors formulated a nonlinear optimization problem using obstacle constraints (e.g. between the arm hand system and the environment) to generate human-like movements for a high-degree robotic arm-hand system. The latter is quite an interesting approach, which neither minimizes structural dissimilarities between the human and the robot, nor takes into account hyper-redundant artifacts.

6.2 Criteria/Metrics for the Quantification of Functional Anthropomorphism

In this section we present a series of criteria of anthropomorphism that result to the minimization of the structural dissimilarity between the human and the robot artifact.

6.2.1 Volume of the convex hull created by human and robot joint positions

In order to incorporate in the objective function an anthropomorphic criterion that will handle redundancy presented at the solution space of a hyper-redundant robotic arm, or if we want to use a metric capable to extract the most humanlike solution of all solutions computed using the analytical IK approach, we first examine for the case of a robot arm the volume of the convex hull created by the human and the robot joint positions, the common base frame (shoulder) and the common end-effector (wrist).

The convex hull of a set of points S in three dimensions is the intersection of all convex sets containing S. For N points $s_1, s_2, ..., s_N$, the convex hull C is given by the expression:

$$C \equiv \left\{ \sum_{k=1}^{N} a_k s_k : a_k \ge 0 \text{ for all } k \text{ and } \sum_{k=1}^{N} a_k = 1 \right\}$$

$$(6.1)$$

The volume formula of a simplex:

$$Vol(\Delta(s_1, ..., s_n)) = \frac{|\det(s_2 - s_1, ..., s_n - s_1)|}{n!}$$
(6.2)

where $\Delta(s_1, ..., s_n)$ denotes the simplex in \mathbb{R}^n with vertices $s_1, ..., s_n \in \mathbb{R}^n$. Moreover, when the triangulation method is used to decompose the polytope into simplices, then the volume of P is simply the sum of the volumes of the simplices:

$$Vol(P) = \sum_{i=1}^{N} Vol(\Delta(i))$$
(6.3)

There are plenty of methods available to compute the convex hull of a set S of points. In this study we choose to use the well known quickhull algorithm for convex hulls, that has been proposed in [117]. More details regarding the decompositions of the convex hulls and their volumes the reader can find in [133] and [134].

6.2.2 Distances between robot joint positions and human elbow.

Another useful criterion of anthropomorphism would be to minimize the distances between the robot joint positions in 3D space and the human elbow. Let $\mathbf{s}_{elbow} \in \mathbb{R}^3$ be the position of the human elbow in 3D space and S_{RA} be the set of the *n* robot joint positions in 3D space. For *n* points $s_1, s_2, ..., s_n$, the distance between the robot joints positions and the human elbow, is given by the expression:

$$D = \sum_{j=1}^{n} \|s_j - s_{elbow}\|^2$$
(6.4)

6.2.3 Area of the triangles defined by human and robot joint positions.

The third criterion is based on the area of the triangles defined by human and robot joint positions. Consider a *n*-link robotic arm, where *n* is in general different from the number of the human arm links. We initially interpolate extra "virtual" joints in both human and robotic arms, according to the normalized length along their links from the common base to the end-effector. In this respect, both arms possess equal number of "virtual" joints with the same normalized length. Selecting one of the arms (e.g., the human arm), the structural similarity is quantified via the sum of the area of all facet triangles that are formed by joining every internal joint (besides the common base and the end effector) of the human arm with the corresponding and its subsequent joint of the robot arm. Such similarity criterion is reasonable since its minimum value, which is zero, implies that all triangle areas are zero and consequently that the triplet of joints that form each triangle, are collinear. Thus, the human arm when the criterion reaches its minimum, coincides with the robot arm. To compute the area of the triangles defined by the human and the robot joint positions in 3D space, we use the Heron's formula:

$$T = \frac{1}{4}\sqrt{(a+b+c)(a-b+c)(a+b-c)(-a+b+c)}$$
(6.5)

where a, b and c are the lengths of the sides of each triangle.

6.3 Mapping Human to Robot Motion with Functional Anthropomorphism for Mitsubishi PA10 DLR/HIT II

In this section we present a human to robot motion mapping scheme for the Mitsubishi PA10 DLR/HIT II robot arm hand system, which is based on the analytical computation of inverse kinematics of both the robot arm and the robot hand. The proposed scheme guarantees humanlike robot motion, employing a metric of functional anthropomorphism.

6.3.1 Kinematic Model of the Human Hand

The kinematic model of the human hand that we use is inspired by the positioning of Cyberglove II flex sensors. More specifically our model consists of twenty DoFs, four DoFs for index, middle, ring and pinky (three for flexion/extension and one for abduction/adduction) and four DoFs for thumb (two for flexion/extension, one for abduction/adduction and one to model thumb's ability to oppose to other fingers). It must be noted that each finger is considered as an independent serial kinematic chain. Although human hand digit lengths, are quite easy to be measured, expressing the base of each finger relatively to the base of the wrist is a difficult problem, which requires advance techniques such as fMRI [107]. In this work we use the parametric models for each digit derived from hand anthropometry studies [108].

6.3.2 Inverse Kinematics

6.3.2.1 Inverse Kinematics of Robotic Arm Mitsubishi PA-10

In this section we focus on the inverse kinematics (IK) of the Mitsubishi PA-10 robot arm. According to Craig [105] due to their iterative nature, numerical solutions are much slower than the corresponding closed-form solutions and according to Siciliano [135], they do not allow computation of all admissible solutions. Closed-form solutions are desirable for fast motion planning for the following two reasons:

- Are much faster than those of the numerical IK solvers. (e.g. closed-form methods can produce solutions on the order of 6 microseconds, while numerical at 10 milliseconds, facing also the issue of convergence).
- We can explore the null space of the solution set. The latter can be really useful in applications where anthropomorphism is required, as we can choose the most anthropomorphic solution of the complete set computed.

Thus, in this section we choose to acquire closed-form solutions provided by an inverse kinematics solver extracted by the IKFast algorithm, that is part of the Open Robotics Automation Virtual Environment (OpenRAVE) [75].

Mitsubishi PA10 is an anthropomorphic - redundant manipulator which can be solved using the above analyses (using submodules) by assuming that the translation and rotation components are separable. Such a kind of separability allows much simpler solutions involving quadratic polynomials. More precisely, Mitsubishi PA10 has seven DoFs while we need only six in order to compute inverse kinematics. In this case we pick a joint that is the least important and we call it **free joint** keeping it fixed, for every inverse kinematics computation for the rest **active joints**. The "least important" joint is chosen so as for the first three or the last three joints, to intersect at a common point. During planning, we discretize the range of the free joint, using a desired step of x rad (e.g. x = 0.01) for it's full range.

The full solution space for specific end-effector position and orientation can be then searched, in order to select a solution that satisfies joint limits and all other planning constraints and optimizes some appropriately defined metric of anthropomorphism. Details regarding the IKFast algorithm and the OpenRAVE can be found in [75] and [136].

6.3.2.2 Inverse Kinematics of Robotic Hand DLR/HIT II Fingers

Regarding the DLR/HIT II robot hand inverse kinematics, we choose to solve the IK analytically, for each of the five kinematically identical robot fingers. It must be noted that each robot finger is considered as an independent serial kinematic chain, that has a finger base frame, expressed relatively to the center of the wrist. It must be also clarified that the last joint of each robot finger is coupled with the middle one, using the aforementioned mechanical coupling. Thus, this coupling as well as joint limits, should always be taken into account when computing the inverse kinematics.

6.3.3 Employing a Metric of Functional Anthropomorphism

The inverse kinematics technique applied for the robotic arm that we described in the previous section leads us, due to the redundant design of Mitsubishi PA10, to multiple solutions. All these solutions achieve desired position and orientation for the robotic end-effector in 3D space, but the robotic arm configuration may be far from anthropomorphic.

Thus we employ a criterion of anthropomorphism that requires minimization of the volume of the convex hull created by the human and robot joint positions in 3D space, as discussed in subsection 6.2.1.

6.3.4 Handling Redundancy Presented at the Solution Spaces of the Robot Arm and the Robot Hand

For the case of the robot arm (Mitsubishi PA10), the problem of acquiring an anthropomorphic solution from the multiple IK solutions computed (due to the redundancy) becomes to find an IK solution that minimizes the volume of the convex hull created by the human and the robot joint positions in 3D space.

Even if a solution is found, it might not be unique. In this case we still have to handle for a specific configuration of the robot arm, the redundancy caused by "internal motions" as described in [135]. Thus, we choose from the remaining multiple solutions, the one that maximizes velocity manipulability at the end effector of the robot arm. More precisely, we choose the solution that maximizes the manipulability measure, which is defined as:

$$w(\mathbf{q}) = \sqrt{\det(\mathbf{J}(\mathbf{q})\mathbf{J}^T(\mathbf{q}))}$$

where **J** is the Jacobian matrix and $w(\mathbf{q})$ vanishes at singular configurations. Maximizing this measure, redundancy is exploited to move away from singularities.



FIGURE 6.1: Subfigure [a] represents human and robot hand convex hulls before "wrist" offset elimination, while subfigure [b] represents human and robot hand convex hulls after incorporating the "wrist" offset elimination, as part of the mapping procedure (without fingertips mapping).

For the case of the robot hand (DLR/HIT II), we explore the solution space of each finger, choosing those IK solutions that respect the joint limits that we have set (e.g., hardware or even software joint limits). Then if/when multiple solutions exist, we choose to acquire the one that maximizes the aforementioned manipulability measure, at the fingertip of each robot finger.

6.3.5 Wrist (Robot Arm End-Effector) Offset to Compensate for Human and Robot Hand Dimensional Differences

Typically the human hand and the robot hand (e.g. DLR/HIT II) may have dimensional differences. In order to achieve same position and orientation for the human and the robot hand fingertips in 3D space, using the fingertips mapping methodology, we must first eliminate those dimensional differences. For doing so, we apply an appropriately defined "wrist" offset, that may move robot "wrist" away from the human, but will bring robot fingertip positions closer to the human's.

In order to acquire this offset we compute the convex hulls created by the robot hand fingertips and the human hand fingertips. The wrist offset is then defined as the translation required to eliminate the distance between the centers of the two convex hulls. In Fig. 6.1 we can see a graphical representation of the wrist offset elimination procedure, which maximizes the covering between the human and the robot hand workspaces.

6.3.6 Mapping Methodology Outline

To summarize, we present the outline of the proposed methodology, that maps human motion to anthropomorphic robot motion using the notion of functional anthropomorphism, for the case of the Mitsubishi PA10 DLR/HIT II robot arm hand system:

- Human wrist (i.e. end-effector) and elbow positions are captured with Isotrak II motion capture system.
- Human hand joint angles are captured with Cyberglove II dataglove.
- Fingertip positions of the human hand are computed using the human hand forward kinematics.
- All possible IK solutions of the robot arm are computed for desired end-effector position (closed form solutions are acquired).
- Redundancy at the solution space of the robot arm is handled with the anthropomorphic criterion of convex hull volume minimization and with the manipulability measure maximization.
- "Wrist" offset is introduced to eliminate dimensional differences between human and robot hands.
- All possible IK solutions for each finger of the robot hand are computed for the desired fingertip positions.
- Redundancy presented at the solution space of the robot hand fingers is handled keeping solution inside joint limits, respecting possible couplings and maximizing manipulability measure.

In order to simulate our models and check the correctness of the forward and inverse kinematics computations, the OpenRave simulation environment has been used together with the ninth version of Robotics Toolbox (MATLAB) developed and distributed by Peter Corke [120].

6.4 Mapping Human to Robot Motion with Functional Anthropomorphism for Hyper-Redundant Robot Arms and m-Fingered Hands

In this section, we propose a generic human to robot motion mapping scheme for the case of redundant or even hyper-redundant robot arms and m-fingered hands. More specifically, we formulate an optimization problem that solves inverse kinematics under position and orientation goals (human imposed functional constraints¹) and handles redundancies with specific criteria of anthropomorphism. Two different approaches are examined; the first typical approach addresses mapping as a combination of independent optimization problems running in parallel for the two subsystems, the robot arm (an open-chain serial manipulator) and the robot hand, while the second approach, formulates mapping as a unique optimization problem for the whole arm hand system (where the fingertips of the hand are considered now to be the end-effector instead of the wrist). Moreover for the case of m-fingered hands we assign human thumb fingertip position as a position goal for one of the robot fingers and we use splines to calculate the rest robot fingertip positions, interpolating between the rest four (index - pinky) fingertip positions of the human hand.

6.4.1 Kinematic Models

6.4.1.1 Kinematic Model of the Human Arm Hand System

For human arm kinematics, we use a seven DoFs model, that consists of three DoFs for the shoulder (one for abduction/adduction, one for flexion/extension and one for internal/external rotation), two DoFs for the elbow (one for flexion/extension and one for pronation/supination) and two DoFs for the wrist (one for flexion/extension and one for abduction/adduction).

The kinematic model of the human hand that we use, is inspired by the positioning of Cyberglove II flex sensors. More specifically our model consists of fifteen joints and twenty DoFs, four DoFs for index, middle, ring and pinky (three for flexion/extension and one for abduction/adduction) and four DoFs for thumb (two for flexion/extension, one for abduction/adduction and one to model thumb's ability to oppose to other fingers). Each finger is considered as an independent serial kinematic chain. The proposed methodology can be used with a more sophisticated human hand model, like the one

¹These are tasks constraints not optimization constraints. More information is provided in Section III.

proposed in [137], in case that there is a motion capture system capable of measuring all DoFs variations of such a complex model. Although human hand digit lengths can be easily measured, expressing the base of each finger relatively to the base of the wrist, is a difficult problem which requires advance techniques such as fMRI [107]. In this work we use parametric models for each digit derived from hand anthropometry studies [108].

6.4.1.2 Kinematic Model of the Robot Arm Hand System

Regarding robot arm kinematics, we create hyper redundant robot arms with n DoFs that consist of $\frac{n}{3}$ spherical joints and $\frac{n}{3}$ links of equal length. In case that a robot arm is created with n DoFs, where n is not a multiple of three, then the last one or two DoFs contribute only to the orientation of the end-effector. The number of the total DoFs as well as the links length can be set arbitrarily. In this work we create hyper redundant robot arms with 9, 11, 18, 20, 27, 29 and 44 DoFs that have a total length less, equal or bigger than the mean human arm length that we use in this study (from 90% to 110%). In order to conclude to a common human arm length, we used the mean value of the 50th percentile of men and women, as reported in [112].

Regarding robot hand kinematics the proposed methodology can be used for m-fingered robot hands with any number of DoFs or phalanges per finger. In this study we create for demonstration purposes, 3, 4, 5 and 6-fingered robot hands that have the same types of DoFs per finger with the human hand, but different phalanges lengths and finger base frames. Such a choice is justified by the fact that we mainly want, the dimensional differences occurred between the human and the robot hand (i.e. palm size etc.), to be easily identifiable in the simulated paradigms.

Remark 6.1. Although the hyper-redundant robot arms are an active topic of research for the last decades [131], nowadays their applications are still limited. Moreover hyperredundant robot arms with 27 or 44 DoFs like the ones that we present in this work don't even exist. In this work we choose to focus on hyper-redundant robot arms and m-fingered hands in order to prove that our methodology can be used with any type of kinematics. Thus, it's quite meaningful to make comparisons and discuss about anthropomorphism of hyper-redundant robot arm hand systems in contrary with some other robot artifacts with arbitrary kinematics (e.g., parallel structures etc.). Nevertheless, we feel that the field of hyper-redundant robot arms and continuum robotics will flourish over the next years and such robot artifacts will be used for teleoperation or rehabilitation purposes. For example, a hyper-redundant robot arm can be used for upper-limb rehabilitation sessions, with users having different forearm and upper-arm lengths, appropriately adapting it's configuration.

6.4.2 Methods

In this section, we formulate the problem of human to robot motion mapping as a constrained non-linear optimization problem. We have experimentally validated that the problem is well formed and even when the algorithm used terminates at a local minima, the solution suffices for our purposes. Such a choice is typical for related studies [24]. In the following sections numerous simulated paradigms and real experiments are presented and discussed in detail, validating the efficacy of the proposed methods.

6.4.3 Mapping Human to Robot Arm Motion: The Case of Hyper Redundant Robot Arms

Let $\mathbf{x}_{RA} = f_{RA}(\mathbf{q}_{RA})$ denote the forward kinematics mapping from joint to task space for the robot arm and let $\mathbf{x}_{RAgoal} \in R^3$ denote the desired end-effector position (i.e. human end-effector position). We can define the following objective function under position goals, as follows:

$$F_{RA}^{x}(\mathbf{q}_{RA}) = (\mathbf{x}_{RA} - \mathbf{x}_{RAgoal})^{T} \cdot (\mathbf{x}_{RA} - \mathbf{x}_{RAgoal})$$
$$= \|\mathbf{x}_{RA} - \mathbf{x}_{RAgoal}\|^{2}$$
(6.6)

Let $\mathbf{h}_c = (a_c, b_c, c_c, d_c), \mathbf{h}_g = (a_g, b_g, c_g, d_g) \in \mathbb{R}^4$ denote the current and the desired (i.e., human) end-effector orientation, expressed in the quaternions representation, to avoid singularities. The distance in \mathbb{S}^3 , between them is

$$\bar{d}_{RAo}(\mathbf{h}_c, \mathbf{h}_g) = \cos^{-1}(a_c a_g + b_c b_g + c_c c_g + d_c d_g)$$
(6.7)

Hence, taking the identification of antipodal points into account [138], we may formulate the following proper SO(3) distance metric

$$d_{RAo}(\mathbf{h}_c, \mathbf{h}_g) = min\{\bar{d}_{RAo}(\mathbf{h}_c, \mathbf{h}_g), \bar{d}_{RAo}(\mathbf{h}_c, -\mathbf{h}_g)\}.$$
(6.8)

Thus, a common objective function under both position and orientation goals, may be defined as follows:

$$F_{RA}^{xo}(\mathbf{q}_{RA}) = w_{RAx} \left\| \mathbf{x}_{RA} - \mathbf{x}_{RAgoal} \right\|^2 + w_{RAo} d_{RAo}(\mathbf{h}_c, \mathbf{h}_g)$$
(6.9)

where w_{RAx} and w_{RAo} are weights that adjust the relative importance of the translation goal with respect to the rotation goal. Typically $w_{RAx} = 1$ and $w_{RAo} = 10$. We must note that we manage to handle multiple goals by combining individual goals into a global objective function using appropriate weight factors. Thus, the problem formulation for our global objective function, can be defined as

minimize
$$F_{RA}(\mathbf{q}_{RA})$$
 (6.10)

subject to the inequality constraints of joints limits

$$\mathbf{q}_{RA}^- < \mathbf{q}_{RA} < \mathbf{q}_{RA}^+ \tag{6.11}$$

where $\mathbf{q}_{RA} \in \mathbb{R}^n$ is the vector of the joint angles for the hyper-redundant robot arm with *n* DoFs and \mathbf{q}_{RA}^- , \mathbf{q}_{RA}^+ are lower and upper limits of the joints respectively.

Remark 6.2. It must be noted that in this work, we use functional anthropomorphism which guarantees the execution of specific functional constraints by the robotic artifacts (e.g., same position and orientation for human and robot end-effectors), but these task constrains are incorporated as position and orientation goals in the objective function and not as equality constraints of the optimization problem, because otherwise for many cases the problem would become infeasible. Moreover formulating the problem using our approach, the user may select the position and orientation accuracies (appropriately defining the related weights), which may be lower for free space motions (focusing on anthropomorphism) and very high during grasping or any other interaction with the environment.

6.4.3.1 Employing a Criterion of Functional Anthropomorphism

In order to conclude to anthropomorphic robot motion, we have to employ a specific criterion of functional anthropomorphism, of those presented in subsection 6.2.1. The efficacy of the presented criteria is assessed with simulated paradigms in Fig. 6.2. All three criteria result to anthropomorphic configurations for the 18 DoF robot arm, in contrary with the no-criterion case.

In Fig. 6.3, Fig. 6.4 and Fig. 6.5, we perform an extensive comparison of the different criteria of anthropomorphism proposed, for 9, 18 and 27 DoF hyper redundant robot manipulators (i.e., robot arms). It must be noted that all metrics perform satisfactory in terms of achieving humanlike configuration for redundant and hyper-redundant robot arms, while their speed of execution is considerably high (C++ implementations perform in "real time").



FIGURE 6.2: Comparison of optimization solutions with and without criterion for anthropomorphism, for a 18 DoF robot arm. DC = Distance Criterion, CC = Convex Hull Criterion, TC = Triangles Criterion.

In this Ph.D. thesis we choose to use the "Distance Criterion", because we concluded that it provides the most anthropomorphic solutions (through qualitative - subjective assessment) and because it's the fastest method examined.



FIGURE 6.3: Human to robot motion mapping using the joint positions distance minimization criterion for hyper-redundant robot arms with 9, 18 and 27 DoFs, H_L = Human Arm Length, R_L = Robot Arm Length.



FIGURE 6.4: Human to robot motion mapping using the joint positions convex hull minimization criterion for hyper-redundant robot arms with 9, 18 and 27 DoFs, H_L = Human Arm Length, R_L = Robot Arm Length.



FIGURE 6.5: Human to robot motion mapping using the joint positions triangles area minimization criterion for hyper-redundant robot arms with 9, 18 and 27 DoFs, H_L = Human Arm Length, R_L = Robot Arm Length.

6.4.3.2 Mapping Human to Robot Hand Motion

We define for the case of a m-fingered robot hand m objective functions under position goals or position and orientation goals, according to the finger kinematics and the specifications of the task. Let $\mathbf{x}_{RH} = f_{RH}(\mathbf{q}_{RH})$ be the forward kinematics mapping from joint to task space for each robot finger and let $\mathbf{x}_{RHgoal} \in \mathbb{R}^3$, denote the desired fingertip position and $d_{RHo}(\mathbf{h}_c, \mathbf{h}_g)$ the distance between the current and the desired orientation (represented using quaternions), for each fingertip of the robot hand respectively, as defined in eq. (6.7,6.8). Then, the objective function can be denoted as

$$F_{RH}^{xo}(\mathbf{q}) = w_{RHx} \left\| \mathbf{x}_{RH} - \mathbf{x}_{RHgoal} \right\|^2 + w_{RHo} d_{RHo}(\mathbf{h}_c, \mathbf{h}_g)$$
(6.12)

Moreover for each finger we may also have equality constraints that will incorporate possible couplings between subsequent joints. Thus, the problem formulation can be defined as

minimize
$$F_{RH}^{xo}(\mathbf{q}_{RH})$$
 (6.13)

subject to the inequality constraints of joints limits

$$\mathbf{q}_{RH}^- < \mathbf{q}_{RH} < \mathbf{q}_{RH}^+ \tag{6.14}$$

where $\mathbf{q}_{RH} \in \mathbb{R}^n$ is the vector of the joint angles for the *m*-fingered robot hand with $m \times n$ DoFs and \mathbf{q}_{RH}^- , \mathbf{q}_{RH}^+ are lower and upper limits of the joints respectively. In case that we have also to confront a hyper-redundant robot hand, we can use the metric of anthropomorphism defined for the case of the hyper-redundant robot arm to guarantee minimization of structural dissimilarity between the human and the robot fingers.

6.4.3.3 Mapping for the Case of a m-Fingered Hand where $m \neq 5$

Typically, a robot hand may have less than five fingers [114]. In order to take advantage of the fingertips mapping methodology in such cases, we must define what the robot fingertip positions will be. Previous studies used the virtual finger approach [139], computing the virtual fingertip position of a robot hand, as a linear combination of the fingertip positions of the less significant fingers of the human hand (e.g. ring and pinky fingers) [140]. In this work, we choose to assign human thumb fingertip position as a position goal for one of the robot fingers (the one that we choose to correspond to human thumb). Then, we use splines to calculate the remaining robot fingertip positions, interpolating between the other four (index, middle, ring and pinky) fingertip positions of the human hand and selecting m-1 equally distant points³ on the extracted curve, where m is the number of the robot fingers. Simulated paradigms of the robot fingertip selection for m-fingered robot hands can be found in Fig. 6.6. Spline is a low-degree polynomial function that is sufficiently smooth at the places where the polynomial curves connect (i.e. knots). Spline interpolation yields smaller errors than linear interpolation so the resulting interpolant is smoother.

Remark 6.3. It must be noted that this latter approach, does not assure that the robotic fingertips will properly touch the object while performing a grasp. To overcome this problem an appropriate controller that alters the fingers stiffness upon contact and/or takes advantage of tactile sensing, can be introduced. Examples of tactile sensing based robust grasping, can be found in [141] and in the video in [142].



FIGURE 6.6: Robot fingertips selection (green circles) with interpolation between the human fingertips positions (red dots) for the case of three and five robot fingers (without counting the thumb).

6.4.3.4 Mapping Human to Robot Arm Hand System Motion

Typically, human hands may be mapped to robot hands with quite different dimensions in terms of palm size, finger sizes, phalanges sizes, finger base frames coordinates etc. Thus, sometimes the solution of the fingertips mapping problem between the human and the robotic artifact becomes infeasible. Previously [92], we proposed to apply a wrist offset in order to compensate for dimensional differences between the human and the robot hand. In this work, we propose as a second approach to address human to robot motion mapping as a unified optimization problem for the whole arm hand system. Therefore, we consider as end-effector of our system the fingertips of the robot hand to be mapped, and not the end-effector of the robot arm, compensating possible

 $^{^{3}}$ Robot thumb (the finger that is chosen to correspond to human thumb) is not taken into account in the fingertips selection procedure, as it must achieve same position and possibly orientation with the human thumb.

dimensional differences and guaranteeing the execution of a specific functionality by the robot fingertips (e.g., to achieve same position with the human fingertips).

More specifically let $\mathbf{x}_{RAH} = f_{RAH}(\mathbf{q}_{RAH})$ denote the forward kinematics mapping from joint to task space for each robot arm hand system's finger and let m be the number of the fingers and $\mathbf{x}_{RAH}, \mathbf{x}_{RAHgoal} \in \mathbb{R}^3$ denote the current and desired fingertip position respectively. We can define the following objective function under position goals:

$$F_{RAH}^{x}(\mathbf{q}_{RAH}) = \sum_{i=1}^{m} w_{RAHx_{i}} \|x_{RAH_{i}} - x_{RAHgoal_{i}}\|^{2}$$
(6.15)

If we want to achieve also same orientations for the fingertips of the human and the robotic hand, we must also take into account the orientation goals, expressed using the distance between the orientation vectors $d_{RAHo}(\mathbf{h}_c, \mathbf{h}_g)$, as defined in eq. (6.7,6.8). Thus, the objective function becomes

$$F_{RAH}^{xo}(\mathbf{q}_{RAH}) = \sum_{i=1}^{m} w_{RAHx_i} \|x_{RAH_i} - x_{RAHgoal_i}\|^2 + \sum_{i=1}^{m} w_{RAHo_i} d_{RAHo_i}(\mathbf{h}_c, \mathbf{h}_g)$$
(6.16)

where w_{RAHx} and w_{RAHo} are weights that adjust the relative importance of the translation goal, with respect to the rotation goal for each finger and can be set according to the specifications of each study.

<u>Criterion of Anthropomorphism</u>: For the unified optimization problem we use exactly the same criterion of anthropomorphism. The only difference, is the fact that now we don't have to guarantee as a functional constraint that the human and the robot endeffectors (wrists) must have same position and orientation in 3D space, as the endeffectors now are the human and the robot fingertips.

<u>Problem Formulation</u>: In order to handle multiple goals we combine individual goals into a global objective function using appropriate weight factors. Thus, the problem formulation for our objective function F_{RAH} for the whole arm hand system, can be defined as follows, considering the criterion that minimizes all distances between the robot joint position and the human elbow in 3D space

$$F_{RAH}(\mathbf{q}_{RAH}) = \sum_{i=1}^{m} w_{RAHx_i} \|x_{RAH_i} - x_{RAHgoal_i}\|^2 + \sum_{i=1}^{m} w_{RAHo_i} d_{RAHo_i}(\mathbf{h}_c, \mathbf{h}_g) + w_D \sum_{j=1}^{n} \|s_j - s_{elbow}\|^2$$
(6.17)

where $\mathbf{s}_{elbow} \in \mathbb{R}^3$ is the position of human elbow in 3D space, s_j represents the positions of robot joints (*n* joints, without considering the "shoulder" and the end-effector) in 3D space, w_{RAHx} and w_{RAHo} are weights that adjust the relative importance of the translation goal with respect to the rotation goal for each finger and w_D is the weight that adjusts the relative importance of the criterion of anthropomorphism. Typically, $w_{RAHx} = 1$, $w_{RAHo} = 10$ and $w_D = 1/1000$.

Weights can be selected according to the specifications of each study (empirically). These latter weights achieve significant trajectory tracking accuracy (both for position and velocity), while guaranteeing anthropomorphic motion.

6.4.4 Results and Applications

In order to test the aforementioned methodologies and prepare the simulated paradigms, we used the ninth version of the Robotics Toolbox [120]. In Fig. 6.8 a series of instances of the simulated experiments - included in the accompanying video - are presented. More specifically mapping human to robot motion is performed for a 18 DoF robot arm, an arm hand system with a 44 DoF robot arm and a 5 fingered robot hand and finally for a 4 fingered robot hand. In all instances the final configuration appears clearly while the initial configuration is blurred. In Fig. 6.7 the trajectory tracking errors both for position and orientation for a 20 DoFs hyper-redundant robot arm "following" the human imposed functional constraints (i.e., human end-effector position and orientation), are presented. The mean error for position (for all axes) is 0.2 mm and the mean error for orientation is 0.0019 rad (0.10 degrees), both less than the accuracy provided by most industrial and research robots.



FIGURE 6.7: The trajectory tracking errors for the position and orientation (in quaternions) of the end-effector of a 20 DoF hyper-redundant robot arm, are presented. The hand is not considered in this case.

Remark 6.4. It must be noted that although the optimization results depend on the initial robot configuration, different configurations have been considered and the optimization scheme always provided anthropomorphic robot configurations, guaranteeing same human and robot end-effector positions and orientations (both errors where insignificant as depicted in Fig. 6.7).



FIGURE 6.8: Instances of the simulated paradigms, mapping human to robot motion for a 18 DoF robot arm, a 4 fingered robot hand and a 44 DoF robot arm combined with a 5 fingered robot hand.

In Fig. 6.9 the trajectory tracking errors for the fingertip positions of a hyper-redundant robot arm hand system, are depicted. The mean error for all the fingertip positions is less than 1 mm, for all axes and fingers. We notice that for the case of the fingertips, the position errors are bigger than for the case of the robot arm end-effector, but the accuracy is still insignificant, for most robotics applications. In Fig. 6.10 we present the trajectory tracking errors for the fingertips orientations. All angles are represented in quaternions. The tracking errors for index, middle, ring, pinky and thumb fingers are depicted with different colors.

In order to validate the efficiency of the proposed methods two different experiments were conducted. The first experiment involved the Mitsubishi PA10 DLR/HIT II robot arm hand system model teleoperated in the OpenRAVE simulation environment, using the optimization approach to map human to robot arm motion and the joint-to-joint mapping to map human to robot hand motion. Typically for teleoperation studies an analytical approach (if feasible) would be better for the case of the arm [101], but this experiment is conducted in order to validate the efficacy of the real-time (C++ based) implementation of the optimization scheme, using the NLopt open-source library for nonlinear optimization [143]. It must be noted that in this experiment the NLopt [143] based C++ code, provides the first solution in 10 ms and the rest solutions at a frequency of 5kHz (every 0.2 ms).



FIGURE 6.9: The trajectory tracking errors for the fingertip positions of a hyperredundant robot arm hand system, are presented. The robot arm hand system model used, consists of a 23 DoFs hyper redundant robot arm and a five fingered robot hand with size equal to the 110% of the human hand. The robot fingertips are considered to be the end-effectors of the robot arm hand system and achieve same position and orientation with the human fingertips.

The second experiment involved a 21 DoFs hyper redundant robot arm model with the DLR/HIT II robot hand model teleoperated again in OpenRAVE, using once again the optimization approach for the arm case, while the joint-to-joint mapping was once again used for the hand case. In this case the optimization scheme is the only available solution, as no analytical solution can be found for the inverse kinematics of hyper redundant manipulators. For the case of the hand, the joint-to-joint mapping is used, which is a simple yet efficient and fast method for teleoperation/telemanipulation studies. It must be noted that real-time performance for the 21 DoFs robot arm is worst than the 7-DoFs robot arm (Mitsubishi PA10), as expected.

Remark 6.5. Although the splines-based fingertips calculation method, is an efficient approach for mapping offline human to robot motion, for autonomous applications with m-fingered hands where $m \neq 5$, is not recommended for real-time telemanipulation studies, for three reasons: it's a complex method, which is slow and doesn't offer intuitiveness.

A video of the anthropomorphic teleoperation of Mitsubishi PA10 DLR/HIT II robot arm hand system model, in OpenRAVE can be found in [144]. A video of the teleoperation of a robot arm hand system model that consists of a 21 DoFs robot arm, combined with the DLR/HIT II robot hand, can be found in [145]. Finally, a video presenting extensive simulated paradigms for hyper-redundant robot arms with 9, 11, 18, 20, 27, 29 and 44 DoFs as well as 3, 4, 5 and 6-fingered robot hands, can be found in [146].



FIGURE 6.10: The trajectory tracking errors for the fingertip orientations of a hyperredundant robot arm hand system, are presented (in quaternions). The robot arm hand system model used, consists of a 23 DoFs hyper redundant robot arm and a five fingered robot hand with size equal to the 110% of the human hand. The robot fingertips are considered to be the end-effectors of the robot arm hand system and achieve same position and orientation with the human fingertips.

6.5 Concluding Remarks

In this chapter, we proposed two different methodologies for mapping human to robot motion, with functional anthropomorphism. The first methodology, proposed for the Mitsubishi PA10 DLR/HIT II robot arm hand system, uses a forward/inverse kinematics mapping approach for both the robot arm and the robot hand (fingertips mapping), an analytical method for the computation of inverse kinematics and a metric of functional anthropomorphism.

For the second case of hyper redundant robot arm hand systems, mapping is formulated as an optimization problem incorporating a criterion of functional anthropomorphism in the objective function. The criterion minimizes the structural dissimilarity between the human and the robotic artifact, guaranteeing specific human-imposed functional constraints (i.e. same position and orientation for the human and the robot end-effector). The proposed scheme is very efficient in mapping both online and offline (depending on the number of DoFs) human joint-space trajectories to anthropomorphic robot jointspace trajectories and can be used in HRI applications where anthropomorphism is required.

 $\label{eq:Experiment 1} \ensuremath{\mathbf{Experiment 1}} \ensuremath{\mathbf{Exper$



Teleoperation of 21 DoFs Robot Arm and DLR/HIT II Robot Hand models







FIGURE 6.11: Mapping human to robot motion experiments.

Part IV - Human Robot Interaction: Applications, Experiments and Design Directions

Chapter 7

Teleoperation and Telemanipulation with Robot Arm Hand Systems

In this chapter the human to robot motion mapping schemes presented in Chapter 6 are used for a series of teleoperation and telemanipulation tasks performed with the Mitsubishi PA10 robot arm and the five fingered DLR/HIT II robot hand.

In order to teleoperate the Mitsubishi PA-10 robot arm we use a human to robot motion mapping scheme, that guarantees functional anthropomorphism. For doing so, two position trackers are used to capture position and orientation of both the human end-effector (wrist) and the human elbow in 3D space. Then we use a forward-inverse kinematics approach computing the analytical IK of Mitsubishi PA-10 robot arm employing the IKFast library solvers of the OpenRAVE simulation environment [75]. In order to handle redundancy we select the solution that minimizes the structural dissimilarity between the human and robot arm configurations (most humanlike solution).

Regarding telemanipulation with the DLR/HIT II robot hand, two different everyday life objects are used: a small ball and a rectangular object. Human to robot hand motion mapping is achieve using the joint-to-joint mapping methodology, taking also into account existing kinematic constraints (e.g., joint couplings). The Cyberglove II motion capture dataglove is used to measure human hand kinematics. A robot hand specific fast calibration procedure is employed in order to map the raw dataglove sensor values to human hand joint angle values and subsequently through the mapping procedure, to DLR/HIT II joint angle values. Finally a novel low-cost force feedback device based on RGB LEDs and vibration motors is developed, in order for the user to be able to perceive the forces exerted by the robot fingertips.

7.1 Introduction

Over the last decades a lot of studies have focused on teleoperation and telemanipulation with robotic arm hand systems. A common research direction is to map human to robot motion so as the robotic artifact not only to move in free space (already covered in Chapter 6) but also to grasp or manipulate everyday life objects or actively interact with the environment. For doing so user's kinematics have to be captured, with appropriate motion capture systems (e.g. vision based, flex sensors, IMUs etc.), while the forces exerted by the robotic artifacts have to be measured with appropriate force sensing elements mounted at the fingertips of robot hands.

Various methods for teleoperation and telemanipulation with multifingered robot hands (using calibrated datagloves), have been proposed in the past. In [51] authors proposed an advanced cyberglove calibration procedure where the thumb and index fingertips remain in contact with the object, approximating - due to the rolling motion and soft tissue deformations - a closed kinematic chain. Moreover they mapped, using the object-based mapping approach, human index and thumb motion to a two fingered robot hand. In [123] cyberglove calibration is performed with a vision system, using coloured LEDs and two stereo cameras to record the 3D position of thumb, index, middle and ring fingers. Moreover, force sensors were built into the HIT/DLR hand fingertips and the CyberGrasp (Cyberglove Systems) exo-skeleton was used to create one dimensional resistive force feedback per finger. In [124] the authors teleoperated the three fingered Barrett hand using a cyberglove and fingertips position mapping, while the robot hand was equipped with force sensors and the CyberGrasp system was once again used for force feedback. A recent study [129] proposes a task space framework for gesture based telemanipulation with a five fingered robot hand like the DLR/HIT II. This latter approach utilizes a library of task specific gesture commands, which replaces the conventional mapping between the human and the robot hands. An experimental validation of the proposed method is performed using a series of manipulation tasks performed with the 15 DoFs robot hand. Finally in [130] a hybrid mapping scheme combining some of the best features of the aforementioned mapping methodologies, is proposed. The efficiency of the proposed scheme is experimentally validated for teleoperation and manipulation tasks performed with the four fingered Schunk Anthropomorphic Hand (SAH).

Regarding force feedback the related literature focuses on different approaches, that range from vibro-tactile feedback, to visual and auditory feedback. Most of the studies concern devices providing vibro-tactile feedback. In [147] the VibroTac, an ergonomic device using vibration motors is proposed, while in [148] a wearable vibrotactile feedback suit for the whole arm hand system, is presented. Other studies focus on a mixture of sensory information including visual and vibrotactile feedback, like [149] where authors propose the RemoTouch, a system providing both tactile and visual feedback to the user. Finally in [150] different feedback strategies for shared control in telemanipulation studies are presented. More specifically authors compare different feedback methods and determine what combinations of force, visual and audio feedback provide the best performance.

7.2 Teleoperation of the Mitsubishi PA10 7DoF Robot Arm using Functional Anthropomorphism

In this section a MCS based teleoperation of a robot arm (Mitsubishi PA-10) is performed, using a human to robot motion mapping scheme that guarantees functional anthropomorphism. For doing so two position trackers are used, to capture position and orientation of human end-effector (wrist) and human elbow in 3D space.

7.2.1 Forward/Inverse Kinematics Mapping

In order to map human to robot arm motion we used a forward-inverse kinematics approach computing the analytical IK of Mitsubishi PA-10 robot arm using the IKFast library of the OpenRAVE simulation environment [75]. Redundancy is handled selecting the solution that minimizes the structural dissimilarity between human and robot arm configurations. This solution leads to a robot arm configuration for which the sum of distances between the human elbow and all robot joint positions, is minimum.

7.2.2 Results

The hereby presented results are an experimental validation with a real robot arm, of the mapping scheme that we presented in Chapter 6. The experimental paradigms involve teleoperation of Mitsubishi PA10 robot arm in different movements in 3D space. The following video discusses methods and results in detail. Regarding future directions the authors plan to use the proposed human to robot motion mapping scheme with the whole robot arm hand system, as described in [90]. The video of the experiment conducted can be found in [76].

7.3 Telemanipulation with the DLR/HIT II Five Fingered Robot Hand

7.3.1 A Low Cost Force Feedback Device based on RGB LEDs and Vibration Motors

In order for the user of the teleoperation scheme to be able to "perceive" the forces exerted by the robot fingertips (e.g., the forces exerted during object manipulation) we developed a low cost-force feedback device based on RGB LEDs and vibration motors. In this section we present the hardware specifications for the arduino open-source physical computing platform, the RGB LEDs and the vibration motors that were used to develop the device. Moreover we present the different modules that formulate the aforementioned device: the RGB LEDs based module and the vibration motors based wrist band.

7.3.1.1 Arduino based Architecture

Arduino [151] is an open-source physical computing platform based on a simple I/O board and a development environment that implements the Processing/Wiring language. More specifically for the development of the force feedback device we used the Arduino Mega, a microcontroller board based on the ATmega2560 (high-performance, low-power micro-controller). Arduino Mega has 54 digital input/output pins (of which 14 can be used as PWM outputs), 16 analog inputs, 4 UARTs (hardware serial ports), a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button. The Arduino Mega is compatible with most shields designed for the Arduino Duemilanove or Diecimila making future upgrades easy to implement. Arduino was used in our project as it has an insignificant cost and is a common solution, widely available in the market. It must be noted that the main disadvantage of Arduino Mega is the fact that it has quite big dimensions, but any microcontroller platform could have been used for our purposes (e.g. possibly a smaller or even a lighter solution like arduino nano, or another ARM based microcontroller).

Arduino RGB LED Vibration Motor



FIGURE 7.1: The arduino platform, a RGB LED and a vibration motor.

7.3.1.2 RGB LEDs and Vibration Motors

The RGB LEDs that we used are the RGB Piranha common cathode LEDs (Brightek Electronics co.) with the 5mm width. The RGB LEDs color ranges are the following; Red (400 - 700 mcd), Green (1000 - 1500 mcd) and Blue (400 - 500 mcd) and their dimensions; width: 0.76 cm, length: 0.76 cm and height: 1 cm. More details for the RGB LEDs can be found in [152].

The vibration motors that we used are 10 mm shaftless vibration motors (Precision Microdrives). The main advantages of the selected vibration motors are their low cost, low weight and small size. These three characteristics are very significant for the implementation of an affordable light-weight force feedback device. The vibration motors have the following characteristics: 3 V voltage, 10 mm frame diameter, 3.4 mm body length, 1.2 g weight, 2.5-3.8 V voltage range, 12000 rpm rated speed and 0.8 G vibration amplitude. More details regarding the vibration motors can be found in [153].

7.3.1.3 RGB LEDs based Wrist Band Module

The RGB LEDs based wrist band module consists of 5 RGB LEDs used to represent visually (fading from blue to red) the amount of force exerted from each robot finger. RGB LEDs relative positions have been chosen to be similar to the finger positions (following the order; thumb, index, middle, ring and pinky), in order for the optical feedback to be more easily interpreted by the user and associated with the corresponding finger. A picture of the RGB LEDs based wrist band module prototype, can be found in Fig. 7.2.



FIGURE 7.2: Screenshot of the RGB LEDs based module. RGB LEDs are positioned so as for their relative positions to be similar to those of the human fingers. The RGB LEDs from left to right correspond to the following fingers; thumb, index, middle, ring and pinky. Such a positioning helps the user to more easily associate the RGB LEDs with the corresponding fingers.

7.3.1.4 Vibration Motors based Wrist Band Module

The vibration motors based Wrist Band module consists of 5 vibration motors used to represent the amount of force exerted from each finger of the five-fingered robot hand through proportional skin vibrations. Vibration motor positions have been chosen so as to be uniformly distributed around the wrist in order to be as easy as possible for the user to interpret the provided vibrations. A picture of the vibration motors based wrist band module prototype, can be found in Fig. 7.3.



FIGURE 7.3: Screenshots of the vibration motors based wrist band.

7.3.1.5 Force Measuring Module

A force measuring module was developed, in order to capture the forces exerted by the robot fingertips. The module consists of: a Phidget Interface Kit 8/8/8 (I/O Board from Phidgets [154]), 5 flexiforce sensors (force sensors, one for each finger) and 5 flexiforce sensor adapters. The Phidget Interface Kit 8/8/8, a flexiforce sensor and an adapter, are depicted in Fig. 7.4. Appropriate software written in C++ was used to perform data acquisition, using the force measuring module that establishes a serial communication with the planner PC (Ubuntu 12.04 x86).



FIGURE 7.4: Flexiforce sensor, Flexiforce adapter and Phidgets Interface Kit 888.

The force sensors used are FlexiForce sensors (Tekscan Inc.) which are ultra-thin and flexible printed circuits [155]. Some important characteristics of the FlexiForce sensors are; the paper-thin construction, the flexibility and their durability. FlexiForce sensors can measure forces between almost any two surfaces and can be used at different environments. Moreover they have better force sensing properties, linearity, hysteresis, drift, and temperature sensitivity than other thin-film force sensors. Their "active sensing area" is a circle at the end of the sensor with diameter of 1 cm. In case that the specifications of the experiment require very low or very high forces exerted and if we want to measure these forces more precisely, the force measuring module can be used with different types of flexiforce sensors, providing ranges 0 - 10 lbs (0 - 4.4 N), 0 - 25 lbs (0 - 110 N) or even 0-100 lbs (0 - 440 N). Finally in order to interface the Tekscan FlexiForce sensors to the phidget interface, the five flexiforce adapters that appear in Fig. 7.4 are used.



FIGURE 7.5: Block diagram of the proposed scheme architecture.

7.3.2 Robot Hand Specific Fast Cyberglove Calibration

In order to calibrate the Cyberglove II motion tracking system, we developed a new calibration module, based on:

- The simplified kinematic model of the human hand that consists of 20 DoFs.
- Tuning of sensor gains (to estimate joint angles from raw sensor values), using two different postures and a free movement phase.

The two postures used during the advanced calibration procedure, appear in Fig. 7.6. The first posture is used to measure the raw cyberglove sensor values when all human flexion and abduction/adduction DoFs are in zero position in joint space. The second posture is used to measure the maximum possible cyberglove sensors raw values that correspond to the maximum abduction/adduction of all human hand fingers. It must

be noted that these values differ among subjects, and are used in order to conclude to specific bounds of the calibrated robot hand specific values that the Cyberglove II will provide to the grasp planner PC (e.g., the one that performs position control of the DLR/HIT II).



Zero Values Posture

Abduction/Adduction Posture

FIGURE 7.6: The two postures used by the calibration procedure. The zero values posture and the maximum abduction/adduction posture.

It's quite typical for the human hand to be more dexterous than a multifungered multi-DoF robot hand [137]. Moreover in most cases the human hand has greater joint limits than the robot hand. Thus if we perform a direct join-to-joint mapping between the human and the robot hand we may lead the robot hand to exceed its limits (software/hardware) damaging some finger, or even causing inter-finger collisions.

The free movement phase used by the calibration procedure manages to measure the maximum values reported in terms of raw cyberglove sensors values, for each joint of the human hand. Thus during the free movement phase, users are instructed to "explore" the finger workspaces, in order to store also the maximum values for each finger (flexion/extension and abduction/adduction are considered). In order to conclude to the gains that will linearly map the raw values of the Cyberglove II flex sensors, to the corresponding DLR/HIT II joints angles, we used the robot hand joint limits. To compute the gain for each DoF, we proceed as follows:

$$k_q = \frac{q_{max}}{|c_{max} - c_{zero}|} \tag{7.1}$$
where k_q is the gain for each DoF, q_{max} is the maximum value that a robot DoF can achieve (joint limit) for the specific DoF, c_{max} is the maximum value of the Cyberglove II flex sensors that was measured and c_{zero} is the value of the Cyberglove II flex sensors, measured at the "zero" posture. It must be noted that the whole calibration procedure comes with a simple user interface and lasts less than 30 seconds. The gains computed are stored in automatically created files, for further use with the data collection software or the DLR/HIT II planner mechanisms.

7.3.3 Joint to Joint Mapping of Human to Robot Hand Motion

Regarding the DLR/HIT II robot hand, human to robot motion mapping is performed using a modified version of the well known joint-to-joint mapping methodology proposed in [49] and [125], based on the robot hand specific Cyberglove II calibration. As we have already mentioned the last two joints of each robot finger of the DLR/HIT II are coupled with a mechanical coupling based on a steel wire. Thus, we are not able to map both the measurements of the Distal Interphalangeal Joint (DIP) and the Proximal Interphalangeal Joint (PIP) of human hand, to the robot hand. In this study we choose to use the cyberglove values of the PIP joints of the human hand and map them to both the PIP and consequently (due to the coupling) to the DIP joints of the robot hand. The choice to use the PIP joint is supported by the fact, that human is able to flex PIP independently, but not DIP due to tendon coupling. Thus if we had selected the DIP there would be cases in which the user would flex only the PIP joint of the human hand and the corresponding robot finger wouldn't move as DIP value measured from the Cyberglove II would be zero. MetaCarpoPhalangeal (MCP) joints of the human hand are directly mapped using a one-to-one mapping to the MCP joints of the robot hand. Regarding abduction/adduction of robot fingers, for the middle finger, abduction and adduction movements are discarded and the DoF is kept fixed, as it cannot be measured by the Cyberglove II. All other abduction/adduction angles (for the rest fingers) are mapped one-to-one, between fingers of the human and the robot hand.

7.3.4 Mapping Exerted Forces to RGB LEDs Color Information and Vibration Amplitude

Regarding RGB LEDs, each led has three different color intensity values (one for each color) that can be controlled through the arduino platform. The value of each color can range from 0 (off state) to 255 (higher state) so in order to create the different color variations, we fuse different intensity levels of different colors. In this study we chose to represent the absence of force exertion with blue color and the maximum possible force

exertion with red color. Thus we set a l_{blue} threshold (e.g. $l_{blue} = 50, 20\%$ of total range), for the blue color to illuminate the led when there is not force exertion and red color is $l_{red} = 0$. Then in order to map exerted forces to color alternations, we simply map them to proportional fusing values of the red color. The gain that linearly maps exerted forces to red color values is computed as follows:

$$k_{red} = \frac{256}{f_{max}} \tag{7.2}$$

where f_{max} is the value of the flexiforce sensor for the maximum force exertion that is expected to occur and 256 is the maximum value of the red color intensity. l_{blue} and f_{max} can be set according to the specifications of each study, resulting to different force sensitivities for the whole system.

Regarding the vibration motors mapping, we simply used a proportional mapping using a gain k_{vibr} equal to the ratio defined, with nominator the maximum voltage v_{max} that can be fed to the vibration motors and denominator the maximum selected force f_{max} that can be exerted by the robot fingertips. The gain for this proportional mapping is computed as follows:

$$k_{vibr} = \frac{v_{max}}{f_{max}} \tag{7.3}$$

7.3.5 Results and Experimental Validation

In order to validate the efficiency of the proposed methods, a series of experimental paradigms were executed with the DLR/HIT II robot hand. Those paradigms included a free space exploration phase where the DLR/HIT II was teleoperated in different postures in unconstrained 3D space, while the motion imposed by the user was far from typical (different speeds and configurations were tested for all fingers). The second task was a combination of grasp, squeeze and rotation movements for a small plastic ball and a rectangle. In Fig. 7.7 we can see a series of screenshots presenting different postures executed during the first task, while in Fig. 7.8 a similar series of screenshots is used to depict the activity during the manipulation tasks execution. For a clearer understanding of the methods proposed, as well as for a "first hand" evaluation of the robot hand "response" during the experiments, the reader should consult the accompanying video, which is available at the video in [77].

Force feedback is of paramount importance especially for those cases where occlusions occur between the user and the robot hand fingertips (e.g. caused by the objects grasped or the environment).



Index, Middle Flexion



Thumb Flexion



Index Flexion



Middle Flexion



Parallel Fingers

Abducting Fingers

FIGURE 7.7: Different postures of the human and robot hands, representing the different instances of the teleoperation tasks. The Cyberglove II motion capture system was used to teleoperate the DLR/HIT II robot hand in different postures, performing different motions with various speeds.



Small Ball Manipulation (Squeezing and Rotation)

Rectangle Manipulation (Squeezing and Slight Rotation)

FIGURE 7.8: Images depicting instances of the executed manipulation tasks, involving two everyday life objects: a small ball and a rectangle.

DLR/HIT II has a maximum tolerance of 10 N force that can be applied at the fingertips, thus the absence of a system that is able to detect contact as well as the amount of force exerted, may lead to severe damages of the robot fingers. It must be noted that in the screenshots appeared in Figures 7.7 and 7.8 when small amounts of forces are exerted, they mainly appear as changes of LEDs luminosities. Moreover the user is able to easily change the sensitivity of the color alternations changing the threshold of the blue color value during colors fusion (the RGB led module can be adjusted to be more sensitive, representing better lower force values). Finally, it's evident in the video that in some cases the fingers may contact the object with some part which is not covered with force sensors, thus in order to refine our study and improve the efficiency of our system we plan to integrate new force sensors, covering a greater part of each finger.

7.4 Concluding Remarks

In this chapter we presented a complete system for teleoperation and telemanipulation with the Mitsubishi PA10 7 DoF robot arm and the five fingered DLR/HIT II robot hand. Various MCS were used to capture human arm hand system kinematics and different mapping schemes were used to guarantee anthropomorphism of robot motion. Moreover, a novel low-cost force feedback device based on RGB LEDs and vibration motors - that can provide real-time feedback of the forces exerted by a robot hand - was used, so as for the user to be able to perceive the forces exerted by the robot fingertips. The choice to employ both a visual and a vibro-tactile module to provide a mixture of sensory information for force feedback, was based on the hypothesis that can lead to more easily interpreted by the user results. The efficacy of the proposed methods is proved, using extensive experimental paradigms with the robot arm being teleoperated in 3D space, and the robot hand performing different teleoperation and telemanipulation tasks. The accompanying videos further validate our claims.

Chapter 8

Closed Loop Anthropomorphic Grasp Planning based on Navigation Functions

8.1 Closed Loop Anthropomorphic Grasp Planning based on Navigation Functions

In this chapter, we present a complete scheme for closed loop anthropomorphic grasp planning based on Navigation Functions (NF) models that can be used by a robot arm hand system like the Mitsubishi PA10 DLR/HIT II, to reach and grasp anthropomorphically a wide range of everyday life objects.

For doing so, we use human data in a "Learn by Demonstration" manner to perform "Skill Transfer" between the human and the robot arm hand system. A human to robot motion mapping scheme (like the one presented in Chapter 6) is used, that is capable of transforming human motion to anthropomorphic robot motion (using specific criteria of functional anthropomorphism). Then NF based models are trained, that use "fictitious" obstacle functions learned in the low dimensional space of the anthropomorphic robot motion. Those models produce "new" human-like configurations, guaranteeing also convergence to the desired goal.

Regarding generalization, the NF based models are trained in a task-specific way, using the two of the three task features, described in Chapter 3: the subspace to move towards and the object to be grasped. The final scheme is able to produce adaptive behavior similar to humans by switching to different grasping primitives based on online feedback from a vision system. The vision system proposed uses RGB-D cameras like Kinect (Microsoft) to perform object recognition and object pose estimation, discriminating the required task features (position and object). Based on the "decision" acquired by the vision system, a taskspecific NF model is triggered, for the closed loop control of the robot arm hand system in performing the identified task.

8.2 Learn by Demonstration for Skill Transfer

Learn by Demonstration (LbD) or Robot Programming by demonstration (PbD) has received increased attention over the last 30 years and is a multidisciplinary topic with numerous applications in the field of HRI. The LbD approach "moves from purely preprogrammed robots to very flexible user-based interfaces" according to [156]. Some characteristic studies are those proposed by Dillman et al. in [157–162], as well as those proposed by Schaal et al. in [163, 164].

In this Ph.D. thesis we perform learn by demonstration using human arm hand system's reach to grasp motions to "teach" the robot artifact how to replicate them. More specifically a human to robot motion mapping procedure is used and human kinematics are mapped to anthropomorphic robot kinematics. Different human to robot motion mapping procedures have been proposed that guarantee anthropomorphism using specific metrics of Functional Anthropomorphism. The mapping schemes are discussed in detail in [92] as well as in Chapter 6.

In order to acquire those human motion data we performed reach to grasp movements towards different positions and objects in 3D space, capturing the full human arm hand system kinematics, with motion capture systems. Those experiments were performed for 22 positions in 3D space, marked on 5 different shelves. Different objects (4) were used for the experiments: a marker, a rectangular box, a small ball and a bottle. For each object and object position combination, 10 reach to grasp and grasp movements were executed and a total of $22 \times 4 \times 10 = 880$ trajectories were collected. An image presenting the objects used in this study appears in Fig. 8.1.



FIGURE 8.1: Image presenting the different objects used in this study.

An image presenting the bookcase used, as well as the positions marked on the different shelves appears in Fig. 8.2.



FIGURE 8.2: Image presenting the bookcase used and the object positions marked on the different shelves.

8.3 Learning NF in the Anthropomorphic Robot Low-D Space

Navigation Functions (NF) have been proposed by Rimon and Koditschek [165], [166]. Their initial formulation is for a priori known sphere worlds, however, application to geometrically more complicated worlds is achieved using diffeomorphisms, which map the actual obstacles to spheres. B-splines have been used to learn the structure of the NF's obstacle function.

More precisely, given a desired final configuration q_d for the robot arm or the robot hand the control law may be constructed as follows:

$$u(t) = -K_p(\nabla_q \phi)(x_t) \tag{8.1}$$

where ϕ is the navigation function responsible for; 1) driving the arm or hand to its final configuration and 2) generating similar anthropomorphic robot trajectories with those used for training. $K_p > 0$ is a constant gain matrix and x is the system's state. The navigation function is given from the following relationship:

$$\phi = \frac{\gamma_d}{\left(\gamma_d^k + \beta\right)^{\frac{1}{k}}} \tag{8.2}$$

where q is the configuration, $\gamma_d(q) = ||q - q_d||^2$ is the paraboloid attractive effect, β is the obstacle function and $k \in N \setminus \{0, 1\}$ is a tuning parameter.



FIGURE 8.3: NF based training procedure.

Thus the NF based controller is capable of producing trajectories similar to those formulated by the anthropomorphic robot motion data that were acquired from human motion data using the human to robot motion mapping procedure. It should be noted that the obstacle function is once again a "fictitious" obstacle. This "fictitious" obstacle is actually introduced in the low-d configuration space (using PCA) and applies repulsive effects on the robot arm hand system so as to reach the anthropomorphic configurations most commonly encountered during the training phase. More information regarding the learning procedure can be found in [102].

Some characteristics of the NF based models are the following:

- Provide closed-loop motion planning.
- Guarantee convergence.
- Have highly nonlinear learning capability.
- Can learn high dimensional spaces using dimensionality reduction techniques (e.g., using PCA).
- Provide continuous and smooth trajectories.
- Learn the feasible space.
- Embed anthropomorphism (through human to robot motion mapping) and can learn human movement characteristics (through "mapped" anthropomorphic robot motions).
- Can generalize to similar-neighboring destinations (goal positions).

As we have already noted, the NF models are trained to learn anthropomorphic robot motion and provide a closed loop (robust) scheme that embeds anthropomorphism. In our scheme, no online human to robot motion mapping is required, thus computational effort diminishes. Moreover we manage to guarantee anthropomorphism, as well as to transfer skills from humans to the robot arm hand system, using the aforementioned learn by demonstration approach.

Regarding generalization, we extended the NF scheme proposed by Filippidis et al. [102], in order to generalize to new grasping tasks. NFs are trained in a task-specific way, using the two of the three task features introduced in Chapter 3, subspace to move towards and object to be grasped. The scheme is able to produce adaptive robot behavior similar to humans by switching to different grasping primitives based on online feedback from a vision system based on RGB-D cameras like Kinect (Microsoft).



FIGURE 8.4: Training of task-specific NF models.

A blog diagram presenting the task-specific training procedure for the NF models, is depicted in Fig. 8.4. Different NF based models are trained for the robot arm and the robot hand. All models require as input the "goal" position in the low-d space of the anthropomorphic robot kinematics. This goal position can be provided for "new" tasks by a vision system and projected in the low-d space of robot kinematics.

8.4 Vision System based on RGB-D Cameras

In order for the proposed NF based methodology to be able to update the "goal" position of the task to be executed, based on online feedback, we created a vision system based on RGB-Depth (RGB-D) cameras like Kinect (Microsoft). Our vision system, is capable:

- To perform object recognition and pose estimation.
- To perform object tracking (e.g. real time pose estimation).

Results of the different functionalities of the vision system are presented in Fig. 8.5. The Point Cloud Library [84] has been used for the development of our vision system. A block diagram of the NF based scheme with the vision system incorporated, is presented in Fig. 8.6. A video presenting an experimental validation of the object tracking functionality, can be found in [167].



Object Recognition Classification **Pose Estimation** Correspondences Matching

Object Modelling

FIGURE 8.5: Examples of the main functionalities of our vision system, developed using the Point Cloud Library.



FIGURE 8.6: Block diagram of the NF based scheme with the vision system included.

8.5 Results

In this section we present the results of the aforementioned methods. More precisely two different experiments were conducted in order to test the efficiency of our scheme. Both experiments were performed with the Mitsubishi PA10 DLR/HIT II robot arm hand system, while the proposed vision system was used to track objects located in an arbitrary positions and orientations inside the workspace. The NF based scheme was used to reach and grasp the object in an anthropomorphic manner. Moreover the generalization capabilities of our methodology enable us to use the proposed scheme for reaching and grasping - in a synergistic manner - a wide variety of everyday life objects, located in various positions.

Results for the first experiment of reaching and grasping an object placed in an arbitrary position in 3D space (using the vision system for pose estimation), are reported in the video provided in [78].

A screenshot representing the robot arm hand system while it has already grasped the rectangular object is depicted in Fig. 8.7.



FIGURE 8.7: The Mitsubishi PA 10 DLR/HIT II robot arm hand system is depicted grasping the rectangular shaped object used in the experiment.

A video of the second experiment, where the Mitsubishi PA10 DLR/HIT II robot arm hand system, performs anthropomorphic reaching and grasping of a bottle of juice which is thrown in an arbitrary position on a flat surface, can be found in [79].



Closed-Loop Humanlike Grasp Planning with Mitsubishi PA10 DLR/HIT II

FIGURE 8.8: Screenshots of the second experiment.

8.6 Concluding Remarks

In this Chapter we presented a complete autonomous grasp planning methodology based on Navigation Functions (NF), that facilitates grasping of a wide variety of everyday life objects. The learning of the NF based models is performed using the anthropomorphic low-d robot space, extracted using Principal Components Analysis (PCA). A "fictitious" obstacle, applies repulsive effects on the robot arm hand system so as to reach anthropomorphic configurations. The scheme is able to produce adaptive robot behavior similar to humans by switching to different grasping primitives based on online feedback (provided by a vision system). A series of accompanying videos, present the experimental validation of the proposed methods.

Chapter 9

Open-Source, Affordable, Light-Weight, Modular, Underactuated Robot Hands

In this chapter we present a series of design directions for the development of affordable, modular, light-weight, intrinsically-compliant, underactuated robot hands, that can be easily reproduced using off-the-shelf materials. The design is coordinated by a robot hands taxonomy that distinguishes and discusses functional and structural aspects for the creation of non-humanlike and human-like robot grippers and hands. The proposed taxonomy follows an order of increased complexity in presenting the different categories and then based on their attributes, the choices made for our design, are appropriately justified. The proposed robot hands, efficiently grasp a series of everyday life objects and are considered to be general purpose, as they can be used for various applications. The possible applications range from autonomous grasping and teleoperation/telemanipulation studies (as parts of robot arm hand systems) to humanoids, mobile and aerial vehicle platforms (which can be modified to be grasping capable), educational robotics (provide a low-cost solution for highly intriguing robotics lessons), or even as affordable myoelectric prostheses, assisting amputees in everyday life tasks and helping them regain part of their lost dexterity. The efficiency of the proposed robot hands has been experimentally validated through a series of experimental paradigms, involving: grasping of multiple everyday life objects with different geometries, myoelectric (EMG) control of the robot hands in grasping tasks, preliminary results on a grasping capable quadrotor and autonomous grasp planning under object position uncertainties.

9.1 Introduction

The problem of grasping has been one of the greatest topics of robotics research, during the last fifty years, as roboticists were always intrigued to understand and be inspired by nature's most versatile and dexterous end-effector, the human hand. The first robot hands, were actually simple robot grippers, with a limited number of Degrees of Freedom (DoFs), which were capable of grasping a limited set of objects with simple geometry, located in a-priori known static environments. Nowadays grippers are still the most common alternative for robotic grasping, both in industry and research [61], [62], due to their low-complexity and relatively low cost. But the state-of-the-art of robot hands follows the road to increased performance and humanlikeness [63], which leads also undoubtedly to increased complexity and of course increased cost. The issue of cost is definitely not negligible and nowadays robot hands cost thousands of USD, due to the materials used, the complex design and the sophisticated actuators and sensors. Are their grasping capabilities analogous to their price? Our subjective opinion is that the answer is no and that the problem of grasping can become remarkably complex or even remarkably simple, depending on the design choices. A nice collection of different robot hand designs was presented in [168].



FIGURE 9.1: A four fingered robot hand model is depicted.

Over the last 10 years a series of studies have focused on low-cost robot hands based on elastomer materials or elastic hinges, that in some cases were also open-source [64], providing directions for the replication of the design. More specifically, in [65] authors presented the development of the humanoid robot hand UB (University of Bologna) Hand 3. This hand is based on an endoskeleton made of rigid links connected with elastic hinges, which is actuated by artificial tendons and the whole hand is covered by compliant pulps. The same hand appears also in [169], where the development timeline of the different UB hand versions is discussed, through a video contribution.

A new design approach for robot hands created using polymer-based shape deposition manufacturing, was first proposed in [170] by Dollar et al. and led eventually to the creation of the highly adaptive SDM hand [66]. The SDM hand is equipped with cable driven fingers, that have viscoelastic flexure joints, stiff links, soft fingerpads and a set of movable pulleys, as a differential mechanism. In [171] an underactuated robot hand with force and joint angle sensors, equipped with a novel movable block differential mechanism, was proposed. Recently, a dexterous gripper with active surfaces, the velvet fingers was proposed [172]. This latter hand, despite its underactuated design, is capable of performing manipulation tasks, using the active surfaces to apply tangential thrust to the contacted object. Another example of a recent underactuated, compliant robot hand, is the i-HY (iRobot-Harvard-Yale) hand [67], which was created for robust grasping, manipulation and in-hand manipulation of everyday life objects. i-HY hand has 5 actuators and fingers equipped with flexure joints and integrated tactile arrays. Finally, an example of a commercially available, compliant robot hand is the Meka H2 hand [68], which consists of 5 elastic actuators, driving 12 joints of four fingers made of urethane, in an underactuated design. It must be noted, that the aforementioned studies have made progress towards the goal of reducing the hand cost and weight. Thus the minimum cost is nowadays 400 USD and the minimum weight is 400 gr (0.88 lb), as reported in [64].

In this chapter we propose a new design approach, for the creation of affordable (less than 100 USD), light-weight (less than 200 gr | 0.44 lb), intrinsically-compliant, underactuated robot hands, that can be easily reproduced with off-the-shelf materials. The possible applications for the proposed hands are numerous, ranging from teleoperation and telemanipulation studies, to grasping capable platforms (e.g., mobile and aerial vehicles, for which light-weight design is a prerequisite), educational robotics or even for affordable, myoelectric prostheses. Extensive experimental paradigms are provided, that involve grasping of numerous everyday life objects, myoelectric (EMG) control of the robot hands, some preliminary results on a grasping capable quadrotor (using an aerial gripper) and autonomous grasp planning under object position uncertainties.

9.2 A Taxonomy for Robot Hands

Over the last decades a lot of researchers have tried to encode in appropriately formulated grasp taxonomies, a series of the most representative grasps that occur in different everyday life environments. Representative studies in this field include some recent works [115, 173] and of course the classic taxonomy of Cutkosky [116].

Recently, Grebenstein et al. created the DLR hand arm system [63], which is equipped with one of the most dexterous and sophisticated robot hands ever built. In his PhD thesis [174], Grebenstein mentions that Awiwi hand (the hand of the DLR hand arm system) is the first robot hand able to perform all grasps of Cutkosky's taxonomy [116]. But the Awiwi is a research hand, not yet commercially available (to the best of our knowledge) and even if it becomes available it will cost dozens of thousands of USD.

A completely different approach is not to try to design a perfect and highly dexterous robot hand that mimics the human hand, but to design multiple low-cost robot hands that are optimized for different grasps - included in grasp taxonomies [116] - or custom made to perform specific tasks. This is the philosophical basis for the proposed design and the ultimate scope of this work.

In this section we present a robot hands taxonomy which is to the best of our knowledge the first attempt to systematically capture the functional and structural aspects that lead from the non humanlike pretty basic robot hands and grippers, to the most versatile end-effector known the human hand. All trees presented in our taxonomy, when read from left to right, lead from low complexity and dexterity designs with non human-like characteristics, to anthropomorphic complex designs, that offer increased dexterity.

9.2.1 Complexity and Dexterity

The hereby presented robot hands taxonomy - inspired by the grasp taxonomy of Cutkosky [116] - is used to justify the design choices made, comparing them with existing alternatives. As we examine the trees from left to right direction, we can notice that both the complexity and the dexterity of the robot hands increase.

9.2.2 Functional Aspects

In this subsection we examine the functional aspects of the different robot hand designs.



Tree 1. concerns the degree of actuation of each robot hand. A robot hand may be underactuated, fully actuated or over-actuated.

In this work we propose an open-source design for underactuated robot hands, since having less motors to control the same degrees of freedom, means low-cost design and therefore affordable robot hands, which is our first priority.



Tree 2. concerns the type of transmission. In this work we choose to use indirect transmission methods (creating cable driven underactuated hands) since we want the simplicity of the underactuated design and the fingers to be as light-weight as possible (a single motor has to control multiple degrees of freedom, avoiding extra motors per finger DoFs).



Tree 3. concerns the mobility of finger base frames. Finger base frames may be fixed, or moving in position, orientation or both. A robot hand that has moving finger base frames, is the Shadow hand [113] (thumb and pinky opposition). We use steady base frames to reduce the number of motors required.

9.2.3 Structural Aspects

In this subsection we examine the structural aspects of the different robot hands designs.



Tree 4. concerns the geometry of the finger base frames workspace, as defined in [137]. In order to conclude to the type of geometry we perform a delaunay triangulation with input the positions of the finger base frames in 3D space. The result, will be a line for only two points, a 2D polytope for 3 or more co-planar points and a 3D polytope (Convex Hull) for three or more non co-planar points. An example of 3D polytope is the workspace of the human hand finger base frames [137] and DLR/HIT II robot hand's [70] workspace. It must be noted, that all types of geometries, can be reproduced with our design. More details can be found in Section III.



Tree 5. concerns the compliance of the robot hand's structure. A robot hand may have rigid [70] or compliant joints [64] and links. Of course multiple degrees of compliance can be chosen, but this tree is proposed in order to discriminate between compliant and non-compliant structures without taking into consideration the level of compliance (which will be discussed in a later section). In this work we use compliant joints but rigid-links, in order to be able to attach at the fingertips (rigid links) of the robot hand, any material, with any level of compliance and friction desired.

9.3 Open Source Design

9.3.1 Bioinspired Design of Robot Fingers

The low-cost design, for affordable, underactuated, compliant robot hands that we present in this study, is based on a simple but yet effective idea: to use agonist and antagonist forces to implement flexion and extension of robot fingers, following a bioinspired approach where steady elastomer materials implement the human extensor tendons counterpart, while cables driven through low-friction tubes implement the human flexor tendons analogous.

Recently we proposed a complete methodology based on computational geometry and set theory methods in order to quantify anthropomorphism of robot hands [137]. The idea was simple and clear, to examine the most versatile end-effector known, the human hand and compare it with robot hands, in order to extract design specifications. Specifications according to which the object surrounding us have been crafted. But in order to conclude to those specifications, a new metric was necessary, a metric that would quantify the humanlikeness of robot hands in terms (at least) of kinematic similarity. This latter metric rates the kinematic similarity of any robot hand with the human hand and derives a score, that ranges between 0 (non-humanlike) and 1 (human identical). Although in this study we are not proposing anthropomorphic robot hands, we used this metric and the related hand anthropometry studies [109], in order to define the lengths for all phalanges for our robot hands, the distances between the finger base frames and finally to conclude to a more humanlike design. Such a choice was made based on the hypothesis that if we design even our simple robot hands as anthropomorphically as possible, we will maximize their ability to grasp most objects created for the human hand. For our design we have used identical robot fingers following the dimensions of human index finger. A future direction of ours, is to formulate an optimization problem to maximize anthropomorphism of robot hands [137], taking also into consideration other functional aspects [175], [176] and [177]. The structure of a robot finger is presented in Fig. 9.2.

9.3.2 Compliant Flexure Joints and Soft Fingertips

Our main goal is to provide a design with the ability to stably grasp a wide range of objects. The envisioned design should be of low-complexity and low cost and of course to be lightweight. In order to achieve this, we were based on conclusions extracted by recent works on the design of underactuated hands. More specifically, it has been shown that mounting compliant joints on their fingers, adds adaptability to the mechanism and thus leads to more robust and stable behavior, even when attempting to grasp objects



FIGURE 9.2: The structure of one robot finger is presented. The elastomer materials appear at the lower part of the image (white sheets), while the low-friction tubes that are used for tendon routing, appear at the upper part of the image (white tubes) together with the rigid phalanges. The finger base is also depicted at the right part of the figure. For the assembly of the robot fingers we use fishing line and needles in order to stitch the silicone sheets onto the rigid links (the links have appropriate holes by design).

with complex shapes [170]. Besides, soft materials are more preferred for designing the fingertips, as their deformation during contact, leads to larger contact areas, which reduce the impact of contact forces to the grasped object and also enhance stability [178]. Both conclusions can also be verified by our everyday life experience; the human hand, the most perfect end-effector known, can be characterized by high joint compliance and soft fingertips.

Motivated by the previous conclusions, we carefully selected the materials for the joints and the fingertips so that they satisfy our specifications. We made a compromise between affordable cost, lightweight design, high force transmission and adaptability. More specifically, the motion of the fingers in our grippers is implemented through flexure joints as a result of the compliance requirement. The flexible material (silicone and polyurethane sheets were considered) on the joints was selected to be lightweight but also stiff enough to be able to produce a force range, that corresponds to everyday life grasping tasks. Thus our robot hands demonstrate a sufficient ability of force transmission, without compromising deformability/adaptability. As for the fingertips, soft material (a combination of spongelike tape and low-thickness rubber, was used to increase also friction) was attached at them. This latter choice was made based on the study presented in [179], where various soft materials are used and compared in order to conclude which one is the best choice for the fingertips of robot hands (sponge-like materials).

The incorporation of these design decisions in the robot hands mechanisms can be described by existing models, proposed in recent literature. In particular, the behavior of flexure joints has been extensively studied by Odhner et al. [180, 181]. Their "smooth curvature model" is a computationally effective tool to predict the stiffness of such mechanisms so that real time closed loop control becomes possible. Currently, our ongoing research involves the incorporation of appropriate low-cost sensing elements

for force measurements (at the fingertips) and joint-positions measurements, as well as of a control system implementing torque control policies in our robot hands. Out ultimate scope is to provide a fully autonomous system with adequate documentation. Finally, the behavior of soft materials at the fingertips, involving the force transmission at the contacts can be modeled with the *Soft Finger Model*, which is described in detail in [182].

Two Fingers	Three Fingers	Four Fingers v1	Four Fingers v2
1			1
P		×	

FIGURE 9.3: Different robot hands created using identical modular fingers and the modular fingers basis. One two-fingered, one three-fingered and two versions of four-fingered robot hands, can be distinguished.

9.3.3 A Modular Fingers Basis with Multiple Slots

In this section we present the modular fingers basis that is used for the creation of our robot hands. As it can be noticed in Fig. 9.3 and Fig. 9.4 the basis is equipped with 5 slots that can be used to accommodate a total of four fingers, creating multiple robot hand types from the robot hands taxonomy presented. More specifically robot hands with various geometries of finger base frames, can be developed. Line and 2D polytope geometries are easily created, while for 3D polytope geometries finger bases/connectors with different heights have to be used (to create vertical offsets). Those hands are very capable of grasping various everyday life objects and each one is specialized for different types of tasks, executing in a more efficient manner different types of grasps presented in the various grasp taxonomies.

9.3.4 A Cross-Servo Modular Actuator Basis

The cross-servo modular actuator basis is a simple but yet effective design paradigm that lets the user of the robot hand to easily select and/or replace different types of servo motors. Appropriately designed slots are able to keep fixed most of commercially available servo motors, regardless of size and brand. For our robot hands four different types of servo motors have been considered, a micro servo with 2.2 kg/cm torque for the aerial gripper (fixed at the front end of the Ar.Drone platform [183]), a standard servo with 12 kgr/cm torque, a Dynamixel AX-12A with 15.2 kg/cm torque and the HerculeX



FIGURE 9.4: The robot hands wrist module is depicted. The wrist module contains the fingers basis (left part of the photo) and the servo basis (right part of the photo).

DRS0201 with 24 kg/cm torque. Of course more sophisticated high-torque servos, with torque control can be considered, according to the specification of each study, improving also the performance of our robot hands in terms of maximum force applied at the fingertips (of course with the counter effect of increased cost and weight).



FIGURE 9.5: Cross-servo modular basis. A standard servo attached at the servo basis is depicted.

9.3.5 A Disk-Shaped Differential Mechanism

A disk-shaped differential mechanism has been developed in order to connect the independent finger cables, with the actuator (servo motor). The differential mechanism allows for independent finger flexions, in case that one or multiple fingers have stopped moving, due to workspace constraints or in case that they are already in contact with the object surface. Our differential mechanism is a variant of the whiffle tree (or seesaw) mechanism, inspired by the interesting work done in [80], where force analysis of connected differential mechanisms was conducted. More specifically in this latter study, authors analyze the concept of underactuation, presenting different categories and discussing appropriate techniques for developing differential mechanisms. A similar triangle-shaped differential mechanism can be found in [81]. An example of the differential mechanism operation, can be found in the accompanying video.



FIGURE 9.6: The disk-shaped differential mechanism used in our robot hands.

9.3.6 Off-the-Shelf Low-Cost Parts

In Fig. 9.7 and Table 9.1 the different components selected for the development of the proposed robot hands are presented. As it can be noticed, all components are created using off-the-shelf, low-cost materials that can be easily found in hardware stores. For example the low-friction tubes can be substituted by common swabs (used for ear cleaning) by removing the parts covered with cotton. Plexiglas (acrylic) has been chosen as the main material for our design for two main reasons: 1) it is low-cost, light-weight and can be easily found, 2) it has good durability, significant ultimate tensile strength, 8.500 - 11.250 psi and almost the same density, 1.19 gr / cubic cm (0.043 lbs / cubic inch), with other common plastics like ABS. Plexiglas can be cut with laser cutting machines or other machinery (even with hand-held rotary tools), that can be easily found, in contrary (at least for now) with 3D printers proposed by other design paradigms [170]. It must be noted that the hereby proposed design can be implemented with any kind of plastic or other material available and of course with the desired dimensions.

Number	Material	Characteristics	
1	sponge-like tape	width: 1.8 mm	
2	Dyneema fishing line	strength: 41.5 kg (91.5 lb)	
3	low friction tubes	d: 2 mm D: 2.5mm	
4	pulleys	d: 3mm, D:12mm, W: 4mm	
5	silicone sheets	3 mm - 4 mm	
6	fasteners	width: 3mm	
7	plexiglas sheets	2 mm - 4 mm	

TABLE 9.1: Parts used for robot hands assembly



FIGURE 9.7: The parts used for the creation of our robot hands are depicted. More details can be found in Table 9.1.

9.3.7 Electronics, Codes and Communication

In order to control the servo motor that actuates the robot hand we use as low-cost, light-weight and small-sized solution the Arduino Micro platform [151]. An xBee (Digi) module [184] is used in order to implement wireless communications (if needed), between the arduino platform and the planner PC (e.g., in case of robot arm hand systems) or the ground station (e.g., in case of aerial vehicles applications). In case that the robot hand is meant to be used as a myoelectric prosthesis, an appropriate low-cost surface Electromyography (sEMG) sensing kit (Advancer Technologies) [185] compatible with the arduino platform, is used. A standard PCB module has been developed on purpose. The PCB connects the arduino platform, with the servo motor and other sensors (current sensor for motor, flex sensors, force sensors etc).



FIGURE 9.8: The different electronics modules used in our robot hands are depicted.

The serial communication between our robot hands and the Planner PC is implemented with Robot Operating System (ROS). An appropriate OpenBionics ROS package, has been developed. The Planner PC runs two nodes, the client node and the service node. The client node, receives from the user the aperture value (0 when the hand is fully open and 1 when the hand is fully close). The service node, sends the desired aperture to the robot hand. All codes are written in Python.

9.4 Results and Possible Applications

In this section we present a series of robot hands created with the proposed design. All robot hands consist of multiple identical fingers. The ratio between the two angles for a robot finger with two phalanges, as well as the finger workspace, are depicted in Fig. 9.9. The maximum force applied (and retained) per fingertip with the standard servo used, is 6 N for the three-phalanges humanlike robot finger and 8 N with the two phalanges robot finger. It must be noted that the maximum force depends not only on the servo used, but also on the quality and the thickness of the elastomer materials, thus the nominal values can also be adjusted according to the specifications of each study. In Fig. 9.10, we present different force exertion experiments for a single finger in different configurations.



FIGURE 9.9: The left subfigure presents the evolution of the ratio between the two angles, of a robot finger with two phalanges. The ratio approximates a constant value (red dotted line). The right subfigures presents the finger workspace.



FIGURE 9.10: Force exertion experiments for a two-phalanges robot finger at two different configurations (30% and 70% flexed). For each configuration, multiple experiments where conducted. The red lines represent the mean values and the blue dotted lines the min and max values per configuration. The high forces values correspond to the 30% flexed case and reach 18 N (peak), with a standard servo.

Regarding the robot hands, an aerial gripper, a two-fingered robot hand, two threefingered robot hands and a four fingered, were created. All robot hands prototypes are depicted in Fig. 9.11. Due to the light-weight materials that are used in this design, the total weight of the robot hands remains low for all robot hand types. For example the aerial gripper's weight is 40 gr (0.088 lb), the two-fingered robot hand's weight is 120 gr (0.26 lb), the three fingered robot hand's weight is 180 gr (0.40 lb) and the four fingered robot hand's weight is 240 gr (0.53 lb), including for all cases the servos and the arduino platform. These are general purpose robot hands that due to their limited cost and significant grasping capabilities can be used for various applications.



FIGURE 9.11: Different robot hand models and robot hands created with the design directions provided, are depicted.

9.4.1 Autonomous Grasping and Telemanipulation Studies

Regarding possible applications, the proposed open source design, can be used by research groups around the world, to create low-cost robot hands for autonomous grasping or teleoperation/telemanipulation studies (as part of robot arm hands systems). For example our lab is equipped with the DLR/HIT 2 robot hand [70], which costs approximately 80.000 USD (of course this price covers also development and manufacturing time, personnel costs etc.) and has a maximum aperture of approximately 7cm failing to grasp numerous everyday life objects and marginally grasping a 500 ml bottle of water. For the 1/1000 of this cost one can have a custom made robot hand, according to the specifications of the desired task to be executed, able to grasp a plethora of everyday life objects (even with large diameters). A future plan of our team is to strengthen the autonomous grasping capabilities of our hands, equipping our design with low-cost sensing elements for measuring force and joint angles, as well as to provide directions, analyses and code for advance control topics.

9.4.2 Creating Mobile and Aerial Grasping Capable Platforms

Another possible application for our robot hands is to be integrated in several aerial and mobile platforms to replace simple grippers with limited grasping capabilities. Examples of such platforms are the Baxter (Rethink Robotics) [61] and the YouBots mobile platform (KUKA) [62]. Moreover their light-weight design makes them the ideal choice for creating aerial grippers, than can be easily incorporated even in non-sophisticated aerial vehicles like the Ar.Drone quadrotor platform [183]. Preliminary results with a grasping capable ArDrone quadrotor platform can be found in the first video presented, at the end of this section.

9.4.3 Towards Low-Cost Task-Specific Myoelectric Prostheses

The idea of low-cost, light-weight prostheses is not a new one [186]. A recent work [187], focused on the findings of multiple studies on upper limb myoelectric prostheses as well as on the comments, suggestions and remarks made by amputees for their prosthetic hands. The subjects of these studies expressed their disappointment for the large initial and maintenance costs of the prostheses, the weight of the prostheses and the difficulties they face with repairs. Moreover the same studies, showed that the involvement of the amputee in the selection of a prosthesis increased 8 times the likelihood of prosthesis acceptance and that the fear of damage, leads most amputees to avoid to use the prostheses in everyday life tasks and use instead simple hooks or grippers, which are reported to have high functional value. Finally it was also reported that an important attribute for amputees, is the prostheses to enable specific motor actions for hobbies, driving/cycling, work etc, in other words to be optimized for specific tasks. Thus our lowcost, light-weight design can be used by millions of amputees around the world (especially amputees from third world countries), which can benefit from the DIY tutorials that we will provide, in order to build personalized, affordable, even task-specific myoelectric prostheses. Those prostheses will assist them in everyday life basis, to grasp various objects and/or interact with the environment, helping them regain part of their lost dexterity.

9.4.4 Videos of Experiments

In Fig. 9.11 the different types of robot hands are depicted both using their 3D models as well as pictures of the actual robot hands developed. In the following video, we present extensive experimental paradigms with two fingered, three fingered and four fingered robot hands. It must be noted, that for all experiments conducted the standard servo was used, in order for the total cost of the hands created to remain below 100 USD. More specifically at the first part of the video we grasp everyday life objects with a fourfingered (each finger consists of two phalanges) robot hand. At the second part of the video, a three fingered robot hand is used as a myoelectric prosthesis (by an able-bodied person) and the subject grasps using the myoelectric activity of his forearm muscles, two different objects. The third part of the video presents some preliminary results on a grasping capable quadrotor (based on the AR.Drone platform [183]) that we created in our lab using a two-fingered robot hand prototype. The forth part presents an example of the operation of the disk shaped differential mechanism. The fifth part presents a robot hand grasping a full 500ml bottle of water with a lateral pinch grasp, while the sixth part presents a precision grasp of an egg. Details on EMG signals pre-processing and EMG-based interfaces can be found in [90]. The video (in HD) can be found in [82].

The second video presents, an experimental validation of the efficiency of the proposed robot hands for the case of autonomous grasp planning and can be found in [188]. More specifically Navigation Function based models are learned for moving the Mitsubishi PA10 7 DoFs robot arm in an anthropomorphic manner, while a four fingered robot hand with two phalanges per finger (attached at the end-effector of the robot arm), is developed on purpose. As it can be seen the robot hand efficiently grasps a series of everyday life objects even, if their position is not accurately known/predefined (in case of object position and shape uncertainties).

The third video presents the Grebenstein test, that we use to test a robot hand's robustness again impacts and can be found in [189].

A website has also been created for our robot hands:

http://www.openbionics.org

It must be noted that OpenBionics initiative is inspired by the open hand project [190] of Grab Lab (Yale University), which was the first attempt (to the best of our knowledge) to create low-cost, open-source robot hands.

9.5 Concluding Remarks

In this chapter we presented a series of design directions for the development of low-cost, light-weight, intrinsically-compliant, modular robot hands, that can be easily reproduced using common, off-the-shelf materials. The hands proposed are general purpose, as they can be used for various applications that range from autonomous grasp planning to grasping capable mobile and aerial platforms, educational robotics or even as affordable myoelectric prostheses. For creating these hands, we first formulated a robot hands taxonomy, according to which, the design choices made were justified. Then we presented an open-source design, for affordable, modular, intrinsically compliant, underactuated robot hands, capable of grasping various everyday life objects. Extensive experimental paradigms with different types of robot hands, were presented in order to prove the efficiency of the proposed design and the significant grasping capabilities of our hands.

Part V - Conclusions and Discussion

Chapter 10

Conclusions and Major Contributions

10.1 Conclusions

In this Ph.D. thesis we presented advanced learning schemes for EMG based interfaces that can be used for different Human Robot Interaction applications. These schemes are able to efficiently decode the human intention and/or motion from EMG signals, taking advantage of both a classifier and a regressor, that cooperate advantageously in order to split the task-space and achieve better human motion estimation accuracy, with task-specific models.

Regarding HRI applications, we focused on anthropomorphism of robot artifacts. More specifically we discriminated between the different notions of anthropomorphism introducing functional and perceptional anthropomorphism, we presented a series of possible applications, we proposed a complete methodology for the quantification of humanlikeness of robot hands and we created advanced schemes for mapping human to anthropomorphic robot motion, even for robot artifacts with arbitrary kinematics (e.g., hyper-redundant robot arms and m-fingered robot hands).

Moreover, we proposed a new design approach for the creation of affordable, modular, light-weight, intrinsically-compliant, underactuated robot hands and prosthetic devices that can be easily reproduced using off-the-shelf materials. These robot hands - owing to their inherent compliance - can efficiently grasp a wide range of everyday life objects in human-centric and dynamic environments, under object position and shape uncertainties. In order to prove the efficiency of the proposed methods, various experiments focusing on different Human Robot Interaction applications have been conducted and a variety of robot artifacts have been used.

10.2 Major Contributions

Summarizing, the major contributions of this Ph.D. thesis are the following.

EMG Based Interfaces

We proposed, a complete learning scheme for EMG based interfaces that:

- Uses both a regressor and a classifier that cooperate advantageously.
- Splits the task-space, introducing three task features: subspace to move towards, object to be grasped, task to be executed.
- Can decode both human intention and human motion from EMG signals.
- Can provide better estimation accuracy with task-specific models.

Anthropomorphism of Robot Artifacts

We proposed a methodology based on set theory and computational geometry methods, for quantifying anthropomorphism of robot hands:

- To grade the human-likeness of existing and new robot hands.
- To provide specifications for the design of the next generation of human-like robot hands and prosthetic devices.

We proposed a series of human to robot motion mapping schemes that:

- Guarantee anthropomorphism of robot motion executing accurately specific tasks (respecting specific human-imposed functional constraints).
- Can provide anthropomorphic robot motion, even for robot arm hand systems with arbitrary kinematics (hyper-redundant robot arms, m-fingered robot hands).
- Can be used for various HRI applications.

Affordable Robot Hands

We proposed a series of low-cost, light-weight, modular, intrinsically-compliant, underactuated robot hands that:

- Can grasp efficiently a series of everyday life objects.
- Are very efficient even under object position and shape uncertainties, owing to their inherent compliance.
- Are considered to be general purpose, as they can be used for various HRI applications (even as affordable myoelectric prostheses).

10.3 Future Directions

- Formulation of semi-autonomous schemes for EMG-based control of robotic artifacts (mainly prostheses).
- Development of open-source, task-specific, affordable, underactuated robot hands and prosthetic devices.
- Development of underactuated robot hands for everyday life manipulation tasks.
Part VI - Appendices

Chapter 11

Initiatives

HandCorpus

During my Ph.D. studies I have participated as part of the CSL-NTUA group, at the "The Hand Embodied (THE)" European Committee (EC) project (http://www.thehandembodied.eu/), within the FP7-ICT-2009-4-2-1 Cognitive Systems and Robotics program. I have also been assigned by THE-consortium, the post of technical coordinator of the "HandCorpus" scientific repository.



FIGURE 11.1: The HandCorpus logo.

The HandCorpus, is an open-access initiative for sharing data, tools and analyses about human and robotic hands. Today (July 2014), the HandCorpus repository contains human hand kinematics data, with suitably provided tools for data visualization, related publications and videos. The HandCorpus provides an accurate and coherent record for citing data sets, giving due credit to authors. Data sets are hierarchically indexed and can be easily retrieved using keywords and advanced search operations. A blog, a newsletter, a publication repository and applications for mobile platforms and social networks are also provided. Furthermore, 5 European Research Council/European Commission funded projects, support the HandCorpus initiative and the HandCorpus community consists of 20 international research groups from 15 universities and 4 research institutes, across Europe and USA. More information can be found at the following url:

http://www.handcorpus.org

OpenBionics

Moreover, I am the co-founder of the OpenBionics initiative, which aims at the development of affordable, light-weight, modular, underactuated robot hands and prosthetic devices, which can be easily reproduced using off-the-shelf materials. More information regarding the OpenBionics initiative can be found at the following url:

http://www.openbionics.org



FIGURE 11.2: A photo presenting some of the OpenBionics robot hands.

Chapter 12

Publications

My research has resulted to 16 peer-reviewed papers presented at international conferences worldwide, 1 peer-reviewed journal paper, 1 book chapter, 3 conference/workshop abstracts and 1 technical report. The list of publications at this time (July 2014), is as follows:

Refereed Journal Papers

 Minas V. Liarokapis, Panagiotis K. Artemiadis, Kostas J. Kyriakopoulos and Elias S. Manolakos, "A Learning Scheme for Reach to Grasp Movements: On EMG-Based Interfaces Using Task Specific Motion Decoding Models", IEEE Journal of Biomedical and Health Informatics (J-BHI), 2013. PDF

Book Chapters

 Minas V. Liarokapis, Kostas J. Kyriakopoulos and Panagiotis K. Artemiadis, "A Learning Framework for EMG Based Interfaces: Introducing Task Specificity in Motion Decoding Domain" in <u>"Neurorobotics: From Brain Machine Interfaces to Rehabilitation Robotics</u>", Artemiadis, Panagiotis (Ed.), Springer Series in "Trends on Augmentation of Human Performance", Springer Publications, 2013 (in press).

Refereed Conference Papers

[16] Agisilaos G. Zisimatos, Minas V. Liarokapis, Christoforos I. Mavrogiannis and Kostas J. Kyriakopoulos, "Open-Source Affordable Modular Light-Weight Underactuated Robot Hands", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Chicago (USA), 2014. PDF

[15] George I. Boutselis, Charalampos P. Bechlioulis, Minas V. Liarokapis and Kostas J. Kyriakopoulos, "Task Specific Robust Grasping for Multifingered Robot Hands", IEEE/RSJ International Conference on Intelligent Robots and Systems (**IROS**), Chicago (USA), 2014. PDF

 [14] Charalampos P. Bechlioulis, Minas V. Liarokapis and Kostas J. Kyriakopoulos, "Robust Model Free Control of Robotic Manipulators with Prescribed Transient and Steady State Performance", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Chicago (USA), 2014. PDF

[13] Shahab Heshmati-alamdari, Charalampos P. Bechlioulis, Minas V. Liarokapis and Kostas J. Kyriakopoulos, "Prescribed Performance Image Based Visual Servoing under Field of View Constraints", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Chicago (USA), 2014. PDF

[12] Minas V. Liarokapis, Agisilaos G. Zisimatos, Melina N. Bousiou and Kostas J. Kyriakopoulos, "Open-Source, Low-Cost, Compliant, Modular, Underactuated Fingers: Towards Affordable Prostheses for Partial Hand Amputations", 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Chicago (USA), 2014. PDF

[11] Christoforos I. Mavrogiannis, Charalampos P. Bechlioulis, Minas V. Liarokapis and Kostas J. Kyriakopoulos, "Task-Specific Grasp Selection for Underactuated Hands", IEEE International Conference on Robotics and Automation (**ICRA**), Hong Kong (China), 2014. PDF

[10] George I. Boutselis, Charalampos P. Bechlioulis, Minas V. Liarokapis and Kostas J. Kyriakopoulos,
"An Integrated Approach Towards Robust Grasping with Tactile Sensing", IEEE International
Conference on Robotics and Automation (ICRA), Hong Kong (China), 2014. PDF

[9] Minas V. Liarokapis, Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos, "Mapping Human to Robot Motion with Functional Anthropomorphism for Teleoperation and Telemanipulation with Robot Arm Hand Systems", IEEE/RSJ International Conference on Intelligent Robots and Systems (**IROS**), Tokyo (Japan), 2013 - <u>Video Presentation</u>. PDF

[8] Minas V. Liarokapis, Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos, "Telemanipulation with the DLR/HIT II Robot Hand Using a Dataglove and a Low Cost Force Feedback Device", IEEE Mediterranean Conference on Control and Automation (MED), Chania (Greece), 2013. PDF [7] Minas V. Liarokapis, Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos, "Task Discrimination from Myoelectric Activity: A Learning Scheme for EMG based Interfaces", IEEE International Conference on Rehabilitation Robotics (**ICORR**), Seattle (USA), 2013. PDF

[6] Minas V. Liarokapis, Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos, "Quantifying Anthropomorphism of Robot Hands", *IEEE International Conference on Robotics and Automation* (ICRA), 2013. PDF

[5] Minas V. Liarokapis, Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos, "Functional Anthropomorphism for Human to Robot Motion Mapping", *IEEE International Symposium on Robot and Human Interactive Communication (RoMan)*, 2012. PDF

[4] Minas V. Liarokapis, Panagiotis K. Artemiadis, Pantelis T. Katsiaris and Kostas J. Kyriakopoulos, "Learning Task-Specific Models for Reach to Grasp Movements: Towards EMG-based Teleoperation of Robotic Arm-Hand Systems", *IEEE International Conference on Biomedical Robotics and Biomechatronics* (BioRob), 2012.PDF

[3] Minas V. Liarokapis, Panagiotis K. Artemiadis, Pantelis T. Katsiaris, Kostas J. Kyriakopoulos and Elias S. Manolakos, "Learning Human Reach-to-Grasp Strategies: Towards EMG-based Control of Robotic Arm Hand Systems", *IEEE International Conference on Robotics and Automation* (ICRA), 2012. PDF

[2] Panagiotis K. Artemiadis, Pantelis T. Katsiaris, Minas V. Liarokapis, and Kostas J. Kyriakopoulos, "On the Effect of Human Arm Manipulability in 3D Force Tasks: Towards Force-controlled Exoskeletons", *IEEE International Conference on Robotics and Automation* (**ICRA**), 2011. PDF

 Panagiotis K. Artemiadis, Pantelis T. Katsiaris, Minas V. Liarokapis, and Kostas J. Kyriakopoulos, "Human Arm Impedance: Characterization and Modeling in 3D Space", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2010. PDF

Contributed Conference Abstracts/Demonstrations

 Matteo Bianchi and Minas V. Liarokapis, "HandCorpus, a New Open-Access Repository for Sharing Experimental Data and Results on Human and Artificial Hands", IEEE World Haptics Conference (WHC), Daejeon (Korea), 2013 - <u>Demonstration</u>. PDF

Workshop Papers/Abstracts

[2] Minas V. Liarokapis, Agisilaos G. Zisimatos, Christoforos I. Mavrogiannis and Kostas J. Kyriakopoulos, "OpenBionics: An Open-Source Initiative for the Creation of Affordable, Modular, Light-Weight, Underactuated Robot Hands and Prosthetic Devices", 2nd ASU Rehabilitation Robotics Workshop, Arizona State University (ASU), Tempe, AZ (USA), 2014. PDF

 Matteo Bianchi and Minas V. Liarokapis, "The HandCorpus Initiative: An Open-Access Repository for Sharing and Retrieving Data, Tools and Analyses about Human and Robotic Hands", 2nd ASU Rehabilitation Robotics Workshop, Arizona State University (ASU), Tempe, AZ (USA), 2014. PDF

Technical Reports

[1] Minas V. Liarokapis, Panagiotis K. Artemiadis, Charalampos P. Bechlioulis and Kostas J. Kyriakopoulos, "Directions, Methods and Metrics for Mapping Human to Robot Motion with Functional Anthropomorphism: A Review", Control Systems Lab, School of Mechanical Engineering, National Technical University of Athens, September 2013. PDF

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