Object Identification and Pose Estimation Using Bio-Inspired Tactile-Enabled Multi-Joint Fingers for In-Hand Manipulation

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Thesis submitted to the Faculty of Graduate and Postdoctoral Studies in partial
fulfillment of the requirements for the degree of

Ph.D. in Electrical and Computer Engineering

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Abstract

In-hand manipulation is a major challenge that has to be addressed in order for robots to achieve human-like skills and manipulation abilities. A new generation of humanoid robots will need dexterous hands able to deal with uncertainties, especially when they are expected to operate in unstructured environments, such as homes and hospitals. Given the human ability to quickly obtain and understand tactile data, one promising direction in order to achieve enhanced robotic dexterous skills is to investigate and emulate human manipulation capabilities. In humans, a combination of somatosensory subsystems deals with everyday manipulation tasks.

This thesis introduces a new approach for estimating the pose of a grasped object by combining tactile sensing data and visual frames of reference inspired by the human Where subsystem. While tactile sensing produces local data about objects during in-hand manipulation, a vision system generates egocentric and allocentric frames of reference. Object recognition in the early grasp phases in unstructured environments is also a fundamental ability for robots to achieve human-level manipulation skills. Humans developed a so-called haptic glance where non-exploratory manipulation perform fast object identification. Tactile sensors contribute useful information about the objects manipulated by robots, especially during in-hand operations. Drawing inspiration from the functionality of the What somatosensory pathway, the proposed solution uses machine learning methods to recognize objects in the early phases of manipulation.

The thesis describes innovative work on object recognition using data collected from bio-inspired multi-modal tactile sensing modules in static and dynamic tasks. The system takes advantage of the modules compliant structure and inertial, magnetic and pressure measurements. During all experiments, a dual fuzzy logic controller autonomously achieves and maintains stable grasping conditions while forces applied to in-hand objects expose the tactile system to various object configurations. This thesis also presents results on simultaneous object characterization during exploratory procedures using teleoperation.

Acknowledgements

First, I would like to thank God, the Almighty. I would like to address my very special thanks to my supervisor, Dr. Emil M. Petriu for his guidance and support throughout this research. I would like to thank my friends and colleagues from BioIn Robotics Lab for their support. Finally, I want to pay my gratitude to my parents and other family members for their priceless support and encouragement.

Table of Contents

List of Tables

List of Figures

Nomenclature

Abbreviations

ANNs	Artificial Neural Networks
DOF	Degrees of Freedom
EXP	Explained variance
FSR	Force Sensing Resistor
IMU	Inertial Measurement Unit
kNN	k-Nearest Neighbours
LR	Linear Regression
MARG	Magnetic, Angular Rate, and Gravity
MCU	Microcontroller Unit
MEMS	Micro-Electro-Mechanical Systems
MLP	Multilayer Perceptron
MLPR	Multi-Layer Perceptron Regression
MSE	mean squared error
MUX	Multiplexer
RIDGE	Ridge Regression
ROS	Robotic Operating System
SVM	Support Vector Machine
SVR	Support Vector Regression

Chapter 1

Introduction

In the new era of robotics, machines are capable of performing high-level, complex and fast reasoning tasks. However, for robots' skills to match human-level capabilities, there are still challenges to be solved [1]. Previously only seen in controlled environments, such as industries, robots are moving towards homes, schools and hospitals, relatively unstructured contexts [2]. Nowadays, robots can walk, communicate and understand situations, but, a human-like hand is still left as, one of the last frontiers to be faced. This evolution requires robots to tackle more dexterous tasks, with the in-hand manipulation as an essential example of a challenge to be overcome. Moravec's Paradox, is still valid in these days, summarizing current robotics challenges [3]:

> "It is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility".

Robots can improve their overall skills by developing a more effective in-hand manipulation ability which is crucial for many human-like activities [4]. In this thesis, Chapter 2 presents plenty of relevant research activities in this field from the past decades, however there is still remains a long path to real-world applications. This type of research needs to tackle manipulation uncertainty aspects, which can follow the human control and somatosensory system inspiration.

The human hand, widely regarded as the “holy grail” of manipulation, has been a gold standard for roboticists for decades. Even though birds, dogs and other animals have manipulation skills, homo sapiens hand and brain control level is rare in other species. It is an ability developed from the humans erect posture that freed our upper limbs, turning our hands into two sophisticated sets of tools [5]. For this reason, human biology quite often inspires advancements in many advanced robotic applications. This bio-inspired approach is quite reasonable since new techniques can be developed based on a well-understood model of solutions already available in nature. Grasping and manipulating objects is a distinctive part of the human skill-set. An anthropomorphic approach to manipulation is justifiable due to the considerable skills and dexterity of the human hand.

Quoting [6] “The human hand has attracted attention in robotics, as it is one of the most dexterous multifingered grippers available in nature, granting humans the ability to manipulate objects precisely. ... Hence, a faithful robotic implementation of human grasping principles would allow robotic manipulation of a wide range of objects designed for human use without further modifications.”

The impressive object manipulation ability of the human hand and somatosensory system to deal with uncertainties inspires several research developments. Recent research shows that the human somatosensory system presents two subsystems. For instance, the “Where” subsystem solve the localization problem while the “What” subsystem is responsible for recognition and memory. Also, an anthropomorphic form is essential for new intelligent prosthesis designs [7]. Furthermore, most commonly used objects and tools are designed with the human hand in mind.

Computer vision and autonomous navigation are examples of robotics topics that have significantly advanced in recent years, but grasping and manipulation are still facing unsolved challenges. Especially in unstructured environments, robots still struggle to accomplish even simple manipulation tasks, such as in-hand object reorientation.

1.1 Problem Definition

Industry still accounts for the vast majority of operations that involve robots. Their tasks are not limited to pick and place operations, but also include moving cameras and various inspection operations. While robots are useful for welding, painting, transport of materials, they are still far from the fanciness of science fiction lacking human-like capabilities [8]. The authors of [9] addressed the increasing interest on the development of better hand skills based on relevant research on human hand operation, a topic recently refreshed in [10].Observing the human machinists operating in industrial settings led to a taxonomy that serves as a reference for grasping and manipulation operations. In ordinary daily operation, the machinists arm brings the part into its right position, while the wrist give the part its proper orientation. The authors also pointed out how subtle corrections completed by fingers and wrists ensure its adequate orientation. Robotic manipulators using only arm joints show limitations when performing dexterous movements. In-hand operations would increase and facilitate the number of tasks a robotic manipulator can accomplish and make robots better fit for working in unstructured environments.

Dexterous manipulation is the human-like ability to interact in a useful way with objects in the real world, while in-hand manipulation is the ability to change the pose of an object within a hand [11, 12, 13]. During dexterous manipulation tasks, a robot changes an objects state from an initial configuration to a final pose. For instance, during pick and place tasks, the goal is to change the position and orientation of an object inside the manipulators workspace updating arm joints. Pick and place operations are an excellent robotic solution in structured environments where the robots have a simple gripper mounted on a 6 degree of freedom arm. Even though a robotic arm with a simple hand/gripper is sufficient for most manipulation tasks, a dexterous end-effector can address restrictions during small reorientation tasks [11]. Also, especially in unstructured environments, obstacles can place unexpected constraints to the arms motions that could be overcome by an ability to perform in-hand manipulation operations. For a set of tasks, in-hand dexterity can achieve a goal state without any reconfiguration of the arm joints. New developments on stable grasping and hand functionality, such as object recognition and pose estimation are essential for expanding current in-hand manipulation tasks.

Hard-to-obtain mathematical models and high non-linearity limit the usage of conventional control techniques in robot manipulators [14]. Fuzzy logic based controllers are potential candidates for applications such as stable grasping due to uncertainties resulting from object interaction in the real world. Using fuzzy logic to address the grasping stability problem is one way to reduce the gap between conventional and intelligent control [15]. Equilibrium is a requirement for achieving a stable grasp on multi-fingered end-effectors. A multi-fingered robotic hand achieve manipulation equilibrium when no resultant force is acting on a grasped object [16]. After achieving equilibrium, a robotic hand is free to perform in-hand manipulation with stability. However, unknown friction forces pose a problem to obtain equilibrium in robotic hand grasping tasks. Fuzzy logic control in manipulation is commonly used to define parameters that deal with unknown friction, allowing a system to achieve equilibrium and perform a stable grasp. Fuzzy logic control has proven to be a useful tool for in-hand manipulation providing for grasp stability [17, 18, 19, 14]. Several researchers proposed open-loop grasping control for experimental data collection, but a new era of robotic hand with a focus on autonomy needs intelligent closed-loop solution such as the fuzzy logic control when possible.

Recent improvements on tactile sensing, with multi-modal and bio-inspired sensors, advanced our understanding of robotics applications on these scenarios [20, 21]. Dynamic interaction with the environment, including sensing, is the primary goal of any useful robotics platform. For instance, while trying to complete a trajectory the mobile robots need to understand their setting through their sensors. Such an ability allows them to interact with the environment while moving. Similarly, manipulation involves sensing an object then interacting with it and the environment in order to complete a task. While there is a rich body of literature on the development of unimodal tactile sensing solutions, the human tactile system is multi-modal and integrates several distributed tactile sensing modules. In order to understand their surroundings and in particular the tactile properties of the objects they interact with, the robots are using touch sensing [12]. Recent research on multi-modal tactile sensors provides robot hands with a more performant human-like touch sensing ability, which allow them to perform texture and object characteristics recognition [22]. In cluttered environments or during partial object occlusion, well-developed feedback and control functions such as vision-based control are insufficient [23]. In-hand manipulation can use multi-modal tactile sensing to extract object characteristics or to conduct feedback control, overcoming vision occlusion.Shape, surface properties and pose are common object properties targeted by the recent in-hand manipulation research. Multi-modal tactile sensing, in addition to a solid understanding of the human somatosensory system, can improve the execution of more complex robotic tasks such as object classification and pose estimation.

The use of machine learning algorithms is essential for modern robotics. Classical robotics solve several problems in repetitive and intense tasks. The integration of machine learning techniques in the robotics loop brings a new perspective on topics where classical robotics techniques are limited or inefficient. Also, to improve well-known tasks, machine learning provides tools for new features such as classification of objects and in-hand pose estimation.

Fast object identification during manipulation, is part of human dexterity [24]. The "haptic glance" is a characteristic of the human somatosensory system reported in several studies [25]. In order to improve a robots ability to manipulate unknown objects, especially in cluttered or occluded environments, object identification is essential. Simple grasping object classification, defined as a non-exploratory component of "haptic glance", is used to extract object information in early phases of a grasping attempt [26]. Extraction of objects characteristics in early grasping phases has the potential to improve in-hand manipulation. Underactuated hands have a distinct advantage in this regard, due to their versatility, they can quickly extract information about an object in early phases of manipulation. In early grasping phases, hands with fully actuated fingers need precise object shape information to generate grasp point candidates [27], while underactuated hands can adapt themselves during a manipulation attempt as they perform stable grasping and object identification. This ability promotes robust grasping performance for the underactuated hands compared to fully actuated hands during the early phases of unknown objects manipulation and matches with the human “What” subsystem.

While it is generally accepted that haptic and visual perception complement each other, the human touch nevertheless plays a major role, as emphasized in the following quote from [28] “... touch can be constructed as the most reliable of the sensor modalities. When senses conflict, touch is usually the ultimate arbiter.” Humans combine vision and touch to estimate object pose and position, creating frames of reference. The “Where” visuotactile subsystem is responsible for creating intrinsic and extrinsic frames of reference. This subsystem uses an intrinsic frame of reference in the sensory organ where it touches an object [25]. Humans also employ an extrinsic frame of reference to guide their manipulation relative to external points in the environment. In robotics, an accurate and fast estimation of objects pose is essential for manipulation [12]. The estimated pose is represented by objects position and orientation relative to end-effectors, or to a global coordinate, frame. Accordingly, robust, accurate and fast pose estimation is essential for any reliable grasping and manipulation task. The manipulation task’s success is compromised, when errors in estimation lead to incorrect finger placement and wrong decisions on grasp stability. Computer vision is the most common technique to estimate an object’s pose. However, even before the hand grasps the object, occlusions can occur and vision-based estimation is not reliable [12, 29]. Tactile sensing provides a useful tool for assisting object pose estimation overcoming the occlusion problem. Underactuation also helps to reduce the amount of information needed for stable manipulation. Underactuated grasping only requires estimation of specific angles and translations, resultant of the initial grasping attempt. Underactuated compliant hands can provide performance and robustness [30] with reliable pose estimation even under after grasp parasitic motions [31].

Using human biology as inspiration for robotics development allows advancements in in-hand manipulation tasks to be translated for the use of intelligent prosthesis design. One of the many challenges towards an intelligent prosthesis construct is the body’s’ natural biological rejection of foreign objects. Highly refined bio-mimetic robotic systems have made significant developments in the past decades due to increased advancements in artificial intelligence and cognitive research areas. Recent dexterous hands with increased grasping and manipulation abilities have focused on bio-mimetic and bio-inspired functionalities [32]. In order to increase bodys acceptance of a new prosthesis, the focus should concentrate on designs that integrate human sensory and biological systems [33]. The overall results of the meta-research [34] are inconclusive due to the multi-method observed in most papers; however, lack of functionality is a highly observed cause. While, in one study, 89% felt that they were more functional without the prosthesis, 91% of myoelectric rejections resulted from prosthetic-related lack-of-function problems in addition to other reasons such as comfort and durability. From 16% up to 47% of body-powered and electric prostheses do not use the dynamic capabilities of their device. Improving prosthesis functionality with tactile feedback and intelligent control has the potential to improve user acceptance with different operating features, especially autonomous grasping and control [35]

Recent advancements on tactile sensing and better understanding of the human somatosensory system motivated the split approach of this research. The where-what subsystems, in addition to the “haptic glance” concept applied for robotics, have the potential to improve in-hand robotic manipulation while combining a bio-inspired tactile sensing approach to human perception systems. Finger compliance and underactuation could also be transferred to prosthetic projects. Developments of tendon-driven and flexible joints open the possibility of anthropomorphic robotics hands able of autonomous grasping as an essential part of achieving human-like manipulation ability.

1.2 Objectives

The goal of this research is to apply machine learning and multi-modal tactile sensing techniques to the dexterous manipulation using concepts from the human somatosensory systems. We developed dexterous manipulation phases such as object identification and in-hand grasp angle estimation using concepts of human “haptic glance”and visuotactile system, respectively.

The research and experiments must shed light on robotic in-hand manipulation phases, in order to develop efficient dexterous manipulation solutions for tendon-driven robotic hand platforms. The project should focus on the use of compliant tactile sensor information for unknown objects identification and pose estimation in phases similar to the human tactile-enabled haptics. This study also must provide insight into the multi-modal sensor fingers placement for efficient data acquisition and hand actuation. The prototype should be capable of performing dynamic and static object feature extraction under an autonomous, stable grasp.

Most of the research on the field focus on object characteristic feature extraction based on single modal tactile sensing. Although it is a valid use of off-the-shelf components, using only the normal force, lots of information is lost when estimating object characteristics, especially during in-hand operations. The ongoing research on multi-modal tactile sensing is still relatively slow, even though there is a growing focus on the study of compliant structures and machine learning algorithms. While most of the research on in-hand dexterous manipulation uses biology as a source of inspiration, little advancements have been made on the use of somatosensory perspective to robotic tactile sensing. The expanding research area of in-hand manipulation can advance with the use and implementation of an approach focusing on the multi-modal sensing and compliant structures and actuators. It is still a challenge to develop a minimalistic hand design for practical applications. The ideal solution is to allow extracting more haptic information while employing a minimum number of actuators and an uncomplicated set of sensors.

Recently, the in-hand manipulation field is focusing on compliance, modularity and the use of tendon-driven underactuated fingers even with the challenges posed by uncertainties inherent for this type of actuators. The experiments aim to meet these challenges with autonomous, stable grasping with fast object identification and pose estimation.

In this context, the work in this thesis has the following objectives:

1. The use of machine learning algorithms and tactile sensing data for in-hand manipulation of underactuated hands. The experimental setup must take into account the flexible and tendon-driven nature of human hands as well as the different phases of human in-hand manipulation. Aspects of the human somatosensory system should

inspire a new approach of grasping and manipulation of robotic hands.

2. Demonstrate the use of tactile sensing and machine learning algorithms for in-hand object pose estimation. In this context, we aim to demonstrate that machine learning using multi-modal tactile sensing can successfully estimate post-grasping object pose in underactuated hands.

3. Confirm the use of single grasping strategies and tactile sensing for object identification during static manipulation. The solution of robotic object identification is crucial, and on this thesis, we propose that object recognition happens during the early phases of manipulation. This thesis should use concepts of the human "haptic glance" to inspire object identification strategies in the early phases of robotic grasping.

4. Provide insight into simultaneous object identification and pose estimation during robotic in-hand object explorations. Object exploration can be essential when there is no enough data to provide accurate object characterization. If the object survey proceeds to investigate more than one feature concurrently, there is a reduction in the costs that arise from this approach. This thesis should explore the possibility of simultaneously identify objects while providing estimations of its pose during in-hand manipulations.

5. Finally, all tasks should be able to be performed under autonomous, stable grasping. This thesis aims to integrate the sensing and intelligence with autonomous grasping, increasing the level of autonomy of robotic hands and future prosthetics.

1.3 Research Approach

The investigation of object feature-extraction using elastic tactile sensors started with the work presented in [36]. This paper presents an initial study that provides a base for the further development on multi-modal tactile sensors and tendon- driven actuation in flexible joints, with [21]showing data captured during autonomous, stable grasping. Results from this work in addition to results achieved in [37] motivated the use of machine learning for object feature extraction.

The use of machine learning also started appearing on similar research topics during the last two decades. More recently, in [26]authors used pressure information for single grasp object identification based on the human somatosensory property of haptic glance where tactile inference happens from brief, non-exploratory motions. Following this approach, unpublished results show satisfactory object recognition performance during experiments under autonomous, stable grasping.

Experiments also demonstrated that another in-had manipulation phase could use multi-modal tactile sensing in order to expand its capabilities. In [38], authors performed object recognition through human in-hand manipulation using a feedback glove that conveys force, vibration, and temperature feedback to the human operators hand. A feedback glove conveys force, vibration, and temperature feedback to the human operators hand. High accuracy in human experiments motivated the use of vision and tactile sensing [39]. This approach uses egocentric and allocentric frames, which uses the somatosensory system as an inspiration for object feature recognition.

The human somatosensory system act as a constant inspiration through this research. Humans have an efficient way of dealing with uncertainties of objects and manipulation, fusing tactile sensing, memory and fast decision making. In summary, the visuotactile approach to object pose estimation, in addition to "haptic glance" and exploratory procedures to reduce manipulation costs, are the main inspirations for this thesis making. In Chapter 4, inspired by the "Where" somatosensory subsystem, a visuotactile approach provides fusion of tactile and vision in aspects not yet found in the literature. The "haptic glance" brings to robotics aspects of the "What" somatosensory subsystem, that in humans are responsible for recognition and memory, and we explore it in Chapter 3. When early phases of manipulation failed to extract the characteristics of the object, we approach pose estimation and object recognition with an exploration of the object using in-hand manipulation in Chapter 5. The simultaneous approach serves to reduce manipulation costs finding in exploratory procedures.

Along with the development of machine learning algorithms for object identification and pose estimation, a fuzzy logic control algorithm has also been developed, initially for one motor [21], with results presenting a dual actuator fuzzy logic control in two phases [39]. This approach reduces the gap in the intelligent control and manipulation for human-like robotic hands.

1.4 Thesis Organization

After this brief introduction, the next chapter follows a literature review of a broad spectrum of research related to this thesis. The second chapter presents a literature review of a broad spectrum of research related to this thesis. The chapter will present past and recent research developments on the thesis topics and will identify challenges still to be faced.

The third and fourth chapters present research and experiments relevant to this thesis. Chapter 4 "Estimating In-hand Object Orientation Using Machine Learning" is based on the paper "Estimating the Orientation of Objects from Tactile Sensing Data Using Machine Learning Methods and Visual Frames of Reference" published in [39]. It proposes an approach for estimating the pose of in-hand objects combining tactile sensing data and visual frames of reference inspired by the human "Where" sensory subsystem.

Chapter 3 "Tactile Object Classification in Early Phases of Autonomous Grasping Using Machine Learning" presents research and experimental results about the single-grasp haptic object recognition. It describes experiments using the human tactile "What" subsystem as inspiration for design a machine learning approach to "haptic glace" for robots. The prototype was able to perform object identification during single grasp attempts with using only information of compliant multi-modal sensors during autonomous grasping.

Chapter 5 "Machine Learning Techniques for Object Identification and Pose Estimation During In-hand Robotic Exploration", in the complement to the previous chapters, explore machine learning for simultaneous object identification and pose estimation using teleoperation.

The last chapter of this thesis presents our final remarks and a closing examination of future works.

1.5 Thesis Contributions

The main contributions of this thesis are in the application of machine learning algorithms using bio-inspired tactile sensing modules, to the robotic in-hand manipulation phases. More specifically, the main expected contributions of the thesis are:

1. **In-hand object characterization for tendon driven underactuated robotic hands using concepts of the human somatosensory system.** Given that this thesis (and publications arising from it) were the first in the literature to study this problem from the somatosensory system perspective, the incremental contribution of this panorama for in-hand manipulation in underactuated hands is the most significant contribution to the existing bodywork.

2. **Demonstration of visuotactile in-hand object pose estimation using multi-modal tactile sensing.** This thesis contributes with visuotactile pose estimation of after grasping object position fusing multi-modal tactile data and visual frames of reference. This contribution is published in [39].

3. **Single grasping object recognition during in-hand manipulation.** This thesis contributes to the fast recognition of objects using tactile sensing in the early phases of robotic in-hand manipulation. Also, our investigation provides exciting results on the use of bio-inspired multi-modal sensing modalities for Object recognition.

4. **Simultaneous object recognition and pose estimation during exploratory procedures** Reducing the time cost of exploratory procedures is essential for fast and reliable in-hand manipulation in robotics. Our approach contributes by demonstrating the results of simultaneous pose estimation and object recognition during teleoperated in-hand manipulations.

5. **Autonomous, stable grasping fuzzy control for double actuated grippers.** Even though this is a well-studied topic in robotics, our contribution is the introduction of multi-modal tactile sensing in the control loop of robotic hand grasping. Our dual fuzzy controller uses pressure and micro-vibrations to get grasp status and define motor actions.

1.6 Publications Arising from this Thesis

Several publications produced during the research and experiments of this thesis are listed below:

1.6.1 Journal Papers

- **V. Prado da Fonseca**, T. E. Alves de Oliveira, and E. M. Petriu, “Estimating the Orientation of Objects from Tactile Sensing Data Using Machine Learning Methods and Visual Frames of Reference,” Sensors, vol. 19, no. 10, p. 2285, 2019.
- T.E. Alves de Oliveira, A.-M. Cretu, **V. Prado da Fonseca**, E.M. Petriu, “Touch Sensing for Humanoid Robots” IEEE Instrum. Meas. Mag., Vol. 18, No. 5, pp. 13 -19, Oct. 2015, 10.1109/MIM.2015.7271221
- **V. Prado da Fonseca**, T. E. Alves de Oliveira and E. M. Petriu “Tactile Object Classification in Early Phases of Autonomous Grasping,” Manuscript submitted for publication to IEEE Access.

1.6.2 Papers in Conference Proceedings

- **Vinicius Prado da Fonseca**, Bruno Monteiro Rocha Lima, Thiago Eustaquio Alves de Oliveira, Qi Zhu, Voicu Z. Groza and Emil M. Petriu “In-Hand Telemanipulation Using a Robotic Hand and Biology-Inspired Haptic Sensing” 2019 IEEE International Symposium on Medical Measurements and Applications MeMeA 2019

- Bruno Monteiro Rocha Lima, Thiago Eustaquio Alves de Oliveira, **Vinicius Prado da Fonseca**, Qi Zhu, Miriam Goubran, Voicu Z. Groza and Emil M. Petriu, “Heart Rate Detection Using a Miniaturized Multimodal Tactile Sensor” 2019 IEEE International Symposium on Medical Measurements and Applications (MeMeA)
- Thiago Eustaquio Alves de Oliveira, **Vinicius Prado da Fonseca**, Bruno Monteiro Rocha Lima, Ana-Maria Cretu and Emil M. Petriu, “End-Effector Approach Flexibilization in a Surface Approximation Task Using a Bioinspired Tactile Sensing Module” 2019 IEEE International Symposium on Robotic and Sensors Environments (ROSE)
- D. Zhi, T. E. A. de Oliveira, **V. P. da Fonseca**, E. M. Petriu, “Teaching a Robot Sign Language using Vision-Based Hand Gesture Recognition,” Proc. CIVEMSA 2018, IEEE Int. Conf. Computational Intelligence and Virtual Environments for Measurement Systems and Applications, pp. 1-6, Ottawa, ON, Canada, June 2018
- **V. Prado da Fonseca**, T.E. Alves de Oliveira, K. Eyre, E.M. Petriu, “Stable Grasping and Object Reorientation with a Three-Fingered Robotic Hand,” Proc. IRIS 2017 - IEEE Int. Symp. Robotics and Intelligent Sensors, pp. 311-317, Ottawa, ON, Canada, Oct. 2017
- **V. Prado da Fonseca**, D.J. Kucherhan, T.E. Alves de Oliveira, D. Zhi, E.M. Petriu, “Fuzzy Controlled Object Manipulation using a Three-Fingered Robotic Hand,” Proc. 11th Annual IEEE Int. Systems Conference - SysCon 2017, pp. 346 - 351, Montreal, Que., Canada, Apr. 2017
- D. J. Kucherhan, M. Goubran, **V.P. da Fonseca**, T.E.A. de Oliveira, E.M. Petriu, V. Groza, “Object Recognition Through Manipulation Using Tactile Enabled Prosthetic Fingers and Feedback Glove Experimental Study,” Proc. MeMeA 2018, IEEE Int. Symp. Medical Meas. and Applications, pp. 1104-1109, Rome, Italy, June 2018
- T.E. Alves de Oliveira, **V. Prado da Fonseca**, E. Huluta, P.F.F. Rosa, E.M. Petriu, “Data-driven analysis of kinaesthetic and tactile information for shape classification,”

Proc. CIVEMSA 2015 - IEEE Int. Conf. on Computational Intelligence and Virtual Environments for Meas. Systems and Applications, pp. 1-5, Shenzhen, China, June 2015

- A.-M. Cretu, T.E. Alves de Oliveira, **V. Prado da Fonseca**, B. Tawbe, E.M. Petriu, V.Z. Groza, “Computational Intelligence and Mechatronics Solutions for Robotic Tactile Object Recognition,” Proc. WISP 2015 IEEE Int. Symp. Intelligent Signal Processing, pp. 72-77, Siena, Italy, May 2015

Chapter 2

Literature Review

2.1 Historical Perspective

With developments traced back to pre-historic times, humans used grasping tools to hold objects which manipulation characteristics such as size or shape, pose difficulty to the human hand. Usually comprising only two rigid links, generally specific for grasping a limited number of objects, those ancient grasping tools presented on rare pictures indicate a fair amount of use of simple grippers and the first artificial hands [40].

Serving as a source of inspiration, the ability of the human hand and its essential role in our daily activities, lead to the emerging technologies of the "artificial hands". The term "artificial hand" is being used to describe a multi-fingered device that imitates the shape or functionality of the human hand designed to be connected to the end of a fully actuated arm [41]. In this thesis, this definition will appear in several situations, from prosthetics to industrial and humanoid robotics. Reported by Plinius the Older in [42], the first development of an artificial hand was for a pretorian Roman official called Marcus Sergius Silus, who had his right hand replaced by an iron cast prosthesis.

Progress on the field was also reported in the 16th century where, Goetz Von Berlichingen, also called the "Knight with the Iron Hand" built a five-fingered device comprising an opposing thumb capable of several grasps [43]. The idea of independent finger motion in artificial hands was introduced later when military surgeon Ambroise Par developed "Le Petit Lorrain", an artificial hand [44]. Since the nineteenth century, with inspiration from simple mechanisms in first grippers from the renaissance, dexterous manipulation has required more complex designs mainly for industrial applications in modern times with mechatronic implementations.

Developments in artificial hands, either for automation or prosthetics applications, had expertise transferred from two-fingered grippers. This trend accelerated mainly because of the availability of multi-DOF manipulators and modern control systems after the 1940s. For instance, the first industrial robot named Unimate was a creation of George Devol and introduced the concept of "universal automation" [45]. Efficiency in grasping an object in order to perform manipulation tasks with it lead the robot-based manufacturing to increase the development of artificial hands. Since its initial development, artificial hands appear in several forms. Initially and continuously today, for prosthetic devices attached to the human body, from end effectors in manipulators to assist or replace human activity, such as risk tasks, factory automation, usually in repetitive tasks or, more recently, with social interaction and assistance.

2.2 Hand Dexterity, Robustness and Operation

Although engineers dreamed about replicate human hand and dexterity since old times, artificial human-level dexterity probably will not be achieved by robots very soon. Essential and inevitable differences exist between the nature and our current technology on actuators, sensors and control. Even the question of when artificial hands should mimic the human hand is not answered and usually depends on expectations from the user to the hand. Hand uses and functions are vastly different depending on the scenario, and it will guide the description of this literature review.

A first discussion will focus on three aspects of artificial hands that are directions for effective hand design in the literature, particularly, hand dexterity, grasp robustness and human operation. Hand dexterity here will denote the capability of the hand to change objects pose and complete an arbitrary task. Grasp robustness on this review is the ability of the hand to maintain a stable grasp despite external disturbances while the object remains in its original form, not being damaged or released. A friendly and straightforward interface to the human operator is another factor evaluated where it is joint level programming, teleoperation of a person using an artificial limb. This review concentrates on the present state of the art on the development of artificial hands, future direction in the field, and which problems are still open.

2.2.1 Manipulation Dexterity

Being a concept that involves stability and skill while performing motions during manipulating objects, "dexterity" usually has a broad definition. In this thesis, and with as a widely accepted concept in robotics literature, dexterity means the ability to change objects pose and orientation configuration arbitrarily to a different one within the hand workspace [46].

Robot hands are articulated end effectors with two or more fingers that use touch to manipulate objects. The presence of touch makes this type of robotic system distinct among other robotic systems. The capacity for modelling or abstracting touch affects the manipulation performance directly. Another important factor concerning contact models are static and kinetic coefficients of friction which has implications on the visco-elastic behaviour, sliding and rolling conditions, and whether contact points rotate in respect of each other.

2.2.2 Classical Designs

The authors of [47] stated that in a dexterous hand with rigid fingers, nine is the theoretical minimum number of degrees of freedom with non-rolling and non-sliding contacts. The number is because one needs three hard-fingers to restrain an object completely, therefore if no sliding or rolling is allowed, for the object to move the fingers must track the object movement using its contacts in three-dimensional space.

Relevant research was carried on at the University of Karlsruhe [48], Technical University of Darmstadt [49], and Delft University [50]. Although not usually anthropomorphic, hands of this type [51], in general have optimized kinematics. Excessive degrees of freedom introduced more flexibility of use in some research designs. Later authors have increased the number of fingers using four or five fingers getting closer to the anthropomorphic hand, and alternating fingers used for a grasp to achieve different manipulation schemes.

2.2.3 Alternative Designs

When faced with crucial application factors such as reliability, reduced size, weight and cost, the high degree of mechanical complexity present on off-the-shelf designs prevented its broader use. With the number of actuators between 9 and 32 for some hands aforementioned, such complexity represented a limiting factor. Researchers venturing on overcoming this impasse promoted reductions on hardware complexity, even below the theoretical number of 9 degrees of freedom.

The particular definition of dexterity used in [47] constrained the minimal design requirements based on a set of assumptions on the contact model. Using soft-finger contacts instead of rigid-fingers can be shown that at least four degrees of freedom can perform dexterous skills in the definition described earlier. With a relaxed concept of dexterity, and consequently modifications on contact models, other ways of achieving dexterity can appear. Most applications do not need a pose and orientation tracking of the object on every instant of the designed path. Preferably, it is enough that the object achieves the desired configuration based on an initial position, being irrelevant what path it follows.

Regrasping and Finger Movement

Manipulation by regrasping [52, 53, 54] involves manipulating an object with a sequence of pick and place operations where the object rests on a temporary workspace between movements. Time-consuming is the main disadvantage of this method, where the need for release and regrasping requires additional calculations and interaction with the environments during manipulation by regrasping.

Another technique for reorienting objects is called "finger gaiting" where three or more fingers, one at a time, changing its contact point on the object's surface, promoting an in-hand manipulation. Author in [55] and [56] demonstrated these possibilities with sphere and stick manipulation, respectively. Minimizing execution times and analysis of regrasping tasks, and the identification of reliability of regrasping plans for complex 3-D objects, are also significant challenges in this topic.

Sliding and Rolling

Sliding manipulation is present very often during human tasks, which a controlled slippage present ubiquitously. An essential part of control slippage is to be able to predict its occurrence, which requires an accurate analysis of friction and any slippage event. In the literature, mechanical fixtures are used as tools to solve to those types of problems in [57] and [58], and in partial form-closures [59].

In recent years has been widely accepted the advantages of curvature effects and rolling on the design of more straightforward dexterous hands. In [60] the authors considered rolling in a dynamic model to recover with tactile information, the objects pose from the contact points of the finger surface. A deep understanding of the kinematic laws, in addition to an analytical model of rolling contacts, is crucial to benefit from its manipulation possibilities. In [61], the authors developed a method using rolling on a flat finger for the reconstruction of the shape of unknown objects while planning the manipulation of generic convex objects. The results presented consider an object with a smooth surface, which is usually the exception. Daily objects usually may have sharp edges and vertices, which would take advantage of a model with a polyhedral description. Several challenges are still open for manipulation by rolling, which is a promising area in terms of hardware simplicity.

2.2.4 Grasping Robustness

"Grasping" is the action of gently holding an object, constraining its motion relative to the hand while possibly resisting against external forces. Grasping tasks is related to manipulation in some aspects and usually trad-offs between dexterity and grasp reliability drives the robotic hand design [46].

Design

Based on observations of the human hand, it is outstanding that humans use their hands in several distinctive ways during different tasks. For fine manipulation, humans usually use their fingertips or distal phalanges. Inspired by the high robustness present on biology manipulation systems, researchers developed robotic devices capable of using inner parts in addition to sensing contact with objects.

In the literature, terms such as “power grasping”, or the similar expression “enveloping grasping” [62] and “whole-hand manipulation” [63], describe tasks of manipulation where an object is maintained under a grasp using the hand’s palm and internal phalanges and not only its fingertips. The power grasping oriented design of a robotic hand was the focus of [64]. Power grasp was also the focus of the hand developed in [65].

Grasp Properties

Grasp robustness definition needs clear notions from concepts of form-closure and force-closure grasps.

Form-closure grasps are by the capacity of holding objects depending only on horizontal contact constraints. New research reveals that grasping an object in the plane needs at least four contacts, with seven needed in the 3-D case. The contact placement or form-closure grasp synthesis to avoid object motions given the object geometry is an active area of research.

Studies on the grasping task often develop under the assumption that the manipulated object is partially or entirely under large contact forces sustained of its end-effector despite external disturbances; therefore, the concept of force-closure is an active topic for robotic object manipulation research. Choosing grasping forces is an essential part of robotic object manipulation to avoid, or reduce chances of slippage.

Stability is another essential property of grasps. Recent literature shows at least two meanings. A first definition, from dynamic systems, refers to the Lyapunov theory, where evaluations on grasp dynamics define stability when a grasped object, even displaced from its original reference position, will stay near to this position. Another definition is Laganges, which emerges on the assumption that a conservative system is stable if it can apply to a strict local minimum of the potential energy. It is an observed prevalence of the second definition of literature usage [47].

Also important to remember that under some aspects Lagranges analysis is limited. In mechanics, there is not a proof for a common sense statement such as a system with more than two degrees of freedom is unstable if an equilibrium point is not a minimum for the potential function. Studies by [66], [67], [68] and [69], among others included stable control of manipulation and grasping. The control of grasping systems in the ubiquitous presence of uncertainties is essential for stable manipulation [70], [71].

Grasping and the Kinematics of the Hand

Some examples in the literature, such as [62], [72], [73] and [74] take in account the end-effector structure concerning grasping robustness, although these characteristics are essential to properties discussed before. In summary, form-closure analysis is mostly geometric, while force-closure aspects usually link with kinematics and other end-effector characteristics. Some end-effectors use an opposed pressure to “squeeze” the object to resist arbitrary external forces. A different end-effector cannot use this strategy because of a lack of side pressure. In [75], the authors propose kinematic-based force-closure gripper definitions in addition to an algorithm for benchmarking this characteristic. In [76], the authors define a device classification based on different passive and active closures.

2.2.5 Human Operability

Several factors define success in artificial manipulation systems, with the human operator being an important aspect that requires an easy to use human interface for the system.

In this thesis, the interface means the circulation of power and information back and forth between human and the artificial hand. In several applications, there is a necessity of substitution of the human hand. When a system uses an interface designed for the human hand operation (such as stick controls, door handles, among others), a well designed anthropomorphic hand would be the best choice for the task. Human prosthetic is the most known case of such devices (e.g., [77], [78], [79], [80]).

High-level interfaces are achievable if the human operator can seamlessly map its natural movements into device commands, which is a possibility with anthropomorphic hand designs. It is a difficult task to define and plan tasks for kinematically complicated robot hands, a fact explained by the scarcity of intricate designs use in practical applications. In another approach, anthropomorphic hands can learn by demonstration, grasp and behaviours directly from human manipulation tasks. In such a schematic, sensor gloves or a mechanical device can be operated by an individual providing hand data and measurements for the robotic hand.

A common approach is the use of telemanipulation (see, e.g. [81], [82], [83], [84], [85] and [86]), where the anthropomorphic hand replicates the operator's movements. Although not complete anthropomorphic examples in the literature, such as [87] present a platform for remote operation, a good match of the artificial hand function to the natural movement provides a sense of immersion for the operator in a remote and possibly virtual environment.

Machine hand programming that uses "learning by demonstration" approach, is a set of artificial hands that learn from a sequence of manipulation examples of the human hand skill set and apply it to solve different tasks, not reduced to a mimicking device. An increase in state of the art on this topic shows the attraction of attention on this particular field (see, e.g., [88], [89], [90], [91],[92], [93], [94], [95], [96]). Finally, it is possible to predict that future robotic systems will interact with humans soon, in a safe, resilient and predictable fashion. As mentioned before, rehabilitation is a task that could use such friendly platforms.

Drawbacks are also part of the anthropomorphic design. Many reasons suggest that an anthropomorphic hand is not the best option for situations where the control is computer-based, and knowledge about the environment is available during the design phase. In the present state of the art, the main disadvantages of human-like hands are a complex kinematic chain, the high volume of actuators, and a limited tactile sensing system.

2.3 Artificial Hands Development

2.3.1 Initial Developments in Artificial Hands

Human operability, dexterous manipulation and robust grasping were the main focus of artificial hands. Until recently, a prosthesis for the upper limb had no more than two degrees of freedom (DOF), with low anthropomorphism and limited of no tactile feedback to the user.

Prosthetic Hands

On the prosthesis area, a significant contribution has been the Scuola Superiore Sant'Anna work with several high skill level hands [97]. Later author studied sensors for the RTR II hand, with a human-computer interface using Electromyography in conjunction to control algorithms [98]. Slippage detection used strain gauge force sensors and hall effect position sensors in the RTR II. Even though the hand development focus is prosthetics, RTR II had its first integration to the robotic manipulation platform WE-4RII [99]. Results achieved included the development of several grasping patterns, study of different methods of hardness estimations, surface recognition, in addition to basic gestures [100].

Authors from [101] considered the user necessity of a high number of grasping shapes, in addition to an elevated level of visual feedback from humans while using it. The group developed a hierarchical control to accomplish dexterous manipulation in multiple degrees of freedom prosthesis, adjusting motion and force from slip detection, force and position feedback [102]. Position and force feedback was possible by a motor placed magnetic encoder and current sensors, respectively. In [103], authors provide In-depth details of the hand sensors and relations of natural and artificial neuromuscular systems.

Authors in [104] developed an ultralight anthropomorphic robot hand where 13 controllable DOF provides movement to five fingers. With internal fluid-based actuators that provide fast complete finger flexion and extension (less than 100 ms) and lightweight finger mechanical construction, this hand presented distinct and innovative features. This hand also incorporated three flex sensors per finger in addition to four tactile sensors. Hall effect-based sensors produced feedback for a control system that used position at each finger joint and fingertip force data. In a bio-inspired approach, regarding the human hand generic tool capabilities, [105] designed a 16 DOF hand with five fingers wrapped with soft rubber. More than 500 tactile points provided position, velocity and force data from several locations on the hand for a control system using a distributed input feedback.

The reduced real state space is a significant challenge for robot hand design due to the limited physical area available for all different parts needed for dexterous manipulation, such as actuation, tactile sensing and electronics. Another single motor hand was The Toronto/Bloorview MacMillan (TBM), implementing a passive adaptative grasp. The prosthesis intended to increase functionality and cosmetic appearance while achieving performance similar to the state-of-the-art [106]. In this thesis, the aforementioned reviewed examples are valuable references, since they represent design choices of reduced sensory feedback and autonomous grasping position, simplifying the control and mechanical solutions.

Research Platforms

Among other directions, research focused on modularity and simplification of platforms. To reduce costs with the assembly and maintenance of platforms, researchers applied modular finger design and simpler skeleton structures [107]. A comparative study, [108] guided the development of sensory feedback that fitted best these objectives. The module responsible for actuation was inside the forearm, which contained 16 motors with a potentiometer-based position sensor in addition to the tendon force sensor.

For research platforms, despite some related limitations, physical space usually is not a restricting condition. More space enabled research platforms to introduce multisensory feedback on robotic platforms control implementations. Artificial hands have been developed by the German Aerospace Research Center (DLR) continuously over almost two decades [109]. The DLR II includes three actuated joints with a potentiometer based position sensor for each finger, containing torque sensor based on a strain gauge. The multisensory hand was complete with a six-dimensional force-torque sensor mounted at each fingertip. A reduction of sensors is also noticeable, where the HIT/DLR hand has less temperature sensors than its predecessors. Hall-effect sensors also replaced the potentiometer used for joint positions measurements [109].

Gifu Hand group in Japan released second and third versions during the first part of the 2000s decade, which is a five-fingered robot hand [110]. Their approach followed by an increase in tactile detection points, in addition to larger width and pitch of electrodes, improved tactile sensing on the hands third-generation [111], promoting a reduction of the insensitive area to 49.1%. In [112], the authors used a peg in a hole experiment to demonstrate a master-slave system with a human operator wearing a force feedback system. The user could perceive tactile sensory data while controlling a robots hand.

With actuation shifting towards the inside on the hand, platforms start to used non-tendon based transmission mechanisms, reducing the use of tendon tension-based force sensors. Author in [113] introduced elastic element deformation used for contact detection with a hand using ultra-sonic actuation and trimmer potentiometers. The use of angular rotation data from potentiometers in this robotic hand enabled force estimation with no further installation of additional torque and force sensor.

Robot Hands for Industrial Robotics

The BarrettHand grasper [114] had its design focused on a programmable end effector for industrial robotics, developed requiring versatility to adapt and allow reconfiguration for different sizes and shape of objects. The authors also developed a spring force sensing compliant actuator used between each motor and the hand mounting, and feedback was achieved measuring torsion deflection using potentiometers. FSR tactile sensing and joint position angle information using a potentiometer were also possible.

Sensor Development for Robotic Hands

Several robotic hand sensors had increase development in the past decades. In [115], authors present an overview of tactile feedback modalities for robotic hands focusing on sensor fusion and use in manipulation tasks.

Many researchers developed light-based sensors during theses years [116, 117, 118, 119] Sensor effectiveness and characteristics were shown with the application of the sensor on a four-finger hand during grasping task experiments.

During these years, researchers tested several materials for tactile sensing tasks. For instance, [120] used a polyvinylidene fluoride (PVDF) and pressure-sensitive resistor ink for fingertip force sensing in addition to slip detection. In [121], authors developed a two-layered fingertip using different hardness silicone to emulate the structure of the human skin. Authors also fused piezoelectric transducers and pressure sensors for hardness classification for a wide variety of objects for biomedical robotic applications.

It is noticeable the focus on intrinsically actuate, standalone, underactuated robot hands. Research during this era also focuses on son adaptative manipulation abilities. Therefore, the tendon-driven transmission was not present in the new hands' design. Various actuation mechanisms are seen, with electrical motors still being widely used. Modular design is prominently used to reduce costs and promote easy maintenance. The facts above inspired sensor design and tactile feedback systems. Research on stable grasp and grip control extensively used force and position sensors in addition to slip detection. The development of sensory feedback interfaces for human operators increased during this period, with significant advancement of sensor systems, in addition to robotic hands improvement in mechanical, actuation and transmission [122].

2.3.2 Additional Developments

The past decade saw incremental achievements in previously developed hand designs.

Recent Prosthetic Hands Developments

Inspiration from the human hand and neural interfaces on prostheses continued to be the main focus of research during this period. Underactuated hands also attract robot hand designers' interest. Using a single ultrasonic motor, in [123], developed an underactuated five-fingered hand. Force feedback included FlexiForce (Nitta Corp.) embedded on a finger phalanges pad to implement force distribution similar to the human hand.

Authors in [124] presented a skillful prosthetic device called Cyberhand, which included user sensory feedback and control based on a neural interface. Modularity, in addition to human hand similarity and functionality, was the main focus of this project. The study presented in [125] employed an early version of the CyberHand used to research if an individual could self-attribute a robotic hand prosthesis.

Research with a focus on neural interface and hand prosthesis also included studies on the anatomy and structure similarity to the human hand. In [126], authors concentrate on mimic properties of the human hand aiming to promote static and dynamic characteristics with an artificial device with a skeletal structure for an Anatomically Correct Testbed (ACT) hand. The hand used tendon-driven transmission and brushless motors.

Advancements in Research Platforms

Research platforms are the most common place where papers present artificial hands and tactile sensors. In 2007 [127] and 2008 [128] authors presented two versions of the DLR/HIT hands. In the previous section, the paper [129] showed the sensors used in the first DLR-HIT hand, while the second version developed two specialized potentiometers for angle sensing. Besides, the second hand used a tactile sensor based on thin and flexible resistive material presented in [130]. This sensor uses a multi-layer approach incorporating a flexible PCB, pressure-sensitive silicon-rubber and a protective silicon film layer.

With a requirement for portability between different humanoid robots, in [131] improved in terms of modularization and intrinsic arrangement of hand components. Also, its fingers implemented passive compliance devices, which provided adaptive grasps abilities. In addition to 241 detection points inside, the "soft skin" concludes the tactile feedback system.

In [132], authors embedded a three-fingered robot hand with proximity, slippage and tactile sensors. Sets of sensors provided stable gasping, force control with manipulation reaction for object retention under slippage detection. The researchers solved this issue with through-hole on the tactile sensor providing phototransistor components exposition. Under the uncertainty of pick and place task conditions, the integrated sensors exhibited positive performance. These sensors also provide tactile feedback and slip detection for [133] while mounted on the [134] hand.

Task-specific sensors also provided information when particular conditions and restrictions arise. The hand presented in [135] aimed for underwater operations incorporates force sensors, distance measurements using an ultrasonic sensor, object shape determination by visual information and Hall effect sensors for finger position. Sensors provide data for human control or autonomous operation during grasping tasks.

Achievements in Tactile Sensors

In [136], authors developed a sensor capable of human interaction and object exploration skills with a device incorporating static and dynamic components for tactile measurements. The static module used measurements of the resistance variation, under applied pressure, between a piezoresistive foil and a second foil with embedded electrodes. Another project developed a new tactile sensor using two piezoelectric materials to achieve more considerable sensitivity, extended measurement scale and pressure resilience [137]. The authors increased the measurement range using an elastic body, also producing pressure resistance while applying vibration piezoelectric sensor for increasing sensitivity.

In a search for robustness and general applicability, authors in [138] pointed out that there is not such a sufficiently reliable sensor outside of structured environments. They developed a bio-inspired tactile sensor with electrodes covering its surface while including a rigid core embedded with sensitive components. Further publication applied this sensor, which was from then referred to as 'BioTAC,' to grip control test using Otto Bock Michelangelo 2 robot hand [139]. Later the same year [140] incorporated previous developments in the form of BioTac^{TM} finger sensors while adding temperature measurements through a thermistor. Information using sensor fusion from combining vibration and temperature improved tactile sensing. The sensor provides high versatility and easy maintenance due to its modular layout. BioTac eventually became commercially available and is used in several artificial hands and research projects.

Artificial Skin

Inspired by the biology of the electric fish, authors in [141] develop a pre-touch sensor using measurements of electric fields in the grasp formation phase. The authors provided an alternative to the vision and tactile sensing during the middle range grasping approach. Non-conductive materials posed a limitation to electric field sensing. To overcome this obstacle for capacitive sensing, authors research dual-mode devices. In [142], authors proposed using copper electrodes in a mesh with Polydimethylsiloxane (PDMS) structure.

Hand control systems thrived in association with advancements in tactile, force, position sensing and slippage detection. Unstructured environments add the necessity of research to aim for unpredictable conditions. The Unknown object strategy described in [143] emulates the human grasping reflex. To provide position and force control for manipulation of objects with unknown mass, friction and stiffness, authors in [144] used 6-axis force sensors, one per fingertip and one in the wrist. During tests with a 12 DoF three-fingered hand, the method displayed fast and reliable intercalation between the position and the force methods. Additional development in [145] introduced a controller that used sensory feedback for uncertainty grasps. Authors used association between grasp primitives and specific physical form to provide indivisible grasp procedures.

Developments in artificial skin also flourish on the emergence of new sensing technologies and the requirement for reliable and precise tactile information for the growing research on complex grasps. In [146], authors present a full-body humanoid skin project. Triangular sensors nodes embedded with 12 capacitive taxels interconnect to integrate these skin modules. For texture and slippage detection, authors in [147] covered the Bionic Hand with strain sensing multiple-layer artificial skin.

2.3.3 Modern Platforms and Research

Compiling great achievements from 2005 and 2010, authors in [148] outlined tactile human-robot interaction concerning the sensors used. Similarly, authors of [149] overviewed tactile sensing for dexterous in-hand operations.

Prosthetic Hands

Authors in [150] develop a prosthetic hand that estimate grasping force and gesture control based on tendon displacement. The method involved detecting the contact event following by measurements of grasping force. The grasping force is calculated based on the mapping of tendon displacement and the stiffness of a set of flexible elements.

Neural interfaces reliability is the focus of research during this era, especially for the control and sensing in dexterous anthropomorphic hands. In [151], researchers conducted a four-week long study where, with electrodes implanted to the stump nerves of an amputee, authors recorded neural signal activity while the subject imagined power or pinch grips and flexion of the little finger. Post-processing machine learning classifiers achieved 85% recognition of grip type. In [152], results demonstrated that for multi-point feedback detection, tests with pressure is better than a vibration. Following these results, a prosthesis could interpret real-time intention from the user [153]. Users could achieve actual grasp control without visual and sound feedback. Object property recognition showed vast improvements in the following experiments. A subject recognized 78.7% between three categories of stiffness while classification between cylindrical, big and small spherical objects achieved 88% of recognition.

Research Platforms

Around the same time, authors in [154] developed a bio-inspired robot hand with a complete set of sensors, including 24 tactile sensors around fingertips and palm, and position encoders and potentiometers. Started in 2008, [155] developed a tactile sensor based on electrode patterns immersed in a three-layer pressure sensitive material. This rubber and urethane gel provides information for object classification of an object under in-hand rotation [156].

Researchers were looking for lower prices and ease of use and maintenance change focus from nontrivial sensor design and manufacturing. The iRobot-Harvard-Yale introduce in [157] provide sensing capabilities based on the finger and palm tactile arrays, flexure joint sensors, magnetic encoders and fingertip accelerometers. The light delivered to phototransistors by an optical fibre provided an estimation of the curvature of the flexure sensor.

Tactile Sensors

From an initial work in [133], the authors proceed to study grasp force control for slip detection using a thin and soft sensor based on pressure conductive rubber [158]. A smooth grasping force causes less object deformation when compared to alternative controllers during slippage is detected using the integral sliding mode.

Bio-inspired approaches aimed to overcome the lack of computational power and limited tactile information for curved surfaces estimation. Tap opening (unscrewing and screwing tasks) used logged data in a biomimetic hand motion approach [159]. Authors used an anthropomorphic solution to rolling contact problems, decreasing hand motion planning complexity and requiring no tactile feedback.

A comprehensive overview of tactile sensing technologies appears in [160]. In the paper, the authors presented force, vibration and thermal sensing modalities of the BioTac© The sensor provides thermal and vibration information used for object property discrimination, such as shape, texture and temperature, in addition to slippage detection. Authors achieved high accuracy showing 99% of hits over ten class identification during 100 experiments. The results also showed that compliance and thermal experiments turned out to be the most reliable results in the rank of the exploratory movements.

The "Roboskin" project applied their artificial skin into iCub, NAO, Kaspar, and Schunk robot hand platforms with a focus on improving reliability and safety during HRI tasks [161]. The only constraint observed during humanoid robot use is the sensor node size and the spacing on this amorphous artificial skin [162]. Texture recognition uses a microphone based vibration analysis of the skin.

An in-depth survey on bio-inspired sensing technologies concerning artificial skins in conducted in [163] The authors pointed out that several human skin properties are present in separate projects. The main paths on artificial skin developments is a multi-modal approach and active matrix addressing with local processing.

Hand Sensing Development

Sensor fusion and simultaneous multi measurements became the focus on the growing emphasis on multimodal sensing in robot hands. Researchers developed a Resistor Network Structure Proximity (RNSP) sensor, based on LED, phototransistors and resistors providing ease of installation [164] The sensor work on measurements of a central position of the current network distribution. It can measure the center of position even if a large object exceeds the sensor's field of view. Experiments with only necessary information from RNSP and tactile sensors demonstrated efficient grasping and pre-grasping estimations.

A new type of stretchable sensors presented in [165] comprises single-wall carbon nanotube films. This new nanomaterial can measure up to 280% more resistive strain when compared to the conventional metal strain gauge. High durability and fast response are also characteristics this sensor showed during twisting and compression tests.

Classic robotics has been using vision systems, such as RGB-Depth cameras, for manipulation applications throughout the time. Several works showed object recognition and pose estimation using camera including in-hand object localization and shape, texture classification [166, 167, 168, 169] Due to sensors construction, these sensors are usually seen outside on the robotic hand. However, compact sensor developments show that camera-based sensors can be attached to the end-effector itself [170, 171].

2.4 Human Haptic Perception

Touch researchers have been concentrating efforts on discussing whether the somatosensory system operates under the presence of two subsystems, a "Where" system that deals with intelligent perception to action, and a "What" system that deals with the identification and information retention.

Studies performed in [172], based on fMRI and behavioural studies, followed by [173], support the understanding of the coexistence of a what/where discrimination in the somatosensory system. Authors in [172] suggest a relationship division between dorsal and ventral visual streams, activating inferior and superior parietal areas under haptic object recognition and localization. Chad and Newell used a dual-task paradigm suggesting that a what/where distinction shows behavioural evidence for a task-dependent modality. Mutual interference was found beyond cross-function tasks in both intramodal and crossmodal conditions, suggesting resource allocation depending on the task but not the modality (vision, haptics). In [174], authors evaluated evidence on split streams under intelligent perception to action used by the somatosensory system, with a focus in separate haptic processing of external object and body locations.

This topic of research consistently faces the issue of whether haptic processing of shape blocks visual "What" system invoking visual imagery, a topic not covered in-depth on this thesis. The present thesis describes its haptic advancements in terms of functional perception distinction, namely "What" and "Where" systems.

2.4.1 The "Where" System

Similarly to the vision system, the "Where" subsystem is responsible for providing a distribution of points, surfaces and objects in the environment. A significant difference exists since, in tactile sensing, localization could refer to the sensor itself or a point in the environment. Therefore, this thesis discusses Two types of tactile localization, localization of a point in the body surface under the stimulus, and where this stimulus occurs in the external world [25].

Frames of Reference for Haptic Spatial Localization

To have useful information about the spatial localization of tactile sensing, first, a frame of reference has to be defined. A frame of reference specifies a structure or a set of parameters for localizing points [175]. Cartesian or polar coordinate systems are commonly used for point localization with its origin being a body part of the individual, or defined based on external landmarks. A given task can use a single or multiple frames of reference from the various frames available.

Spatial processing, it being localizing points in the external space or a place in the body, is based on the contact between the sensing organ and the external object; however, the frames used are entirely different. Localization on the body results from a local frame of reference, such as the axes of the fingertip. When perceiving points or objects external to the user refers to an "egocentric" frame of reference, those parameters are specified related to a point in the actor, which is called ego center. Differently, when points are represented using external landmarks and references, it is called "allocentric" frame of reference.

2.4.2 The "What" System

The human somatosensory system uses the "where" subsystem to examine surfaces, objects and their characteristics. Experiments using touch alone demonstrate the efficiency of this subsystem pathway, with results of high accuracy during familiar objects recognition [176]. This ability comes from peripheral receptors sending sensory primitives. Neural processing further provides a broader spectrum of properties, with recent research observing the computational characteristics of this processing.

In this thesis, we analyze the haptically available object properties into two main classes based on material and geometry. Geometry characteristics describe the structure and shape of the object, while the material is independent of a particular target.

2.4.3 Haptic Glance

Restraining type and amount of spatial tactile and kinesthetic information can reduce haptic object processing. Manual exploration with a limited amount of time has essential contributions, on human exploration, material properties appear earlier than geometric features. Based on [177], which provides a visual search paradigm, [178] developed a tactile version of the same experiment. In this experiment, material features, such as roughness, softness and temperature, in addition to the presence of edges, are available for neural processing considerably earlier than geometric characteristics, such as orientation, curvature, and relative position. Active touch experiments in [179] also showed similar effects for texture. A model proposed in [180] estimate haptic serial search for geometric features and the parallel detection of line targets.

The concept of "haptic glance" suggested in [181] argues that sometimes, haptic identification needes not more than 200 msec for identification of familiar objects feature either geometric or material. Concluding, the duration can influence the haptic processing of features on a global level of object structure processing. Individuals during experiments demonstrated the first focus on local shape features during a haptic evaluation, with additional manual exploration, observers switch focus to global shape recognition. This focus switch does not occur for objects holding different global shapes with similar local characteristics [182] (see also [183]).

Chapter 3

Tactile Object Recognition in Early Phases of Robotic Grasping

3.1 Preamble

This chapter contains the unpublished results of tactile object recognition in early phases of autonomous grasping. This chapter expands previous [39, 21] work presenting an approach to the human "What" subsystem using bio-inspired tactile sensing to perform single grasp object identification. Humans developed a so-called "haptic glance" where non-exploratory manipulation perform fast object identification. Based on that, this chapter applies machine learning algorithms to non-exploratory object recognition tasks, which reproduce a scenario of early robotic manipulation where fast recognition of objects is required. These experiments reproduces a scenario in early robotic manipulation phases where fast recognition of objects is required. Experimental results using different classification techniques achieved 96.67% of correct classification.

3.2 Introduction

While robots are currently capable of performing many high-level, complex tasks; however, several challenges still prevent them from achieving human-level capabilities. Robot hand technology is still clumsy when compared to human hands and fingers. The commercially available touch sensing techniques lack resolution and usually encounter barriers due to the complexity of interpreting sensor information [37]. However, even with these limitations, the prevalence of robot applications is shifting from controlled environments to unstructured settings such as homes, airports and hospitals [2]. In unstructured environments, robots can navigate, understand, and communicate but lack useful hand skills to perform dexterous manipulation. Recognizing objects in early phases of manipulation are essential for the development of dexterous robots able to operate in unstructured environments.

Underactuated hands provide a viable and versatile solution to the problem of unknown object grasping in unstructured environments. They can achieve considerable versatility because they can easily adapt to different object shapes. During basic manipulation tasks, when some level of uncertainty is acceptable, smart hand design choices overcome joint estimation imprecision. While the fully-actuated robotic hands need precise joint position calculations even for simple tasks, these hands do not suffer from the same level of kinematic uncertainties as the underactuated hands when performing similar tasks [26]. The underactuated hand designs have a higher level of joint uncertainty, but allow for faster object grasping even with a lack of knowledge about the targeted object [27]. Underactuated hand adoption also brings several advantages if provided with intelligent actuation and control Reduced actuation requirements generally result in a decrease of the design costs and an improved grasp planning efficiency, especially for unknown objects. In addition, using the human somatosensory system as a source of inspiration on how to process robotic tactile data can reduce the manipulation efficiency gap between the fully- and the underactuated robotic hands.

The “What” and “Where” human somatosensory subsystems are pathways used by humans while manipulating objects. The “What” sensory pathway is responsible for aspects of perception and memory, while the “Where” subsystem combines control and action [25]. In [39], the “Where” subsystem inspired the development of a robotic system capable of learning the relationship between tactile data and visual frames of reference to estimate object poses. Research on the “What” subsystem demonstrated that familiar objects are recognized faster, independently of vision involvement. The human "What" subsystem is also responsible for single grasping non-exploratory object recognition, using the initial grasp contacts to identify objects. This capability is essential for human-level manipulation and dexterity since it enables finger kinematic planning and fast hand re-positioning in early manipulation phases.

Single grasping object classification, also defined as "haptic glance" [24], consists of extracting object information in early phases of manipulation. Humans execute decision making routines during this manipulation phase by changing finger or hand position to best fit a known target object (e.g. reaching keys inside a bag or finding a binding between several books.) Object identification during initial grasping phases may also enhance the overall performance of the robotic manipulation tasks. Robots using single-grasp object identification can update the end-effector parameters based on previous knowledge of those objects early on the grasping attempt, improving their performance. Robotic "haptic glance" requires integration of touch sensing and underactuated stable grasping in order to extract tactile features feeding machine learning algorithms for object identification. Our work investigates the application of multi-modal tactile sensing for object recognition during single grasping tasks to improve early manipulation phases.

Tactile sensing for control feedback or object characteristics extraction expands robotic possibilities during in-hand manipulation. As vision-based control [23] often is insufficient when faced with cluttered environments or object occlusion, there is a pressing need to design a new generation of robot tactile sensors for robotic object handling in unstructured environments From a simple estimation of the normal force applied to surfaces to the detection of skin deformation, several developments on bio-inspired tactile sensing appeared in recent years. In [184], authors present a tactile sensor module capable of estimating pressure and deformation of a compliant structure under contact.

This chapter proposes a data-driven approach for object classification inspired by the human tactile somatosensory "What" subsystem. The "haptic glance" concept inspired the single grasp approach to the object problem of object recognition during initial manipulation phases. Our setup aims to reproduce the early phases of robotic grasping in order to evaluate the concept of robotic “haptic glance”. Measurement data produced by four bio-inspired tactile sensor modules mounted on the underactuated fingers provided input for five machine learning methods during classification tasks In-hand object classification experiments were performed under a fuzzy controlled stable grasp system, promoting constant force for different objects. The single grasp experiments were conducted using square- and circle-shaped 3D printed objects as shown in [26] to produce training and test data. The main contributions of this chapter include: (a) single grasp object identification during initial manipulation phases using autonomous, stable grasping; and (b) evaluation of different classification algorithms for multi-modal tactile sensing object identification.

Section 3.3 presents some related works on robot gasping, object classification, tactile sensing and fuzzy control. Section 3.4 presents our experimental setup description and system overview. Section 3.5 shows experimental results for single grasp tasks. Finally, the conclusions are presented in Section 3.6.

3.3 Related Work

In this section, we analyze previous work on the underactuated recognition of objects using multi-modal tactile sensors and the role of the human somatosensory system during initial phases of manipulation. In recent years, several papers reported work on different aspects of robotic grasping and manipulation. These include contributions to the design of new end effectors, stable grasping control, dexterous manipulation, and tactile sensing, but only a small number of these papers have used the human somatosensory system as an inspiration.

3.3.1 Single Grasping Object Classification

The “haptic glance” is part of human dexterity [24], and provides fast object identification during manipulation tasks. Humans use previous knowledge to discriminate between several different objects during the early phases of manipulation, even during short interaction. When reaching an object inside cluttered environments or without a visual aid, humans use the “What” system pathway to perform object identification (e.g. reaching for coins inside a pocket full of other objects) [25]. After identification, humans make initial kinematic decisions, such as finger and hand joint position after a brief, non-exploratory object association. Non-exploratory object identification, especially in cluttered or occluded environments, has the potential to improve robots’ ability to manipulate unknown objects providing fast decision making during early phases of manipulation. In this scenario, underactuated hands capable of object identification can be used to grasp unknown objects while helping on kinematic decisions based on previous knowledge and associations.

Authors in [26] investigated single grasping object classification by collecting tactile data on early phases of an open-loop grasping task. This work used a stall motor position to detect a stable grasp and collect force data for the identification of a set of objects using a Random Forest classifier. Open-loop control offers reliable, stable grasping for underactuated hands; however, experiments using active tactile feedback resulted in an improved perception performance while providing constant grasp force. In [185], authors successfully applied active tactile sensing to relocate bio-inspired tactile sensors, while [186] showed results using tactile feedback for an underactuated prosthesis. Considering this, we investigate the classification of objects during an autonomous grasp operation. Fuzzy logic has proven to be a useful tool for in-hand manipulation in the literature, working as a controller for grasp stability [17, 18, 19, 14].

Although suitable results were achieved using a barometer array sensor for single grasping, we investigated the use of compliant multi-modal tactile sensor modules during similar experiments Previous work on data-driven texture characterization used multi-modal tactile sensors mounted on fully actuated fingers for exploratory classification tasks [184]. Achieving accuracy from 85.1% to 98.9%, authors demonstrated the value of traditional MEMS as tactile sensors embedded into flexible substrates. Data-driven applied for contact localization [187] and post-grasp manipulation [188] confirm that the high complexity of in-hand manipulation aspects can be overcome using a data-driven approach.

Several classification algorithms have emerged in the literature as good candidates for object recognition. Among them, in addition to the Random Forest classifier, we have also considered an exploratory strategy using Extra-Trees, Support Vector Machines, and Ridge machine learning techniques.

3.3.2 Stable Grasping

Autonomous grasping control is essential for robotic hand versatility and robot autonomy. In [189], the author describes the problem with open-loop control solutions during the Amazon Picking Challenge, showing the disadvantages of the methods which do not use tactile feedback. Daily tasks such as removing a book from a bookshelf can use tactile sensing during a closed-loop control to maximize the contact surface [190]. Even though a stable grasping situation could be achieved with stall motor detection [26], there is a lack of contributions on object recognition during autonomous grasping operations. Using a fuzzy logic approach to tackle the grasping stability problem is one way to reduce the gap between traditional and intelligent control [15]. Building on this idea, we increases functionality of our experimental gripper by using a fuzzy-based grasping controller during the object identification tasks. Experiments used tactile data collected before and after a stable grasp. This approach enabled investigations of the classification with an increased functionality provided by a closed-loop grasping control.

Equilibrium is a requirement for achieving a stable grasp. When no resultant force acts on a fully restrained object, a multi-fingered grasp equilibrium occurs [16]. However, unknown friction forces pose a problem to obtain such an equilibrium. Building upon the tactile sensing and fuzzy control system able to deal with the unknown friction and the mass of the grasped object reported in [19] we developed a fuzzy controller able to perform grasping tasks with a minimum fingertip force.

Even though a single motor is commonly used in grippers, a multi-motor grasping is essential to increase the efficiency of multi-fingered robotic hands. To investigate the relations between micro-vibrations and grasp stability, [17] developed dual-motor fuzzy control using BioTac© sensor feedback. Pressure and micro-vibration sensor data provided information for a first fuzzy controller that estimated grasping status and stability values. This information served as input for a second fuzzy controller that was responsible for defining pull, pushing, or hold directives to fingers.

This chapter uses two different sources of feedback for the fuzzy grasping controller. The barometer and gyroscope data provided feedback for a different fuzzy controller. The later controller used micro-vibrations, detected from the sensor's gyroscope and force from the tip of the phalange sensor, to control each finger separately.

3.4 Experimental Setup

In the present chapter, a compliant gripper uses stable autonomous grasping to collect tactile data for object classification. Our approach is to use the versatility of a modular underactuated hand in an autonomous grasping control to achieve in-hand manipulation with stable grasping. The work described in this chapter presents research on a dual actuated underactuated hand with multi-modal tactile sensing modules to evaluate single grasping object classification.

This section setup details of single grasp experiments with details on hand characteristics, system overview, sensor specs and placement, double actuated fuzzy controllers, object characteristics and position.

3.4.1 Underactuated Robotic Gripper

Underactuated hands are an excellent solution for grasping in unstructured environments due to their ability to adapt to unknown objects [191]. The work presented in [157] describes the design of a tendon-driven underactuated hand. Their design criteria were to have a reasonably dexterous robotic hand with flexible joints that were durable and inexpensive. They demonstrated that power and precise grasping are possible with two pivoting fingers and a single actuated finger on the opposite side. Having different actuators working on finger orientation and pulling allows for reasonable dexterity to be achieved. Although those characteristics fit our project requirements, this solution has little space for customization. One missing aspect in [157] is the support of only barometer-based tactile sensing modules, restricting our investigation, which includes multi-modal tactile sensing.

With similar goals, the authors in [192] presented the design of a single actuated robotic gripper that supported up to six modular fingers pulled by a differential disk. This design was the base for our initial experiments; however, we used modified phalanges to incorporate tactile sensor modules on a single actuated gripper. Later, we developed a modified base plate for two motors, enabling additional in-hand dexterity. Our design falls in between the examples mentioned above concerning the level of actuation. It is a customized version of a simple gripper, as seen in [192], using more actuators as the prototype in [191].

In our experiments we used a 3D printed robotic gripper with modular underactuated fingers that provide an easily customizable platform [192]. Modifications provided space to mount tactile sensors that were not previously supported. We also used a customized version of the base plate for two motors, while using a similar palm and same fingers.

The underactuated robotic fingers had intermediate and distal flexible joints made of Vitaflex© 30. It had strings fixed to the tip phalanges and motors configured for velocity control. Each finger was connected directly to a different Dynamixel© motor.

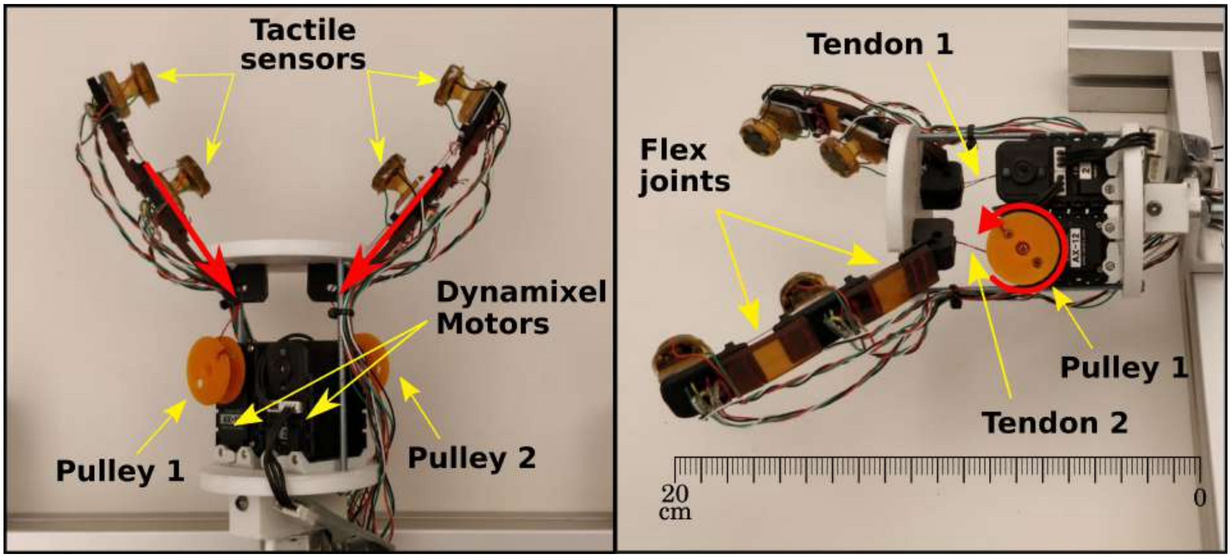

Figure 3.1: Top (left) and side view (right) of dual actuator hand experiment setup.

Our experiments were performed with the robotic hand fixed to a frame on a workbench. Figure 3.1 shows the top and side views of the dual-motor actuated gripper. The left-side image shows pulleys 1 and 2, actuator placement, tactile sensor position and the direction of motor actuation. The right-side image shows the flexible joints, a detail of the tendons and the pulleys direction (red arrows)

Our prototype uses bio-inspired multi-modal tactile sensor modules [22] mounted on the grippers finger phalanges. This set-up provided tactile information about the grasped objects. The dual-motor gripper maintained a stable grip with information from the aforementioned tactile modules. Training and testing of classification algorithms used post-processed tactile data.

3.4.2 Tactile Sensor

While robot manipulation tasks could use several types of non-contact sensors, tactile sensing is indispensable for an efficient manipulation [193]. In the literature, several types of tactile sensing technologies appears in the past decades Some examples are piezoresistive sensors, capacitive, piezoelectric sensors, optical sensors, barometric based pressure sensors, multi-modal sensors, and structure-borne sound sensors [194]. Among them, multi-modal sensors provide advantages to sensor fusion. It is capable of closely matching the human hands different types of tactile sensing modalities.

Alves de Oliveira et al. [22] developed in our lab at the University of Ottawa a bio-inspired multi-modal sensor module that emulates the functionality and placement of the mechanoreceptors in the human skin. Figure 3.2 presents the developed sensing module where a compliant cone-like structure (2) supports a Magnetic, Angular Rate, and Gravity (MARG) transducer (1) and guides the forces applied on the modules surface to the pressure sensor localized on the bottom of the structure. In addition to force, the inertial measurement provides information about the deformation of the artificial skin when pressure is applied.

Two of these tactile sensor modules are placed on each finger of the gripper providing multimodal tactile data during the experiments. The modules internal conical structure and flexible material add compliance to the gripper functionality without losing grasping capability. As shown in Figure 3.3 the built-in compliance of these tactile sensor modules

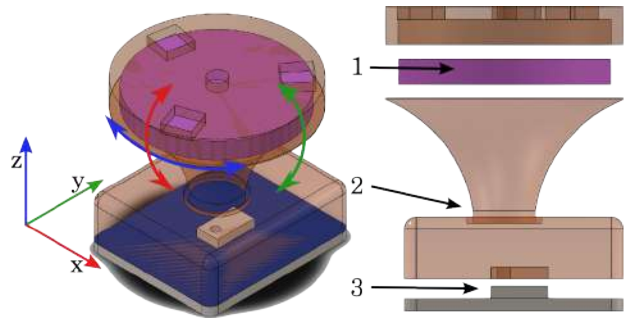

Figure 3.2: Components of the multi-modal tactile sensing module: 1 - MARG (Magnetic, Angular Rate, and Gravity) sensor; 2 - compliant structure; 3 - barometer [22].

allows the robotic fingers to passively adapt to the differing shapes of objects instead of placing the contact part of the finger in a planned position [22].

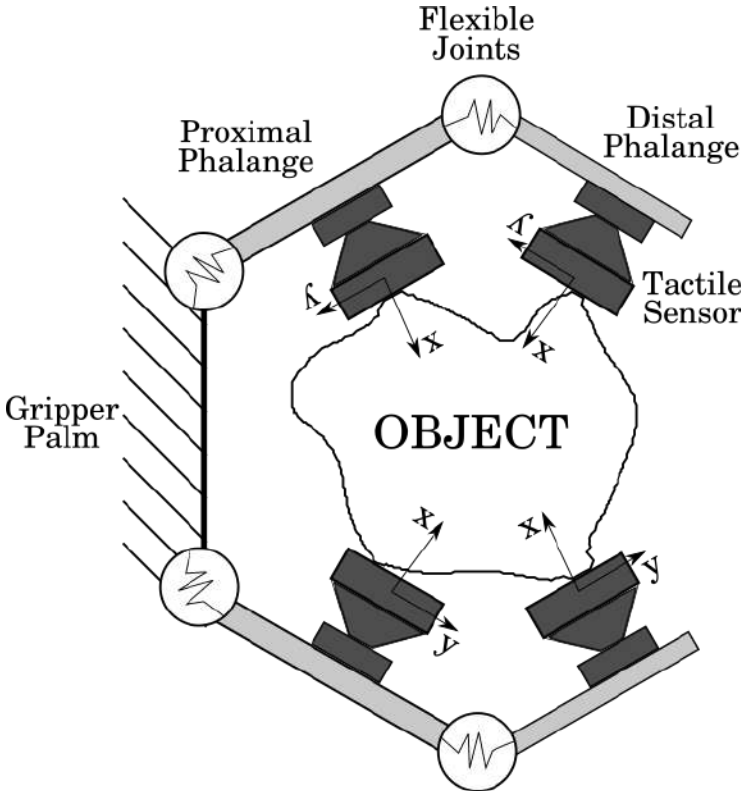

Figure 3.3: Top view of the gripper illustrating the placement of the sensors and their frames of reference.

During experiments, the object is placed in the middle of the gripper. Figure 3.4 shows a side view of object placement before the grasping attempt. The other two columns of

Figure 3.4 show different instance of a single finger actuation: (a) rest position, no motor rotation; (b) initial movement with motor pulling; (c) continuous motion brings the finger to closer to the palm, and (d) around the maximum safe finger curvature.

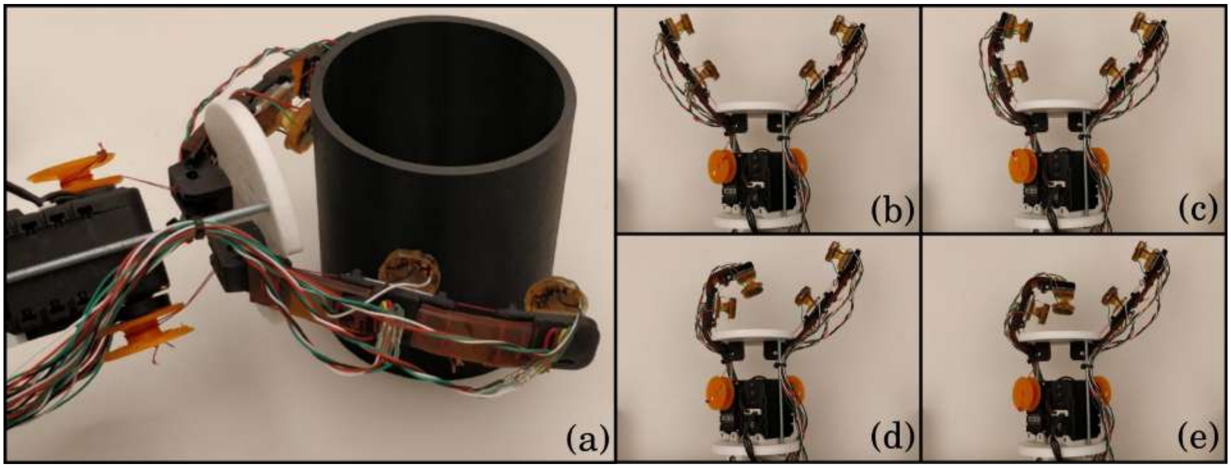

Figure 3.4: Top view of the gripper (a), and the left-fingers movement range (b-e) and object placement.

3.4.3 System Overview

The software developed for this prototype is a distributed system using the ROS framework [195]. Figure 3.5 presents all primary ROS nodes developed for this experimental setup. A ROS node centralizes control and data collection functions. Both experiments used the same system presented in Figure 3.5. The flowchart shows tactile sensors using i^{2}c connection and multiplexers to transmit data. MUX 0 connected a total of four Magnetic, Angular Rate and Gravitational (MARG) sensors to microcontroller MCU 0, while MUX 1 was used to transmit data to microcontroller MCU 1. Microcontrollers operated running ROS nodes in USB serial mode, transmitting data to the main computer. The central ROS node subsequently demultiplexed the signal at the main computer.

The flowchart in Figure 3.5 additionally presents ROS bag data collection for further processing by machine learning algorithms. The central box of the flowchart also shows the motor control workflow from tactile data to motor control.

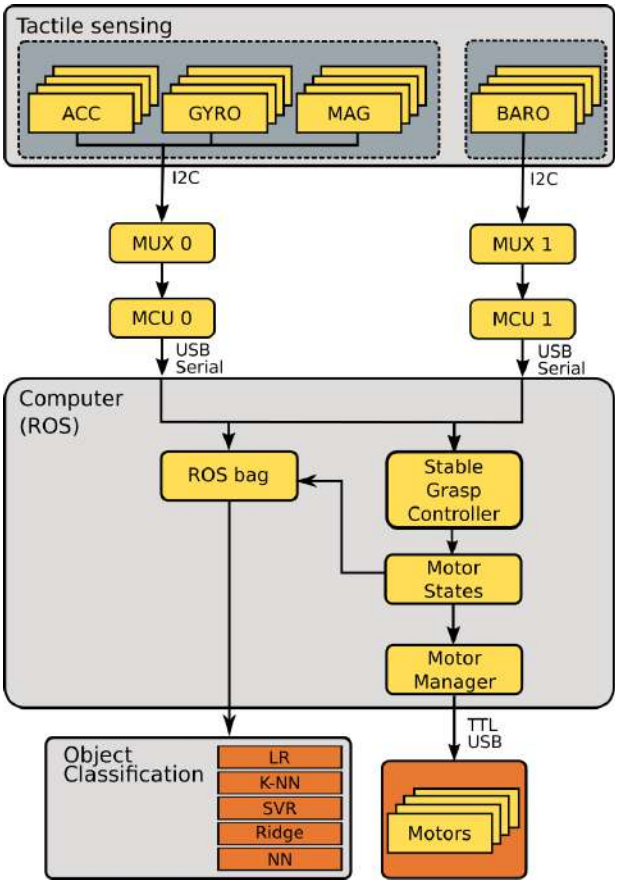

Figure 3.5: System block diagram.

3.4.4 Fuzzy Controller for Stable Grasp

Before any data collection takes place, a fuzzy controller maintains a stable grasp. Tactile data provide the feedback for the control of the actuators responsible for pulling the underactuated fingers. The fuzzy controller is active during all data collection processes.

Experiments in this chapter used a double fuzzy controller. The details of this setup are presented in [21]. With each finger actuated independently, more possibilities emerge for more complex in-hand manipulation operations. After satisfactory results using a fuzzy controller on a previous work [39], we developed a double actuated version of a fuzzy grasping controller. This fuzzy controller is explained in details in Chapter 4 Section 4.4. Authors in [17] presented a double actuated fuzzy tactile controller based on pressure and micro-vibration outputs from BioTac© sensors. In our work, pressure sensors provided force inputs and gyroscope produce micro-vibration information as feedback for a fuzzy controller scheme shown in Figure 3.6.

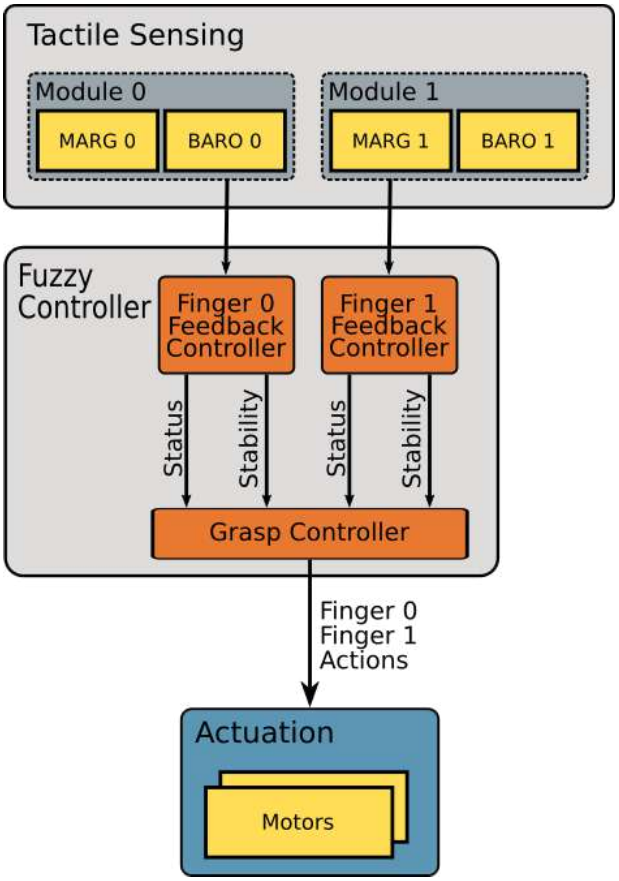

Figure 3.6: Double motor fuzzy controller flowchart.

Figure 3.6 shows the dual-fuzzy controller receiving barometer and gyroscope sensor data which inform about the degree of finger contact with the object and the stability of the grasp. The flowchart shows outputs from the fuzzy controller outputs for each finger, which provides finger status and stability values for a second grasp fuzzy controller that established action for each motor: “go forward,” “go backwards,” or “hold.” This controller is based on [17] and use rules and fuzzy sets presented in Section 4.4. One adaptation is a change required to use gyroscopes for micro-vibrations and adopting a new set of micro-vibration sensor data. Figure 3.7 show the modification, where data from the gyroscope is equal to zero if there are no micro-vibrations. For that reason, instead of a trapezoidal set, this chapter uses a ramp-like set.

In a search for an autonomous robotic hand, the fuzzy controller proved to be an

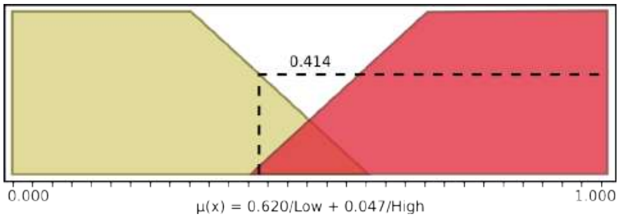

Figure 3.7: Fuzzy set for micro-vibrations [39].

efficient grasp controller [196, 18] that increases automation.

3.4.5 Objects

The experiments in this chapter uses a set of objects based on [26]. Figure 3.8 shows the employed objects which have different sizes and shapes. Circular shaped objects are 50 mm, 70 mm and 90 mm in diameter while square shape objects have the same dimensions for its sides.

Figure 3.8: Objects with size and shape variation for the classification test.

This set of objects was 3D printed in PLA plastic, with a wall thickness of 4 mm. During experiments, each object was placed on the table inside the reachable gripper workspace. The fuzzy control was active during the grasp attempt until no further changes to the motor display a stable grasp. The experiment with a single grasp attempt was executed 25 times for each object.

3.5 Experimental Results

This section presents experimental results of the machine learning object identification during single grasping.

3.5.1 Data Collection

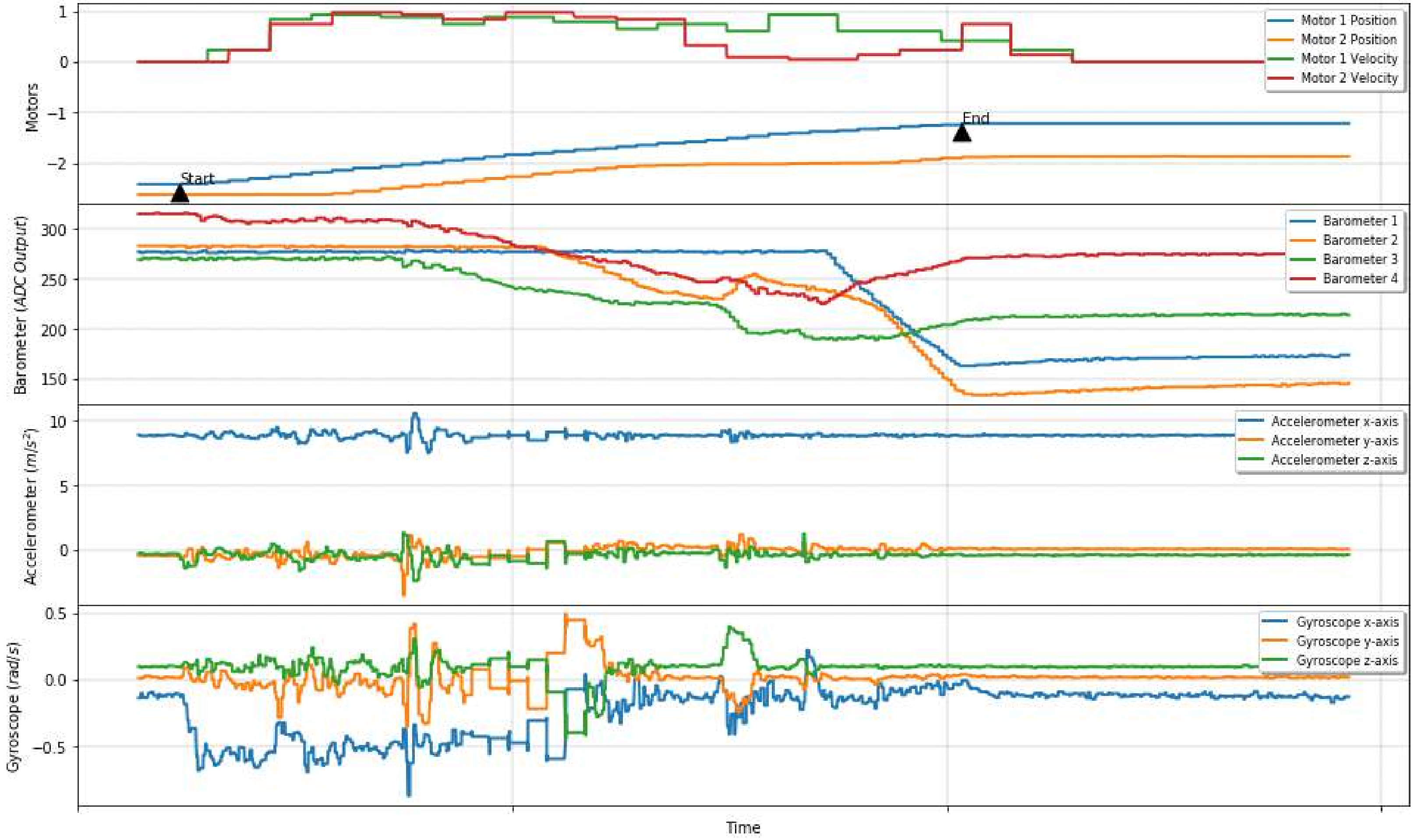

Figure 3.9: Actuator velocities during stable grasping. Barometer, accelerometer and gyroscope data are varying until the stable grasp is achieved and sensor data are stabilized.

Two instances of time during the grasping task were selected to provide actuator and tactile information defining a dataset used for discrimination between the objects [26]. Different from stall motor detection, the lowest value in the data set for the motor position is considered to be the start position. No further motion detected in the actuator position, indicates grasping equilibrium, and then a second instance define the end position.

After an object is placed inside the grippers workspace, a closed-loop grasping controller maintains a stable grasp by pulling the fingers around the object. During the dual actuation tests, multimodal information from tactile modules was used as input for a different fuzzy controller.

Real-time sensor data provided feedback for grasping control, while ROS bags recorded the information from the actuators and the tactile modules for further object classification. Motor- and tactile sensor-data at two different time instances of the autonomous fuzzy controlled grasping process are used as inputs for the classification task.

Figure 3.9 shows actual data during autonomous grasping operations. All motor- and sensor-data display relatively constant values after grasping is achieved, indicating grasping stability. For the classification task, experiments took 25 measurements for each object. After experiments, post-processing used two values of actuator positions, which are labelled as “start” and “end” in Figure 3.9 Tactile data includes 36 values of inertial data (from the 4 modules, each with 3-axis gyroscopes, 3-axis accelerometers, 3-axis magnetometer) in addition to four pressure values at start and end instances All this information results in a feature space of 81 features for each sample

3.5.2 Machine Learning for Object Identification

The performance of five machine learning classifiers was compared for the object identification task In addition to the Random Forest Classifier [197], Ridge Classifier [198], Support Vector Machine (SVM) [199] and Extra-Trees Classifier [200] were also evaluated.

Random Forest Classifiers were grown with ten trees and with one hundred trees; the Ridge Classifier was trained using $\alpha = 40$; the SVM used different kernels and parameters;

the Extra-Trees Classifier used fifty trees. Table 3.1 presents the performance of all these classifiers.

Table 3.1: Machine learning object classification results.

Classifier	**Double Actuator**
Extra-Trees	96.67%
Random Forest (10 trees)	83.33%
Random Forest (100 trees)	93.33%
Ridge Classifier	91.67%
SVM	90.00%

The gripper results in the second column of Table 3.1 shows that all machine learning algorithms achieved excellent results with only Random Forest (10 trees) with less than 90% of hits.

Extra-Trees Classifier for Autonomous Grasping Object Recognition

Even though all classifiers provided highly accurate results, the Extra-Trees Classifier outperformed all other methods for double actuated autonomous grasping object classification. Figure 3.10 shows results obtained when using the Extra-Trees Classifier for the following list of object classes: 0 - 50 mm cylinder; 1 - 70 mm cylinder; 2 - 90 mm cylinder; 3 - 50 mm square; 4 - 70 mm square; 5 - 90 mm square.

Confusion arose around similar sizes, such as class 1 and 4, respectively round and squared objects with 70 mm in length. The multimodal sensors provide useful information concerning skin deformation. For similar sized objects with distinct shapes, the compliant multimodal tactile sensor produces information that allows to discriminate between them.

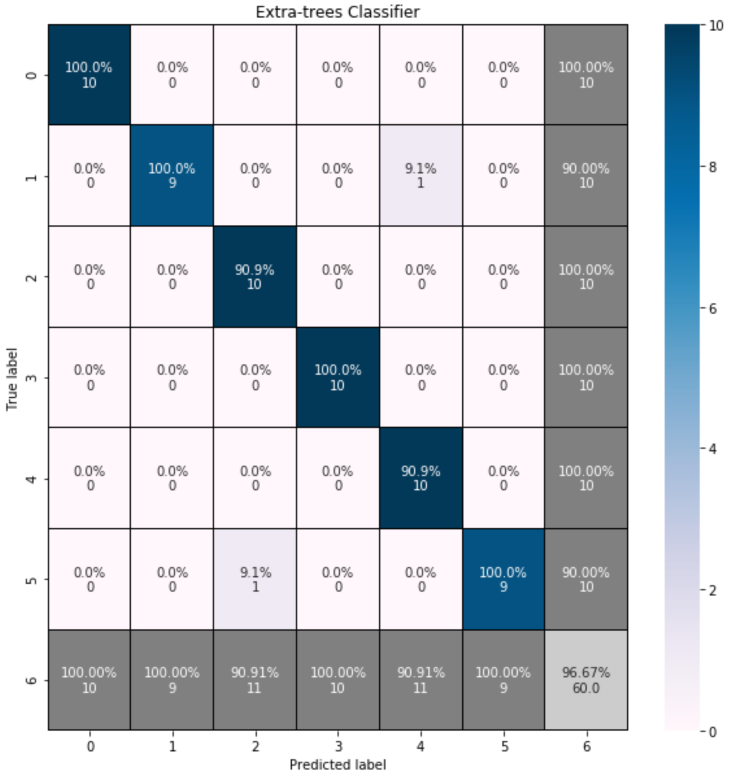

Figure 3.10: Confusion matrix when using the Extra Tress classifier for different objects.

3.5.3 Single Grasp Object Classification

Pursuing on a data-driven approach, similar to previous studies [26], no information regarding gripper kinematics or actual joint angle was available, so we applied a model-free machine learning methodology. Classification used a data-driven approach with non-calibrated raw sensor data, although linear barometer calibration was performed to normalize feedback to the fuzzy control system.

In order to compare our multi-modal sensor approach to previous published work, a Random Forest classifier was applied to the data Our results for autonomous single grasping experiments achieved 93.33% for the same *'Model 1 Size & Shape'* set of objects as [26]. In comparison, the work mentioned above achieved 93.57% using barometer data during open-loop single grasping operations. Even though [26] achieved a slightly higher classification rate, our results show that a closed-loop autonomous grasping does not affect the single grasping classification of objects. The results show a little to none loss of classification accuracy fuzzy controller to provide regulated grip forces In Figure 3.11, the confusion matrix shows for comparison Random Forest classifier performance.

Similar to the situation mentioned above, confusion arises with objects 5 and 2 regarding their similar size. Objects 0 and 3 also have similar size confusion, while 4 and 5 experience similar shape confusion. However, the resulting accuracy supports the use of autonomous grasping in combination with multi-modal tactile sensing for single grasping object classification.

Figure 3.11: Confusion matrix with classification using Random Forest algorithm.

3.6 Discussion

This chapter discussed object identification using tactile sensing data collected during robotic grasping operations. We borrowed the human perception concept of haptic glance, and the presence of a What pathway system to improve robotic in-hand manipulation. During the early phases of manipulation, robots can use object recognition while grasping unknown objects, which is a behaviour similar to that shown by humans. We presented and evaluated a new approach for non-exploratory object classification during autonomous grasping using fuzzy logic control. The fuzzy controller provided stable grasping using pressure and micro-vibrations sensor data in the double actuation case.

Experiments were conducted to evaluate the performance of using multimodal tactile sensor data collected during single grasping for object classification. Dual-actuation experiments exhibited high accuracy in object classification. Results demonstrated that robots could improve in-hand manipulation early phases using a single grasping approach inspired on What system and the haptic glance seen on humans tactile pathways in addition to autonomous grasping control. This double actuated gripper using pressure and micro-vibration sensor data, compatible results with previous work were observed, achieving 96.67% accuracy.

Chapter 4

Object Angle Estimation Using Machine Learning

4.1 Preamble

This chapter is based on our paper "Estimating the Orientation of Objects from Tactile Sensing Data Using Machine Learning Methods and Visual Frames of Reference" [39], which expands previous work [21] presenting a visuotactile angle estimation based on the human somatosensory "Where" subsystem. It includes a detailed description of a double fuzzy control approach, accompanied by an evaluation of machine learning algorithms on the estimation of object angles using bio-inspired tactile sensors. The evaluation aims to analyze the system approach during an autonomous grasping situation where the object is under external object disturbances to acquire finger workspace information. In this setup the estimation achieves high performance when tested against data not seen during training. In a second experiment, object exploration was performed using an open loop approach with the gripper performing rotations on the object. Both tasks show that data collected can be used to estimate object angle variations after an initial object visualization to create an initial frame of reference.

4.2 Introduction

Widespread in controlled environments such as industries, robots are moving towards unstructured settings like homes, schools, and hospitals where they are facing new high-level, complex, and fast reasoning challenges which require robot skills with human-level capabilities [2]. Although the intelligent robots can nowadays perform several tasks such as walking, picking-up and placing objects, understanding and communicating with people, they are still lacking hand dexterity. Improvements on tactile sensing for in-hand manipulation and an increased understanding of the human perception-to-action synergy inspire and could advance robot applications in the scenarios mentioned above [37].

Manipulation skills of humans hand and brain have a level of ability rarely seen in other animals. Grasping and manipulating objects is a distinctive part of the human-being skill set. It is an ability evolved from the erect posture that freed our upper limbs, turning our hands into two sophisticated sets of tools [5]. Not surprisingly, humans' hand dexterity and reasoning are the holy grail of bio-inspired robotics control and actuation. Hand dexterity is the ability to interact in a useful way with objects in the real world. During robotic manipulation, a robot changes an objects state from an initial configuration to a final one. For instance, during pick and place tasks, the goal is to change the position and orientation of an object inside the manipulators workspace. Comparatively, in-hand manipulation is the ability to change the pose of objects, from initial orientation to a given one, within one hand. Implementing robots that change objects' orientation while maintaining a stable grasp has the potential to amplify even more robot area of activity [4]. Robotic manipulator literature comprises a long list of examples of robotic hands with many levels of dexterity. From there, underactuated hands arise as an option that can achieve a reasonable level of dexterity with simplicity.

Research on haptic perception over the past decades has developed an in-depth knowledge of the psychological aspects of human touch employed to manipulate objects and perceive their characteristics. Lederman et al. [25] presented the somatosensory system divided into two subsystems: The "What" system that carries out perception and memory; and the "Where" system that deals with perception to action. In humans, the "What" system performs the recognition of surfaces and objects through their tactile properties [201]. Robots having similar recognition systems demonstrate their efficiency when similar objects are identified promptly even without visual feedback [202]. From this perspective, reference [203] is one example of recent research, where authors employed camera-based sensing and deformable material as input to an object recognition system integrating grasping and object recognition. On the other hand, the "Where" system, which has a counterpart in vision, produces a description of points, surfaces, and reference frames in the world. Different from vision, touch refers to a location in the sensory organ, the skin itself, and localization in the environment. The human sensory system combining tactile perception and vision had attracted research interest due to increased reliability when both sensing modalities are combined [204]. Recent literature presents several approaches to this issue with a significant contribution on the tactile feedback topic, which were inspired by the concept of the tactile perception in humans, and improvements have been on the development of tactile perception systems for robots [205]. Although our work is also inspired by the human somatosensory system, we took a different approach. Instead of using the human tactile data flow as a base for our research, we developed a pose estimation technique based on the human visuotactile interaction, the Where system This technique combines vision and touch sensor data about different objects and uses that for inter-object interaction or allocation of attention [25].

During visuotactile interaction, multiple frames of reference are simultaneously available on human haptic spatial localization [25]. In the "Where" system, two types of touch spatial localization are considered, one being a position on the body where the stimulus is applied, or otherwise, in the external world from where the stimulus comes. During a task, humans can use a single frame or combine multiple frames of reference, the origins of which may be visible landmarks or a body part from the individual. Even though the aforementioned haptic frame describes the contact between the skin and an external object, one could use landmark axes to specify a frame of reference external to the body (an "allocentric" frame of reference). Similarly, a local frame of reference, such as a fingertip axis, is used for localization on the body (an "egocentric" frame of reference).

Investigations on tactile sensing have the potential to improve robotic in-hand manipulation, including, but not limited to, object characteristics extraction and feedback control. Tactile sensing provides essential information about object manipulation, solving problems due to object occlusion and object's pose estimation under stable grasping. Form, shape, and functionality of the human skin also inspired research on the tactile sensing field. A bio-inspired approach to tactile sensing has significant results in the literature, including successful works on texture classification and control feedback. The present work uses a visuotactile approach to pose estimation using data collected from bio-inspired multimodal tactile modules in conjunction with camera feedback.

Successful robotic manipulation starts with a stable object grasp; therefore, robots are expected to have robust grasping skills. Considering grasp as a control problem, in contrast to decomposing a grasping procedure into planning and execution, they do not require any specific hand–object relative pose and are more robust under pose uncertainty [206]. A model-free solution in addition to computationally inexpensive control laws uses simpler hand designs, still ensuring a stable grasping solution. Fuzzy logic control for grasp stability is presented as a useful tool for in-hand manipulation [17, 18, 19, 14]. Multifingered hands achieve stable gasping when no resultant forces act on a fully restrained object [16]. This work was developed using a fuzzy controller that was able to perform stable grasp tasks with controlled fingertip force single and dual actuated versions.

The main contributions of this chapter are: (1) Tactile information to estimate the pose of unknown objects under autonomous, stable grasp; (2) Integration of bio-inspired multimodal tactile sensing modules and visual information to describe in-hand object pose; (3) Analysis of five different machine learning algorithms for tactile pose estimation. The system uses visual information similarly to how humans allocate visual attention to determine frames of reference for the objects of interest. Tactile information is used to learn vision-defined reference frames so that the vision system can be freed to perform other tasks [25]. Concretely, we used vision to extract an allocentric frame of reference where the object pose is located in the environment. Further, five machine learning methods using tactile sensor data inferred the relation between egocentric and allocentric reference frames during haptic spatial localization. Post-grasp object rotations were performed to collect tactile information, exposing the learning system to object angles outside of the finger's actuation workspace. For this purpose, the object was submitted to external forces on two different axes, including an open-loop finger actuation experiment. A closed-loop stable grasp fuzzy controller also used the same sensory feedback signals. From all six machine learning algorithms, results using ridge regression achieved an average mean squared error for all sizes of 1.82°for all sizes.

In this chapter, Section 4.3 presents some literature review of human haptic perception, in-hand robotic manipulation, tactile sensing, fuzzy control, and regression algorithms. Section 4.4 presents our prototype description, a system overview, and experimental setup. Section 4.5 shows experimental results for two in-hand manipulation tasks performed, followed by conclusions in Section 4.6.

4.3 Related Work

Several papers in recent years have approached the robotic grasping and manipulation in its different aspects. This section contains related works that guided the development of experiments on this chapter. The present work approaches in-hand manipulation aspects of control and sensing using the human "Where" sensory system as an inspiration to in-hand object pose estimation.

4.3.1 The Human "Where" System

Studies on the human somatosensory divided it into What and Where systems, the former being the system that processes surfaces, objects, and their characteristics, while the latter being responsible for describing points, surfaces, and objects in the environment. With a counterpart in vision, the Where system is investigated in the present chapter as an approach to solve in-hand manipulation pose estimation of objects. A notable difference from vision, however, is that the localization can be related to the sensory organ, the human skin, or to the world. Accordingly, investigations focus on two types of visual–spatial localization on the human tactile field, one determining where on the body a stimulus is being activated, and another wherein the external world a body tactile sensing is being touched [25].

In order to study human touch as a spatial localization, researchers need to know how humans specify frames of reference [204]. A frame of reference defines Cartesian or polar coordinate systems, where its origins may be an individual's body parts or distinct points to build environment landmarks. Humans can use a single frame of reference to perform a given task, while multiple frames of reference are available. As an example, [25] defines points of the body, such as fingertip axes that act as local frames of reference. When facing the task of localizing points in the external space, humans usually refer to an egocentric frame of reference, which specifies distances and directions relative to the individual. By contrast a person uses an "allocentric" frame of reference when using landmarks and external axes as guidelines. The ability to use multiples frames of reference is also essential to the allocation of attention that human dexterity is known to offer. Higher-level visual-touch interactions are a good example of how the human somatosensory system uses those frames of reference to collect information about different objects, during interobject interaction or allocation of attention.

4.3.2 Manipulation and Tactile-enabled Underactuated Hands

Biology inspiration in robotics has gained a growing interest over the years with significant focus on neuroscience, even though the neuroscience background has had a relatively small impact on the final robotic application [5]. Recent research on visuotactile-based control of grasping and manipulation operations has shown that robots have improved manipulation skills when simulating human tactile and visual perception to action. Bimbo et al. [207] combined vision and touch for the estimation of an object's pose during in-hand manipulation where the camera suffers from finger occlusion. A visuotactile control was developed by Li et al. [208], achieving robust in-hand manipulation and exploration of unknown objects performing robust manipulation even in the presence of accidental slippage or rolling [209]. Their paper provides another example of reliable grasps using underactuated hands, where flexible hands and visual clues were used to perform after-grasping pose estimation for high-precision assembling

Adaptive hands, such as those used in the works mentioned above, have become an exciting topic of research over the last decade, with recent development in several areas, such as new designs [192, 157], reliable grasping [210, 17], and dexterous in-hand manipulation [211, 212]. Due to their unique ability to grasp and adapt to unknown objects, special attention has been devoted to the use of underactuated hands in unstructured environments. The advantage of underactuated hands is that they allow for n Degrees of Freedom (DOF) while using less than n actuators. This is possible because kinematic compliance of the fingers are provided by passive elements, e.g., springs of flexible joints, which allow the finger kinematic shape to adapt to the grasped object shape. Dynamics of underactuated hands is also remarkable when using tactile-based force control on top of the slippage detection [191]. Odhner et al. [157] described a design where power and precise grasping are made possible by flexible joints and two pivoting fingers. Reasonable dexterity was achieved by having opposed fingers with individual actuators controlled by haptic feedback provided by force sensors. Even though little space for customization is observed in the solution as mentioned above, Zisimatos et al. [192] designed a single actuated robotic gripper that supported up to six fingers pulled by a differential disk. Following on this idea we redesigned the base and each finger used on our robot hand to enable dual actuation for the opposed fingers which, in conjunction to modified phalanges, allowed us to mounted multimodal tactile sensing modules. Shortly, the work presented in chapter uses a prototype that employs a modified version of [192]'s ffingers and base, using two actuators, borrowing ideas from [157].

Tactile Sensing

Tactile sensing plays a vital role in providing accurate local data for the intelligent control of dexterous manipulation operations [193]. Using tactile data and feedback, the objects pose can be inferred using statistical and intelligent techniques [213, 187]. Due to its importance in manipulation, tactile sensing has massive known a notable development in recent years.

Among the different available transducer technologies used for the development of new tactile sensors [194], the multimodal techniques provide touch sensing capabilities that closely match those of the human skin. In Chapter 3, Figure 3.2 presents the sensing module where a compliant cone-like structure (2) supports a Magnetic, Angular Rate, and Gravity (MARG) transducer (1) and guides the forces applied on the module's surface to the pressure sensor localized on the bottom of the structure. In Chapter 3, Figure 3.2 presents the bio-inspired multimodal tactile sensor module developed in-house in our laboratory [184] which has a compliant cone-like structure (2) that supports a MARG transducer (1) and also guides the forces applied on the modules surface to the pressure sensor localized on the bottom of the module. In addition to force, the inertial measurement provides information about the deformation of the artificial skin when pressure is applied.

This chapter presents an application of bio-inspired tactile sensing and of visuotactile approach to the development of new machine learning algorithms for the in-hand object pose estimation. Similar to the human somatosensory system, the skin itself provides an egocentric frame of reference where the objects interaction to the artificial skin occurs. The real-time information from the multimodal tactile modules was used to maintain a stable grasp during the experiments with an underactuated robotic hand.

4.3.3 Fuzzy Logic Control for Stable Grasping

Using fuzzy logic to address the grasping problem is one way to reduce the gap between conventional and intelligent control due to the uncertainties and complex mathematical models involved in that task [15]. During a recent edition of the Amazon picking challenge, the authors of [189] described problems when using an open-loop control system for pick and place tasks; therefore, achieving and autonomous stable grasping is an essential challenge for the in-hand manipulation. The authors of [190] presented a closed loop control using tactile sensing for the task of removing a book from a bookshelf when the maximization of the contact surface is required.

Another aspects investigated by [17] is the relation between microvibrations and the grasp stability, while using dual motor fuzzy controller using BioTac© sensors. Grasping status and stability values were estimated using pressure and microvibration data. A second fuzzy controller provides finger directives such as pull, push, or hold using the previous stability values. In multifingered hands, when no resultant force acts on a fully restrained object, equilibrium is achieved, which is a requirement for stable grasp [16]. The present work uses a fuzzy controller that is able to perform grasping tasks with minimum fingertip force. Our controller uses microvibrations, detected from the sensors gyroscope and force from fingertips sensor to control each finger separately.

4.4 Experimental Setup

This section presents the experimental setup used for visuotactile object pose estimation. Several aspects of the prototype were already covered in Chapter 3 Section 3.4.The Figure 4.1 shows a schematics of this experiment. Our first aproach is shown where a human opetator promotes external forces disturbances to the object in the z axis while a camera oeffers a fixed frame of reference. Data collecte

4.4.1 Robotic Gripper

Our robotic gripper, previously presented in Chapter 3, has two independently controlled fingers. We kept Zisimatos et al.'s [192] top plate, but a modified base accommodates two motors needed to pull each finger separately. From base to fingertip, the gripper is about 20 cm long. Figure 4.2 shows in detail the opened gripper during experiments before a grasp attempt and one finger operation at the bottom.

When compared to the human hand, these underactuated robotic fingers have intermediate distal flexible joints. The top plate, including the fingers, exerts a maximum force applied (and retained) of 8 N per fingertip during tests with a standard servo. Strings are attached to tip phalanges, and two fingers are pulled independently by two Strings are attached to the tip phalanges, and two fingers are pulled independently by two motors.

The top left image in Figure 4.2 shows the four tactile sensors mounted on the finger phalanges, motors, and pulleys. This viewpoint is used to place the camera, as shown in

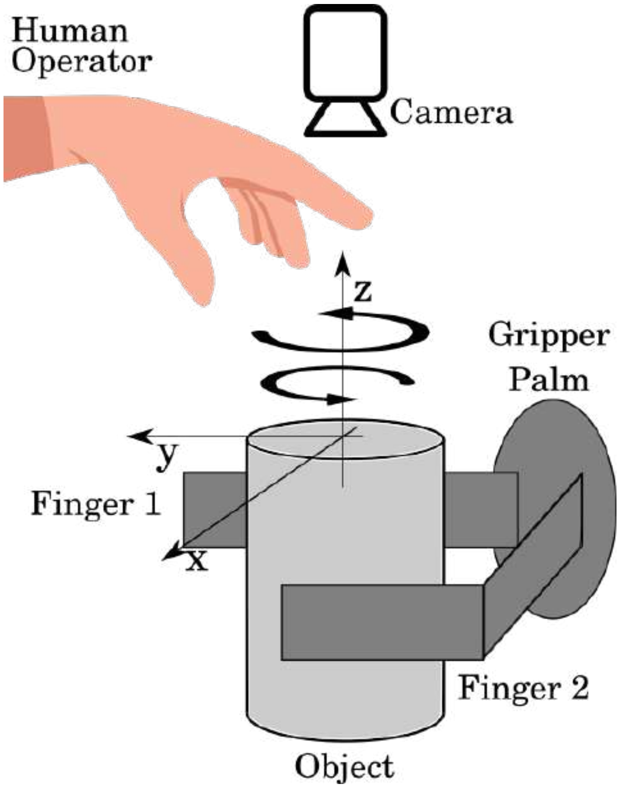

Figure 4.1: Object under grasp angle of rotation by the human operator with camera on top

Section 4.4.3. The red arrows indicate the direction of force applied by the motors. The image on the top right of Figure 4.2, shows details of tendons and flex joints. A detail of the pulley one appears with a red circular arrow indicating the motor actuation direction during the pulling phase. The bottom row of Figure 4.2 shows steps of a single finger actuation: (a) rest position, no motor rotation; (b) initial movement with motor pulling; (c) continuous motion brings the finger to closer to the palm; and (d) around the maximum safe finger curvature.

Each finger phalange has a tactile sensor module mounted on it. The top row of Figure 4.2 shows the multi-modal tactile sensor modules placed on each finger. The modules structure and material flexibility provide a convenient compliance for the fingers functionality. All tactile modules send data to micro-controllers acting as nodes to the central computer. The software developed uses Robot Operating System (ROS) [195].

The experimental gripper discussed in this chapter uses the same distributed system

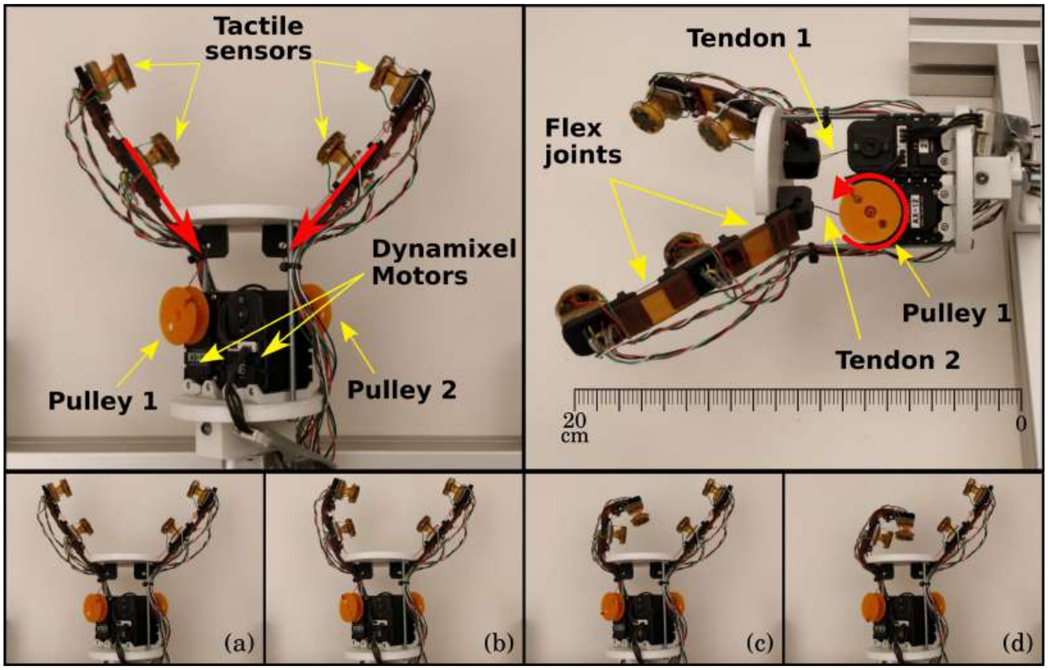

Figure 4.2: The modified gripper: (a) rest position; (b) initial movement; (c) finger actuation; (d) maximum safe curvature.

from Chapter 3 with the exception of the FSR sensor connection which is not needed anymore. Figure 3.5 shows all primary ROS nodes used in this experimental set up. The central node runs on a laptop that concentrates the control, data collection, and pose estimation. All data were collected in ROS *bags* for post-processing and pose orientation estimation. Figure 3.5 also shows the fuzzy control node that receives the sensor data and updates the motor controllers. MCU 0 and MCU 1 are micro-controllers acting as ROS nodes. These micro-controllers receive data from the magnetic, angular rate, and gravity (MARG) and barometer sensor components of via the I^{2}C protocol that is represented by arrows from the "Tactile sensing" module in Figure 3.5, which also shows I^{2}C communication from tactile modules multiplexed to via MUX 0 and MUX 1. There is also a USB camera represented in a blue box and a USB Serial connection from the "Motor Manager" yellow box used for computer control of the Dynamixel motors represented in an orange box at the bottom of Figure 3.5.

4.4.2 Tactile Sensors

A total of four bio-inspired multi-modal tactile sensing modules, previously shown and discussed in Chapter 3. Figure 3.2, shows the sensor schematics provide tactile information needed during visuotactile perception experiments. Each module contains a 9 DOF MARG sensor, a flexible, compliant structure, and a pressure sensor placed in a structured way similar to human skin [184]. From the previous chapter, the same connections are present where Figure 3.5 shows how the MARG and deep pressure sensors are connected to the micro-controllers MCU 0 and MCU 1 The master ROS node running at the central computer demultiplexes the data and stores tactile information represented in Figure 3.5 by arrows from the USB serial connections.The experimental results section presents data provided by the tactile modules during the rotation using both external forces and open-loop in-hand manipulation.

4.4.3 Fuzzy Controllers for Stable Grasping

Before any manipulation takes place, two fuzzy controllers maintain a stable grasp by sending proper signals to each actuator responsible for pulling the fingers [17]. The autonomous fuzzy grasping controller must provide a consistent grasp force while handling different object sizes.

The present gripper setup uses a dual fuzzy controller for fingers based on pressure and microvibrations provided by the deep pressure sensors and respectively by the gyroscopes. The pressure sensor shows the degree of contact with the object. The indicator that the object under grasp is moving is the angular velocity used here to detect microvibrations In conjunction, angular velocity and pressure provide tactile feedback about stability and status to a second fuzzy grasp controller. Two gray boxes, namely the *Tactile Module 0* and the *Tactile Module 1* in Figure 4.3 provide the separated barometer and MARG I^2C signals sent to the independent finger fuzzy controllers.

Figure 4.3 presents the data flow occurring during the experiments. Data from tactile sensing modules (top left) provide information for the fuzzy controller (bottom left) with

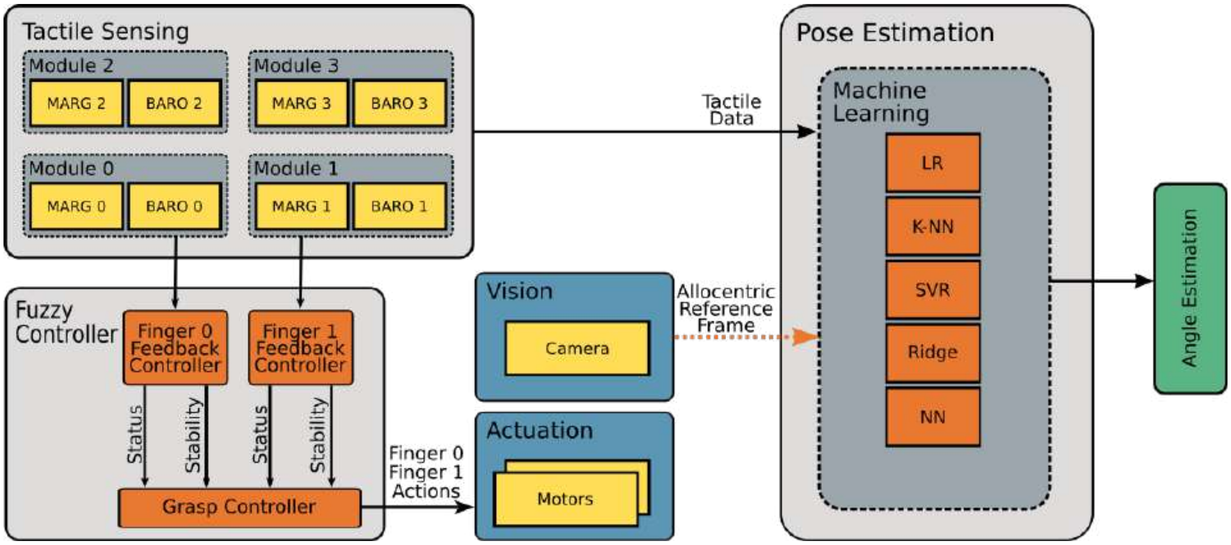

Figure 4.3: System flow chart.

details described in the following sections. With a grasp controller making decisions based on stability and status, the finger actions modify the actuators status (blue box middle). Vision (middle blue box) provides an allocentric reference frame to the machine learning pose estimation. This allocentric reference frame uses data from all four tactile modules to provide an egocentric frame of reference used as input to the pose estimation module (right gray box). The last step is to use machine learning techniques and return the angle estimation (green box).

Each *finger fuzzy feedback controller* provided status and stability information to the *grasp fuzzy controller*, shown as a gray box in Figure 4.3.The *grasp fuzzy grasp controller* decides the appropriate action for each finger (go forward, go backward or hold) based on status and stability information from both fingers.

Finger Fuzzy Feedback Controller

The *finger fuzzy feedback controller* uses sensor data to provide pressure status and grasp stability information to a *grasp fuzzy controller*.In order to describe finger fuzzy feedback controller inputs, Low and High fuzzy sets were defined for the microvibrations input, and No-pressure, Low-pressure, Normal-pressure, and High-pressure fuzzy sets for the pressure input Stable and Not-stable fuzzy sets describe finger fuzzy feedback stability output while

Not-touching, Touching, Holding, and Pushing define status output.

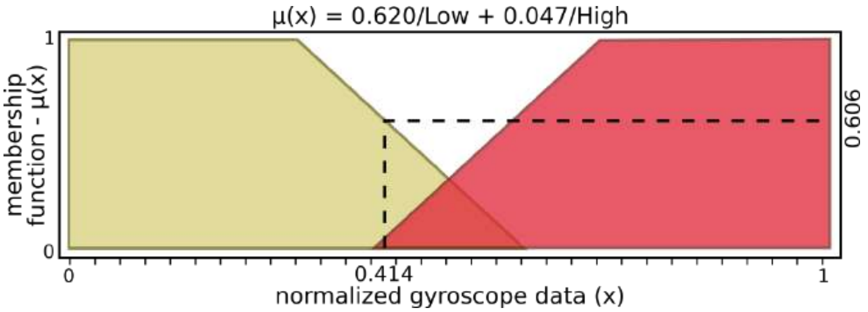

Figure 4.4: Input sets of microvibrations.

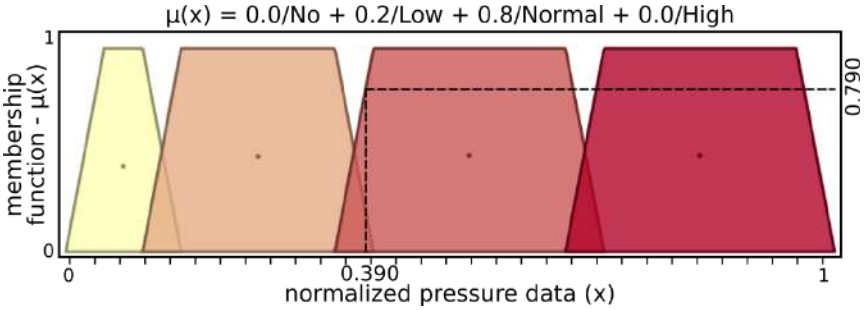

Figure 4.5: Input sets of pressure.

Figures 4.4 and 4.5 illustrate the input values for the microvibrations and pressure fuzzy sets, respectively. The tactile information used here was normalized data from the barometer part of the tactile module as pressure, and the raw gyroscope data measure the angular velocity variations of the respective module. An example of possible output, Figures 4.6 and 4.7 show the stability and status fuzzy-outputs, respectively. We used the Mamdani fuzzy inference system. The second fuzzy controller uses status and stability from this both fingers controller in order to produce appropriate finger actions.

A rule book based on [17] was used for this tactile in-hand manipulation fuzzy feedback controller. Table 4.1 summarizes the rules. Possible outputs for the status are NT for not-touching; T for touching; H for holding; and P for pushing. Stability has two possible outputs, S for stable and NS for not-stable

As shown in the example above, microvibrations data activate 0.620 of “Low” and 0.047 of “High” sets, resulting in $\mu(x) = 0.606$ membership function.In a similar way, the

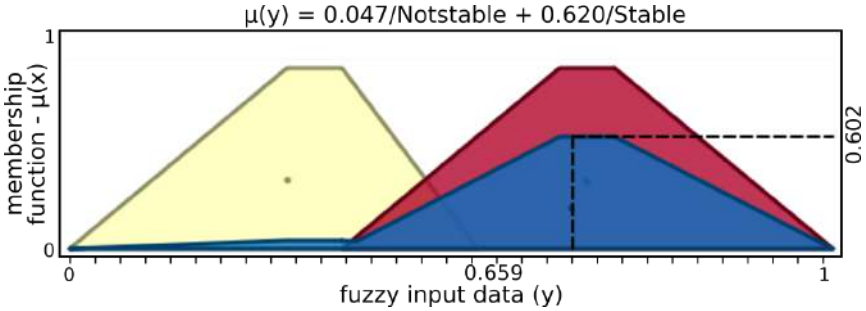

Figure 4.6: Output sets of stability.

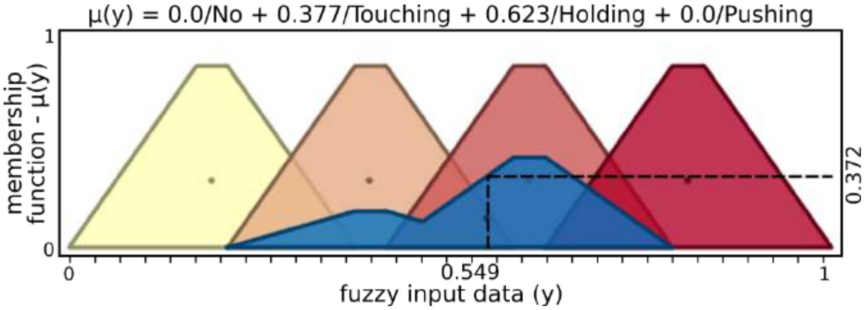

Figure 4.7: Output sets of status.

Presssure Microvibrations	No	Low	Normal	High
Low	NT/S	**T/S**	**H/S**	P/S
High	NT/NS	T/NS	NS	P/NS

Table 4.1: Finger fuzzy feedback controller rulebook

pressure has $\mu(x) = 0.790$ with 0.2 of “Low” and 0.8 “Normal” pressure sets.The stability has $\mu(y) = 0.602$, activating 0.620 of “Stable” and 0.047 of “Nonstable”, while status has $\mu(y) = 0.372$, with 0.377 of “Touching” and 0.623 of “Holding”.

Grasp Fuzzy Controller

Based on both finger status and stability, a second fuzzy controller is responsible for the motor inputs needed to maintain a stable grasp. Figure 4.3 shows a box labeled *grasp fuzzy controller*with the stability and status data from each finger used as inputs, while its outputs control the motor velocities.A *finger fuzzy feedback controller* provides status and stability information from each finger. It is important to observe that input from both fingers is essential during the inference phase of the *grasp fuzzy controller*. Although both fingers are needed for inference, for simplicity the Figures 4.8 and 4.9 only present in one finger input example. The inference system used was also Mamdani based on the center of gravity. Both outputs control the finger motor velocity, updating the Dynamixel motor controller manager node as shown in Figure 4.10, while Figures 4.8 and 4.9 show the fuzzy inputs for the finger stability and status, respectively.

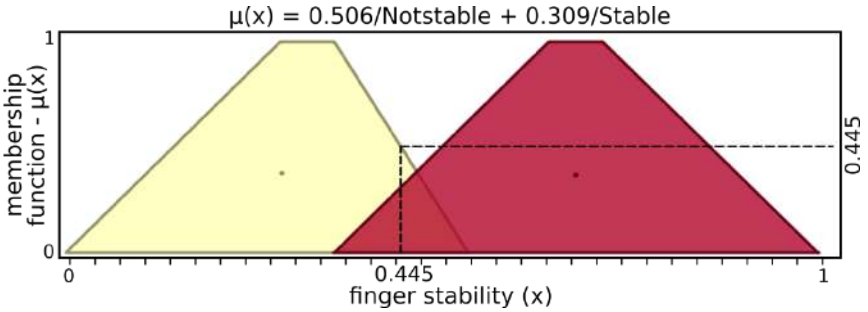

Figure 4.8: Input sets of stability.

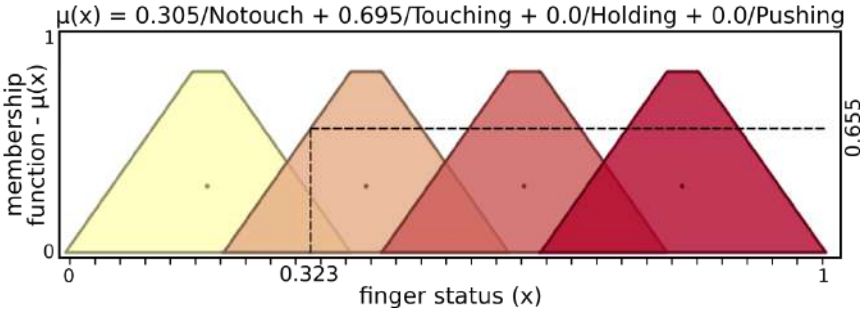

Figure 4.9: Input sets of status.

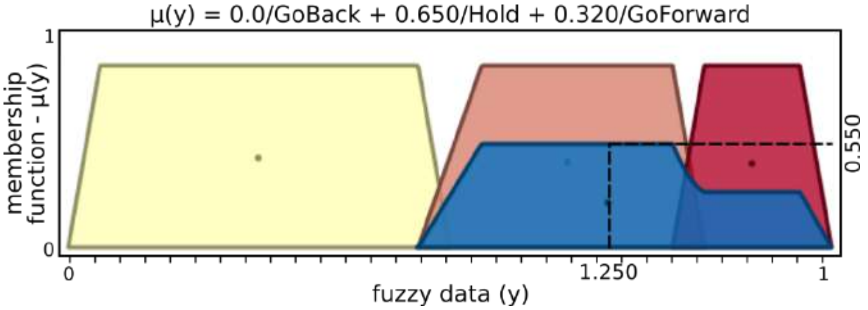

Figure 4.10: Action output sets.

Another rule book also based on [17] summarized in Table 4.2 was used for the *grasp fuzzy controller*. Possible outputs for updating motor velocities are GF1 for *finger 1 go forward*; GF2 for *finger 2 go forward*; H1 for *finger 1 hold*; H2 for *finger 2 hold*; GB1 for *finger 1 go back*; and GB2 for *finger 2 go back*.

Finger 2 Finger 1	NT	T	H	HS	HNS	PS
NT	GF1/GF2	H1	GF1	GF1	GF1	H2
T	H1	GF1/GF2	H2			H2
H	GF2	H1			GF1/GF2	H2
HS	GF2			H1/H2		H2
HNS	GF2		GF1/GF2			H2
PS	H1	H1	H1	H1	H1	GB1/GB1

Table 4.2: Grasp fuzzy controller rulebook

In the example shown above, the stability input has a $\mu(x) = 0.445$, with 0.506 of "NotStable" and 0.309 of "Stable". Similarly, the status input has a $\mu(x) = 0.655$, with sets No-touch of 0.305 and Touching of 0.695, while Holding and Pushing are not activated. After inference, the *grasp fuzzy controller* produces an output with a $\mu(y) = 0.550$, with contributions of 0.650 from "Hold" and 0.320 from "GoForward".

Video Camera

We use a top video view of the gripper during manipulation in order to recover the object pose variations using two color markings on the object of interest The middle of the camera image provides a frame of reference fixed at the top of this setup. Figure 4.11 shows the object angle when using *Open CV* library [214] to capture in-hand angle changes between an object and the cameras visual frame of reference.

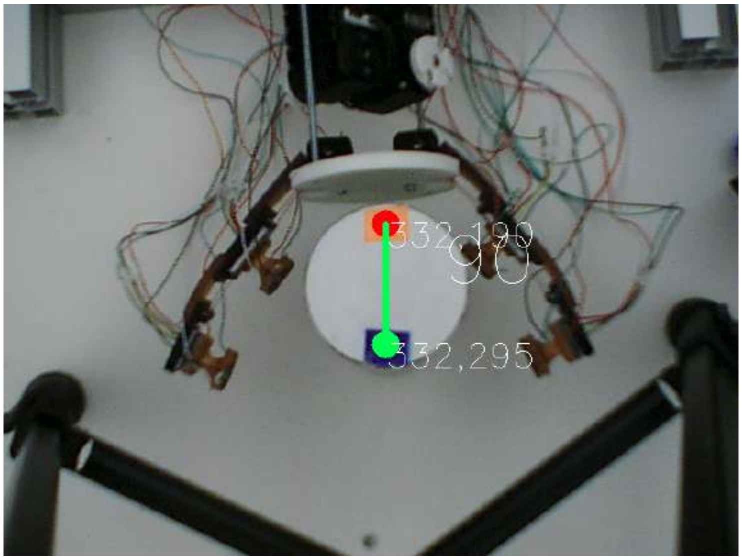

Figure 4.11: Angle measured from the center of color blobs in the diameter of the object.

4.5 Experimental Results

This section presents results of two visuotactile experiments on pose estimation using machine learning algorithms. The first experiment used external forces, while the second one performs estimations using open-loop finger self-actuation to rotate an object. In both experiments, video images were used to train machine learning algorithms for the dynamic changes in the objects pose. During all operations, a dual fuzzy controller performs an autonomously maintained stable grasp

4.5.1 Object Rotation Using External Forces

During data collection for this first experiment, a human operator executed rotations on a previously grasped object. Figure 4.12 shows the three objects used during this first experiment and its respective diameter information.

Different diameter sizes were used to test the force consistency provided by the autonomous fuzzy controller for different objects while still allowing smooth rotation. A piece of paper with a color scheme on object top plate extremities provides a visual cue of the angle to be estimated. A color markup on each object top plate extremity provides a visual cue allowing for a quick estimation/recovery of the rotation angle.

Figure 4.12: Objects used during the first experiment.

Figure 4.13 shows the barometer and accelerometer sensor data collected during the object rotation using external forces.The first row shows the angle captured by the video camera during the execution of clockwise and counterclockwise rotations, at least three times each way. The second row shows the human operator rotating a grasped object. The third row of Figure 4.13 shows the pressure sensor data collected while the object pose is changing. The fourth row presents the accelerometer sensor data streams on three axes. While the X-axis data have smaller amplitude, they are essential for the recovery of the direction of rotation, information that the pressure sensor data alone are not capable of providing.

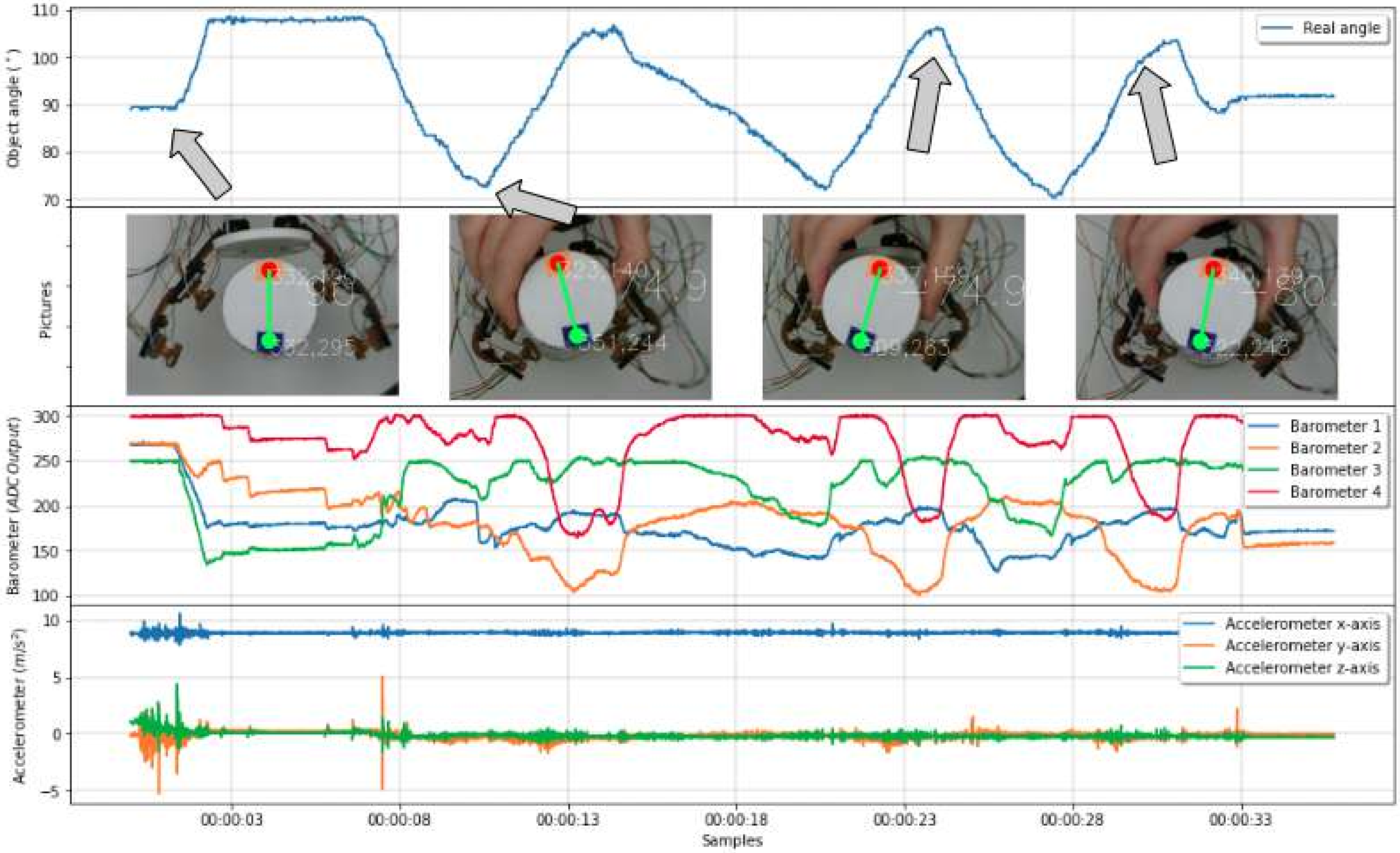

Figure 4.13: Sensor data collected during objects rotation using external forces.

4.5.2 Machine Learning for Object Orientation Estimation

In our visuotactile approach, this stage is where the robot has its camera pointed to the object, learning an egocentric frame of reference. Later, it will find an allocentric frame of reference, reallocating its attention, and use only tactile information to feel any object pose changes. From grasping to rotations, we used five executions for each object with 70% of the randomized data for training. Table 4.3 shows the results, with the *ridge regressor* outperforming all other algorithms.Denormalizing the angle, the average mean squared error for all sizes for the *ridge regressor* was 1.82°.

Table 4.3: Angle estimation using external forces with blue indicating best results.

	Large			Medium			Small		
Regressor	MSE	R^2	EXP	MSE	R^2	EXP	MSE	R^2	EXP
Linear Regression	0.173 (0.13)	0.825 (0.12)	0.903 (0.02)	0.159 (0.12)	0.836 (0.11)	0.898 (0.04)	0.077 (0.05)	0.898 (0.05)	0.946 (0.002)
K-Nearest Neighbors	0.289 (0.15)	0.691 (0.16)	0.760 (0.09)	0.515 (0.54)	0.501 (0.41)	0.683 (0.18)	0.102 (0.02)	0.859 (0.03)	0.899 (0.02)
Support Vector Regression	0.199 (0.12)	0.794 (0.11)	0.874 (0.04)	0.228 (0.15)	0.762 (0.11)	0.829 (0.11)	0.116 (0.03)	0.836 (0.06)	0.892 (0.01)
Ridge Regression	0.173 (0.13)	0.825 (0.12)	0.903 (0.02)	0.159 (0.12)	0.836 (0.11)	0.898 (0.04)	0.077 (0.05)	0.898 (0.05)	0.946 (0.002)
Neural Network	0.171 (0.10)	0.821 (0.09)	0.890 (0.05)	0.240 (0.13)	0.743 (0.09)	0.864 (0.07)	0.085 (0.02)	0.880 (0.04)	0.925 (0.007)

Figure 4.14 shows the real values and the estimations using ridge regression of the angle for each of the three objects used in this experiment. The real and the estimated values are shown on each row from top to bottom, respectively, for the arge, medium, and small diameter objects. On the second and third lines, angle estimations for medium and small diameter objects show high accuracy for all test data presented to the *ridge regressor*.

It is possible to observe that the results in the case of the large diameter object (on the first row) show slightly less precision, with the predicted line not following the real angle line on some occasions That observation is compatible with what is shown in Table 4.3, where the large object has a mean squared error (MSE) of 0.173, while medium and small objects show 0.159 and 0.077, respectively, for the *ridge regressor*, while achieving a better result using a *neural network*.

Log files (rosbags) contain angle information at 30 frames per second, with sensor data

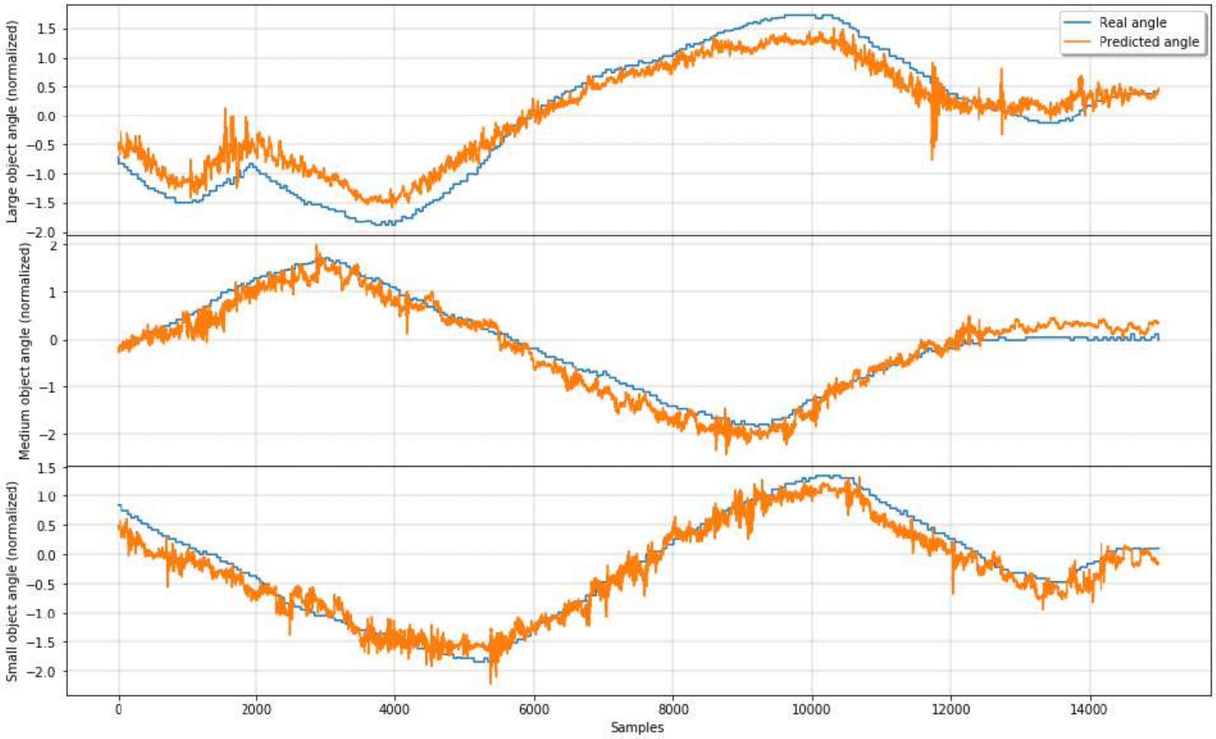

Figure 4.14: Angle prediction compared to real angle when using ridge regression.

collected at its maximum frame rate. Table 4.3 presents results from five methods, namely: *linear regression*, *K-nearest neighbor regression* (KNN), *support vector regression* (SVR), *ridge regressor*, and the *neural network*. The KNN used five neighbours and the Minkowski metric; SVR trained with the RBF kernel and degree 3; the ridge regressor was trained using $\alpha = 0.5$; moreover, the MLP neural network contained a single hidden layer with one hundred neurons. All these prediction/estimation methods used the same sensor data: accelerometer, barometer, and magnetometer. We used three metrics to evaluate each method accuracy: mean squared error (MSE), coefficient of determination (R^2), and the explained variance regression score (EXP) [198, 199, 215, 216].

4.5.3 Angle Estimation In Open-Loop In-Hand Manipulation

During the second experiment, one finger performed in-hand manipulations, rotating the object while it was under a stable grasping. Figure 4.15 presents sensor data collected during an open-loop self-rotation experiment with the object's angle in the first graph, followed by a data sensor on subsequent lines.

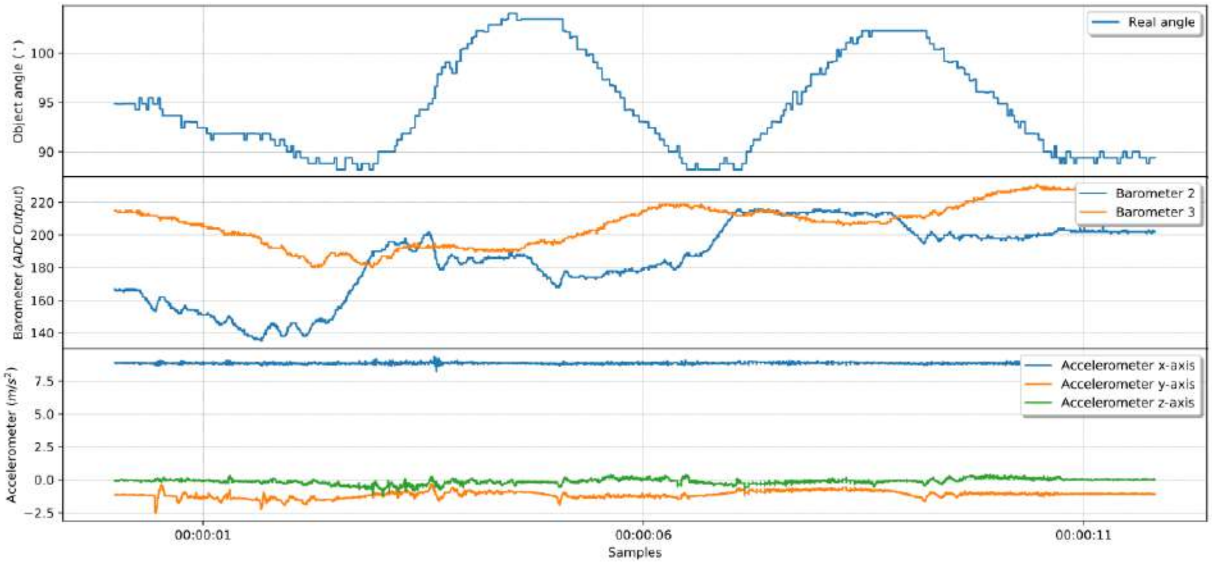

Figure 4.15: Sensor data varying in accordance with the object rotation angle.

The first row shows the rotation angle during in-hand manipulation when the finger changes the object angle four times. Corresponding pressure data are shown in the second row, with both barometer measurements changing accordingly to object angle as expected. One could also observe changes in accelerometer data presented in the third row.

Table 4.4 presents the results of three experiments where the *multilayer perceptron* (MLP) outperforms all other methods during the three in-hand self-rotations of the middle-size diameter object. Figure 4.16 shows extracts of real data and the predicted angle using MLP during self-rotation experiments. After retraining, all the machine learning techniques mentioned on Section 4.5.2 show similar results for the middle-size object used in the three experiments.

It can be seen that the angle estimations during all three experiments shown in the three rows are not only following the trend of the actual angle-measurements, but are also achieving reasonable precision for all the test data presented to the neural network. This is compatible with the results shown in Table 4.4, which shows multilayer perceptron (MLP) results with a mean squared error (MSE) of 0.77, 0.051, and 0.067 for the first, second, and third experiments, respectively.

Table 4.4: Self-rotation angle estimation with blue indicating best results.

	Exp 1			Exp 2			Exp 3		
Regressor	MSE	R^2	EXP	MSE	R^2	EXP	MSE	R^2	EXP
LR	0.175	0.858	0.958	0.524	-0.155	0.781	0.531	0.492	0.743
KNN	0.389	0.686	0.686	0.203	0.552	0.553	0.193	0.814	0.818
SVR	0.218	0.824	0.830	0.107	0.762	0.812	0.268	0.743	0.770
RIDGE	0.175	0.858	0.958	0.524	-0.154	0.78	0.531	0.493	0.744
MLPR	0.077	0.937	0.976	0.051	0.885	0.898	0.067	0.936	0.946

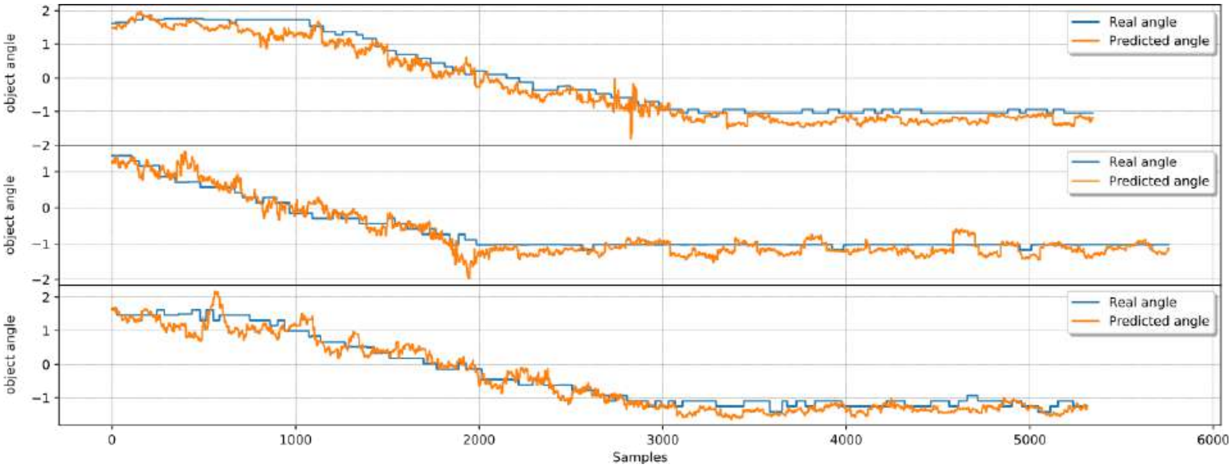

Figure 4.16: Prediction of angle compared to real angle using Multilayer Perceptron (MLP) during self object rotation.

4.6 Discussion

Underactuated hands are a useful tool for in-hand manipulation tasks due to their capability to seamlessly adapt to the contour surfaces of unknown objects and maintain such objects under grasp even when disturbed by external stimuli. These hands are quite versatile while grasping unknown objects, but after grasping, estimating the pose of in-hand objects becomes a challenge due to the flexibility of the fingers in such devices. To reduce the uncertainty of recovering the orientation of the manipulated objects, we used a visuotactile approach inspired by the human somatosensory system combining visual and tactile sensing information.

The human manipulation system operates with two subsystems with the “Where” system dealing with perception to action building egocentric and allocentric frames of reference [25]. This chapter introduced a visuotactile approach for robotic in-hand pose estimation of objects. In this research, it was used as inspiration for after grasping object pose estimation combining visual and tactile sensing information. During the experiments, autonomous, stable grasping using a dual fuzzy controller provides consistent force while handling different objects Two sets of experiments achieved accurate angle estimation using tactile data.

In the first experiment, external forces were applied to the object during a stable grasping, forcing it to change its orientation, while during the second experiment, autonomous open-loop promoted object rotation

The efficiency of different machine learning methods was compared for the recovery orientation of an object under grasp given by intermittent allocentric reference frames. The ridge regressor method achieved an average mean squared error of 0.077 during experiments using external forces. Compatible results using an MLP neural network achieved a mean squared error of 0.067 during autonomous open-loop rotation in the second experiment. Since this approach is model-free, the performance of the machine learning algorithms will improve as more information will be available when using robot hands with more fingers.

Chapter 5

Tactile Object Recognition and Yaw Angle Estimation During In-hand Robotic Exploration

5.1 Preamble

This chapter presents research on the exploratory object recognition and pose estimation by a three-fingered hands using bio-inspired tactile sensing modules This chapter expands a previous approach [39, 21] to the human "What" and "Where" somatosensory subsystem. Object exploration is another aspect of the in-hand manipulation shared among humans when there is necessity of increasing recognition. Building on the work presented in in Chapter 3 and Chapter 4, this chapter presents experiments on the exploratory object classification by a human-like robotic had equipped with bio-inspired tactile sensors on its fingers. On a different approach from the concepts of "haptic glance" where non-exploratory manipulation was used for fast object identification, this chapter is inspired by the human somatosensory exploratory characteristic on multi-characterization for robotic systems. While investigating this new approach for in-hand manipulation and robot dexterity, a teleoperated thumb performs object rotation while the other two fingers maintain a stable grasp. The sensor data collected during experiments provide input for the machine learning algorithms used for classification and angle estimation.

5.2 Introduction

Several aspects of the tactile object recognition by underactuated in-hand manipulation have already discussed in the previous two chapters. Chapter 3 covered the static single-grasp object identification and Chapter 4 covered aspects of angle estimation using external forces and self-exploratory object movements. This chapter continues on this path presenting new aspects of the object recognition and angle estimation by in-hand manipulation using a teleoperated underactuated more human-like robotic hand having two fingers and a thumb.

In humans, two or more exploratory procedures (EP) promote the integration of redundant properties under simultaneous execution for multi-attribute object identification. Research on the human somatosensory system [217, 218] shows rapid object classification when information of two dimensions is produced even with some level of redundancy. Information redundancy shows advantages if EP delivers multi attributes from objects and when different exploration can execute together.

Spatial and temporal information sources represent a specific origin of information for human characteristic extraction. Human manual exploration provides information about object recognition under several moments on the process of in-hand manipulation. Researchers use constrained haptic exploration to analyze the contribution from spatial and temporal sources of the object movement during grasping tasks. The resulting reduction in performance shows the contribution of each missing information source. In this chapter, we consider two examples of this restricted-exploration approach in the context of robotic in-hand manipulation.

Precise hand manipulation and object reorientation are essential abilities for modern robotic systems. Usually, a stable hand grasp and precise arm movement accomplish this. However, as robots are increasingly being designed to perform daily tasks, their in-hand operations need to become more dexterous. In-hand manipulation is also a fundamental ability for robots manipulate objects in situations where only limited arm movements are possible. The simple two-finger gripper connected to an arm manipulator, commonly seen in industrial settings, has reached obsolescence as more robots are designed to operate in human environments, such as homes, hospitals, and commercial settings.

Tasks that are trivial for a human hand such as rotating or reorienting objects while maintaining a stable grasp, represent high-complexity challenges for the robotic systems. If the robotic hands were identical to the human hands, they would have intricacies that are hard to operate. While there was research work on robotic hands that mimic the human hand, it has only made minimal contributions from the kinematics and dynamics of this mechanism to the in-hand manipulation [219]. While the robotic hands with underactuated fingers are simpler to control and can perform stable grasps of many objects [191], they shown little potential for in-hand applications. The ability of the underactuated hands to perform in-hand operations could be improved if at least a fully actuated finger is added simulating the human hands ability to manipulate objects followed by a stable grasp.

In-hand manipulation is prevalent when complex situations arise, such as having a constrained arm, when having only a partial view of an arm, or when performing precision manipulation tasks. In several human activities, tasks occurring in complex situations are successfully performed using the hands dexterity to reorient objects following a grasping action [220].

In order to enhance the efficiency of many robotic applications (specially in-hand manipulation), tactile sensing is a topic of major interest [21, 39]. Traditionally, the robots have been used in controlled environments such as industrial factories, but now, robot use is moving towards unstructured settings like homes and hospitals [2]. Dexterity is essential for many applications such as in healthcare, eldercare and assist robotics. In such scenarios, the data obtained from tactile sensors can be used to determine object characteristics which are essential to enabling proper manipulation tasks. The object's classification and its position related to the hand provides useful information to in-hand manipulation control algorithms. Although vision is a useful approach to grasping, tactile sensing is necessary to dexterous in-hand manipulation [184].

This chapter presents a hand prototype with two tactile enabled underactuated fingers and a fuzzy controller providing stable grasp, and a teleoperated thumb for in-hand manipulation. The compliance provided by the finger tactile sensors and the flex joints allow the grasped object to be reoriented by the smart thumb performing exploratory procedures. Visual and tactile feedback provides information on the object's orientation, while machine learning algorithms recognize the object and estimate its orientation.

5.3 Related Work

In recent years, different researchers approached robotic grasping and manipulation in various ways (e.g. design, control, and sensing). This chapter presents a novel approach to the in-hand manipulation with a fuzzy underactuated gripper and a three degrees-of-freedom (DOF) robotic teleoperated thumb. Also, a strategy based on the human somatosensory system is used, aiming to reduce the costs of exploratory procedures while achieving pose estimation in addition to object classification.

Manipulation costs arise when using exploration procedures for object characterization [204, 24]. In this thesis, the term cost refers to an increase in execution time and probable interference with other tasks performed; Those costs could follow accidental object properties acquisition what is not optimal. For instance, as seen before in Chapters 3 and 4, static contact is quick to execute and it can provide texture, volume, position, and pose information under holding and enclosure positions. On the cost side, no exploratory execution can be done while performing static object recognition. For instance, [221] analyzed human exploration costs while looking for the most efficient way to recover the properties of an object by grasping and lifting it. During experiments, human subjects perform grasp and lift of objects when asked about their properties. Only subsequently, they performed other types of exploratory procedures to answer specific object characteristic questions.

In [217] the authors mention that the traditional visual object recognition methods focusing on spatially aligned edges are inappropriate for haptics. Usually, borders and edges are poorly extracted by haptic systems due to a limited spatial sensitiveness. So, the basic concepts of haptic object recognition, voluntary exploration procedures of objects should be investigated with its costs and benefits. In humans, complementary properties from two or more exploratory procedures facilitate identification of object attributes. When humans explore objects under no temporal constrains, the geometric properties are less important than material properties. There is other information of spatial and temporal nature to be used for the tactile object characteristic extraction. The limited-time duration of the contact during exploration is also useful to consider.

5.3.1 Robotic Manipulation

Inspiration from human manipulation skills is present in several papers, as we discussed in Chapter 2. For instance, in [222] studied manipulation on industrial machinists while working. During the development phase in robotics, the choice of the robotic hands takes into consideration the specific task they have to perform. Authors of [223] discussed strategies for task-oriented, multi-fingered grasping hands. The authors also proposed a strategy for modelling and performing reactive manipulation abilities between different types of manipulators. In [224], a reinforcement learning method is proposed for in-hand manipulation tasks, avoiding the use of analytic dynamics or kinematics models. Examples of simple grippers show capabilities and complex manipulations. Using external forces for grasping, [225] performed in-hand manipulation of three different objects while switching grasping positions. Our strategy is using an underactuated gripper for stable grasping, while a fully actuated thumb performs in-hand object rotation.

Underactuated Hands

While each new design faces new challenges, appropriate reuse of previous solutions is crucial when trying to solve some old problems. In this chapter, we are reusing appropriate solutions developed in Chapters 3 and 4. In this chapter we are using a similar experimental setup because the underactuated hands proved to offer an excellent solution for grasping [191]. As there is a lack of sensing, control, or analytical solutions for the kinematics and dynamics of this type of hands, we decided to use the versatility of the underactuated hands and follow a multimodal control approach to achieve the in-hand manipulation with stable grasping [192, 226].

The Thumb and In-hand Manipulation

Off-the-shelf robotic hands still do not achieve the same dexterity as the human hand [6]. The hand used in our experimental has a thumb placed on the side of the two gripping finger. Even though the placement of the thumb in this position does not guarantee that the robotic hand has a dexterity similar to that of the human hand, it decreases the gap between the robotic- and human-hands. Research in reinforced learning developed by [227] explored the role of the thumb in the manipulation operations. As the thumb is decidedly crucial for manipulation skils of the human hand; we decided to develop a thumb endowed robotic hand prototype that is capable of reorienting objects under power grasping conditions.

5.3.2 Tactile Sensing

Tactile sensing proved to be essential and indispensable for the intelligent control and manipulation [228]. The robotic hand used in this chapter employs tactile sensor modules mounted on the finger phalanges. Accurate robotic hand tasks require precise finger movement and sensing [193]. With tactile feedback and information, the objects pose can be inferred using statistical and intelligent techniques [187, 210]. Our prototype uses a multimodal tactile module fixed on finger phalanges providing information about the objects position and orientation in space. Real-time information obtained by the tactile modules is used to maintain a stable grasp and as input to machine learning algorithms. Tactile data also are used for object identification after a single grasp classification ass seen in Chapter 3. In this way, we could investigate the simultaneous exploration of pose and object orientation.

5.3.3 Fuzzy Stable Grasping

This chapter also uses fuzzy logic to address the grasping problem to reduce grasping uncertainties and avoid complex mathematical solutions involved in task [15]. Using tactile sensing and fuzzy control to deal with unknown friction and mass of an object was developed in [16]. Input displacement investigations on [14] ended up with a neuro-fuzzy strategy of a compliant two-fingered gripper with embedded sensors. The present work implemented a similar concept but for a multi-fingered gripper embedded with a force-sensitive sensor.

5.3.4 Teleoperation

As mentioned in the previous chapter, the human operator is still necessary in several situations. The role of human supervision on intelligent-control as a reasoning module is discussed in [87]. It provides autonomy, flexibility, and fault-tolerance. In this chapter, the human-operator provides valuable data for machine learning algorithms, and teleoperation for data collection of manipulation tasks as presented in the literature [229] The teleoperation for assisted grasping in this chapter is similar to a shared grasping strategy [230]. Distinctly, it focuses on thumb skill integration in the fuzzy control grasping task and tactile sensing data collection. Data collected from a teleoperation setup during in-hand rotation tasks are used to object angle estimation and object recognition.

5.4 Experimental Setup

The robotic hand presented here is based on the gripper presented on Chapter 3 integrated with a fully actuated 3 Degrees of freedom (DOF) thumb. Based on the premise that a person needs (without external forces) three fingers to execute in-hand manipulations, a prototype was built with two fingers for stable grasping and a third one to change the object's orientation.

The prototype developed has modular underactuated fingers in addition to a fully

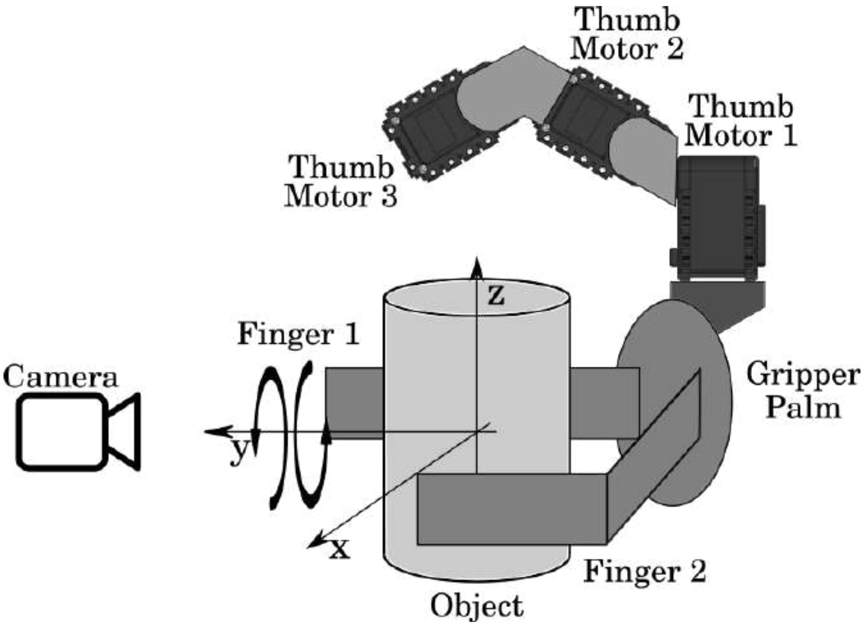

Figure 5.1: Hand prototype overview (top), flexible finger movement and range of motion (a-d).

actuated thumb which facilitate grasping operations for further in-hand manipulations. Figure 5.1 shows the schematic where a camera placed in front of the hand visualize the object being rotated by the y axis in both directions by the fully actuated thumb.

The hand shown in Figure 5.2 consists of a 3D-printed modular gripper based on the open- source design from [192]. The underactuated robotic fingers have intermediate and distal flexible joints made of Vitaflex®. Strings are attached to the tip phalanges, with distinct motors configured for torque control pulling each finger.

The top row of Figure 5.2 how the complete hand with the thumb and its actuators. The left picture shows the tactile sensor modules placement on the fingers, the flexible joints and the actuator assembly. The right image shows the motor base with one pulley (orange) mounted. The bottom row of Figure 5.2 shows one finger movement and range of motion.

Figure 5.3 shows a series of thumb motions. The thumb has 3 degrees of freedom shown by the red arrows on Figure 5.3. Analogously to the human hand, the images (a) to (d) in Figure 5.3 shows the distal-proximal and proximal-metacarpal joints of the thumb, while

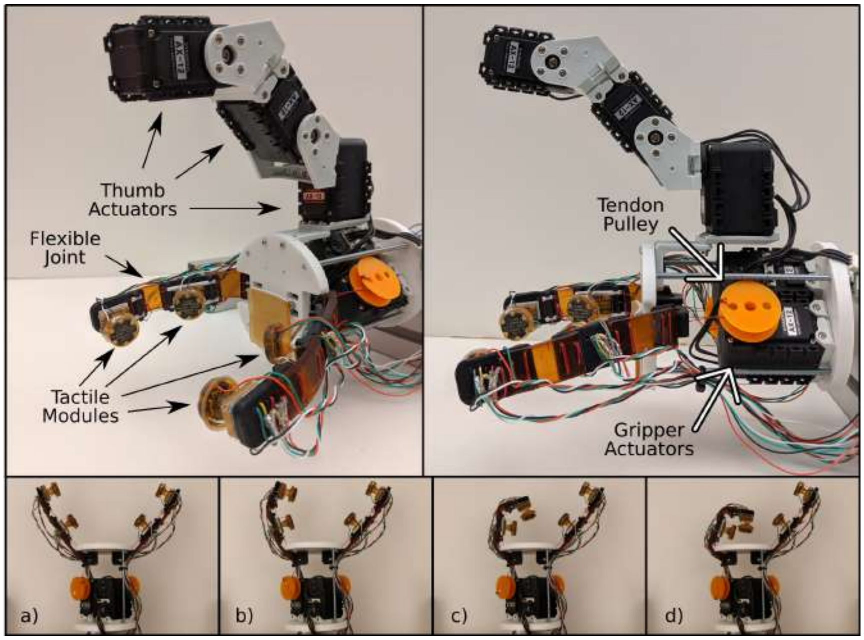

Figure 5.2: Hand prototype overview (top), flexible finger movement and range of motion (a-d).

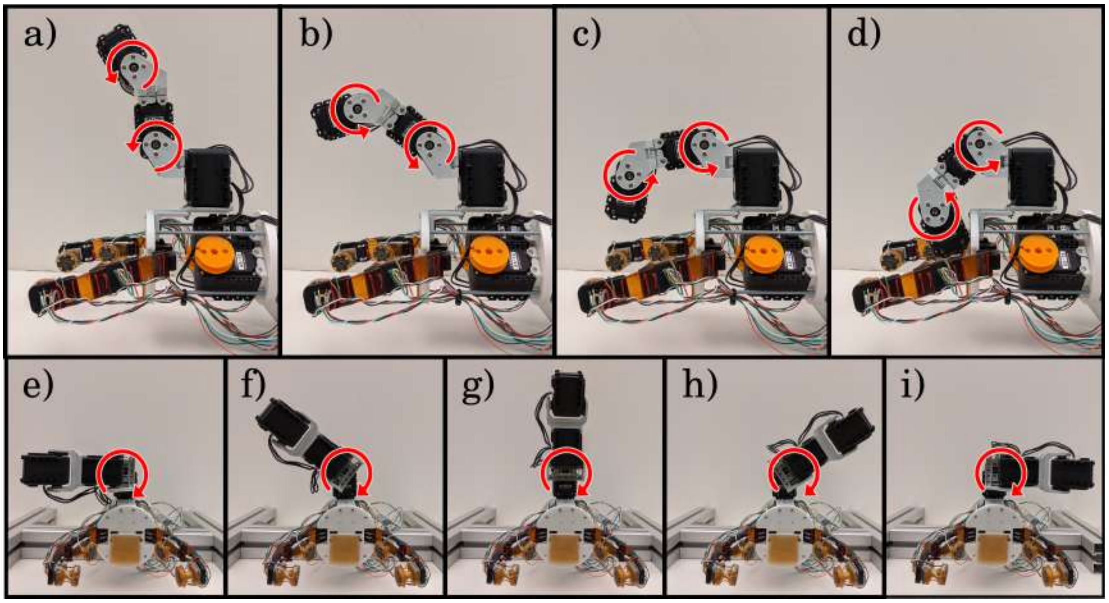

Figure 5.3: Thumb placement and degrees of freedom (a-i).

images (e) to (i) display movements of the the metacarpal-wrist joint.

5.4.1 System Organization

The hand fingers have two tactile sensor modules mounted on distal and proximal phalanges each. They are multimodal tactile sensors [184] emulating the functionality and placement of the mechanoreceptors in the human skin.

The multimodal sensor modules are similar with one used in the previous two chapters. The module, described in Figure 3.2, contains a compliant cone-like structure (2), which supports a MARG inertial sensor system (1). The cone also guides forces acting on the module's surface to the pressure sensor localized on the bottom of the structure (3). The inertial measurement data provide information about the deformation of the artificial skin when pressure is applied As shown in Figure5.2, each finger phalange has two tactile modules mounted on it. The tactile modules structure and material used enhance the fingers ability to hold objects.

As shown in the block diagram in Figure 5.4, the control system has two multiplexers connecting four deep pressure sensors and four MARG systems to distinct micro-controllers. A master *ROS* node running on the central computer does tactile sensor data collection and storage.

Figure 5.4 also shows the teleoperation connection from the *Leap Motion* sensor to the motors. Another aspect in this setup is that for the object recognition experiments, kinematic information recorded in *ROS* "bags" is used to playback thumb motor information for in-hand manipulation tests. Figure 5.4 shows a playback connection from the rosbag module to the motor states. *ROS* "bags" stored in the main computer also provide data for machine learning algorithms used for object classification and pose estimation.

5.4.2 Teleoperation

A *Leap Motion* sensor captures human operators thumb motions, providing kinematic information to be used by the control interface of the robotic thumb. All information was collected based on a fixed frame at the center of the sensor shown in Figure5.5 (left). Figure 5.5 (right) shows the operator's finger joint angles used by the teleoperation system

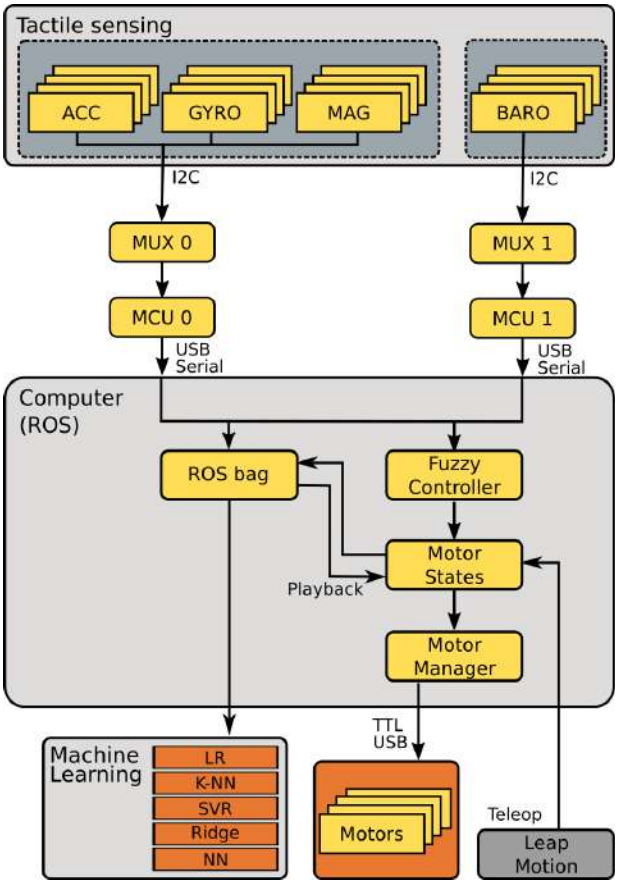

Figure 5.4: System overview with connections and data-driven approach.

to send signals for the motors to perform object rotations. The teleoperation system uses angles $\theta1$, $\theta2$, and $\theta3$ from the distal, intermediate joints and the angle between the thumb fingertip and palm, respectively.

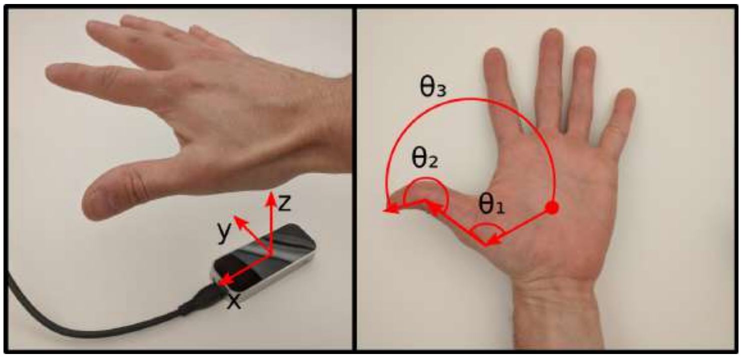

Figure 5.5: The *Leap Motion* frame of reference and operator's hand joints.

Simple linear mapping solves the angle $\theta1$ and $\theta2$ from the operator's hand to the robotic thumb. Due to the absence of direct translation from the human hand to the thumb 0 actuator, when the operator inverts the hand position across the z-axis (when the palm faces upwards), the teleoperation control promotes a signal inversion of the motor. This choice maximizes the robotic thumb's workspace during in hand teleoperation.

5.4.3 Fuzzy Controller

Similarly with the previous two chapters, 3 and 4, this chapter also used a fuzzy controller as illustrated in the diagram shown in Figure 5.6.Differently from previous chapters, this case includes teleoperation which is shown in Figure 5.6. A double fuzzy controller in the left side of Fig 5.6 presents the two module input for force and micro-vibrations that make decisions about stability and grasping status. A second grasping fuzzy controller uses that information to decide motor controls.

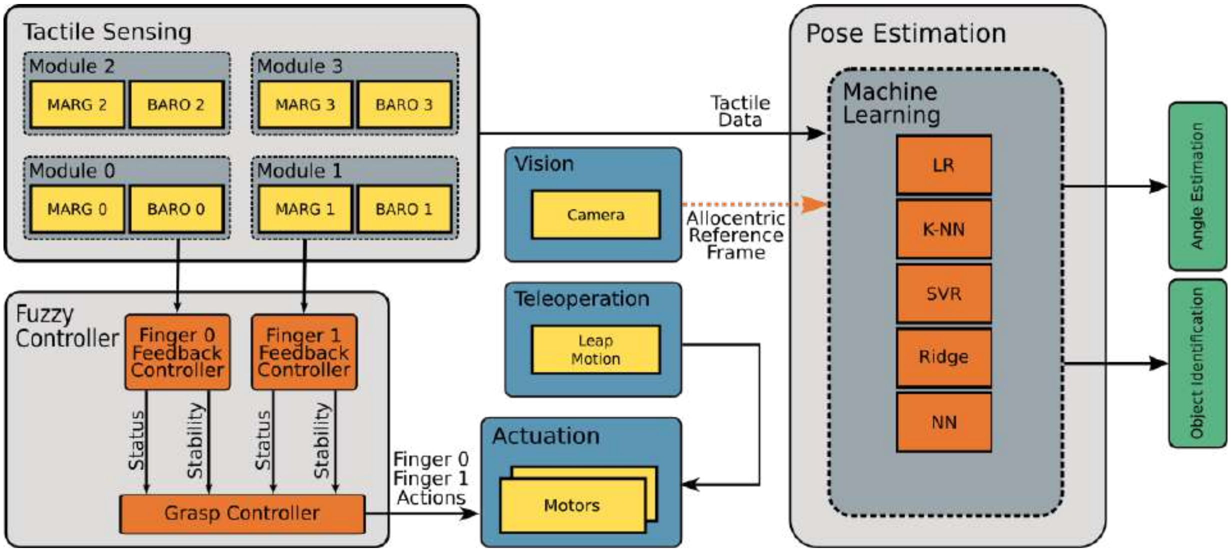

Figure 5.6: System overview with fuzzy controller, actuators, vision, teleoperation and machine learning modules.

Figure 5.6 also shows the vision and teleoperation connections in addition to a dual machine learning system. The former provides an allocentric frame of reference for the tactile estimation of object pose. The later includes remote actions for the in-hand manipulation tactile sensing system aiming to improve object recognition after grasping. A full description of the nodes and connections developed for this thesis can be found in Figure A.1 presented in Appendix A.

5.5 Experimental Results

This section presents the results of two in-hand manipulation experiments on pose estimation and on object identification using machine learning algorithms. The first experiment used the telemanipulation system presented in Section 5.4 to provide the needed rotation of the grasped object for pose estimations during a stable grasp. The second experiment used exploration in the same axis of the first experiment in order to evaluate object identification during post-grasp exploration during recorded thumb movements. The human somatosensory system reduces the processing costs by simultaneously extracting different characteristics from objects under manipulation, which inspired this investigation. During all operations, a dual fuzzy controller performs an autonomously maintained stable grasp.

5.5.1 Pose Estimation During Telemanipulation

This section presents an experiment that expands on previous chapter results and explores pose estimation related to a perpendicular axis to the first approach. While the experiments found in Chapter 4 estimate angle related to an axis parallel to the hand's palm, this section uses similar techniques to estimate a perpendicular axis. This section uses the telemanipulation of the robotic thumb for object exploration. Machine learning algorithms use images to track the changes in objects pose. Fig 5.7 shows the experimental setup used for this section.

Circle A shows the *Leap Motion* sensor's position with the operator's hand (circle E) right above it. Circle B shows the video camera directly in front of the object under manipulation (circle C). The circle C also shows the marker used to provide the object's angle in the allocentric frame of the camera. Circle F shows the robotic thumb behind the object at a rest position waiting for the operator's commands.

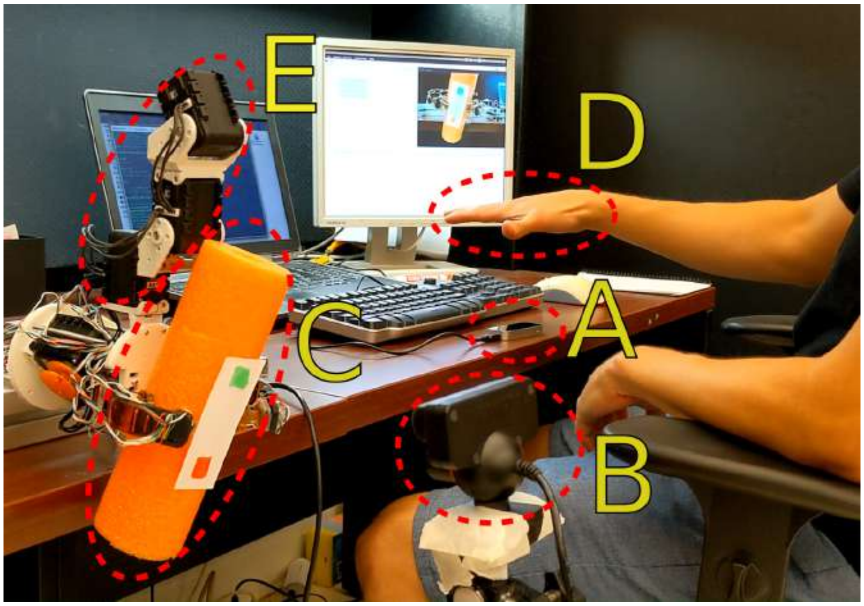

Figure 5.7: Teleoperation experiments overview.

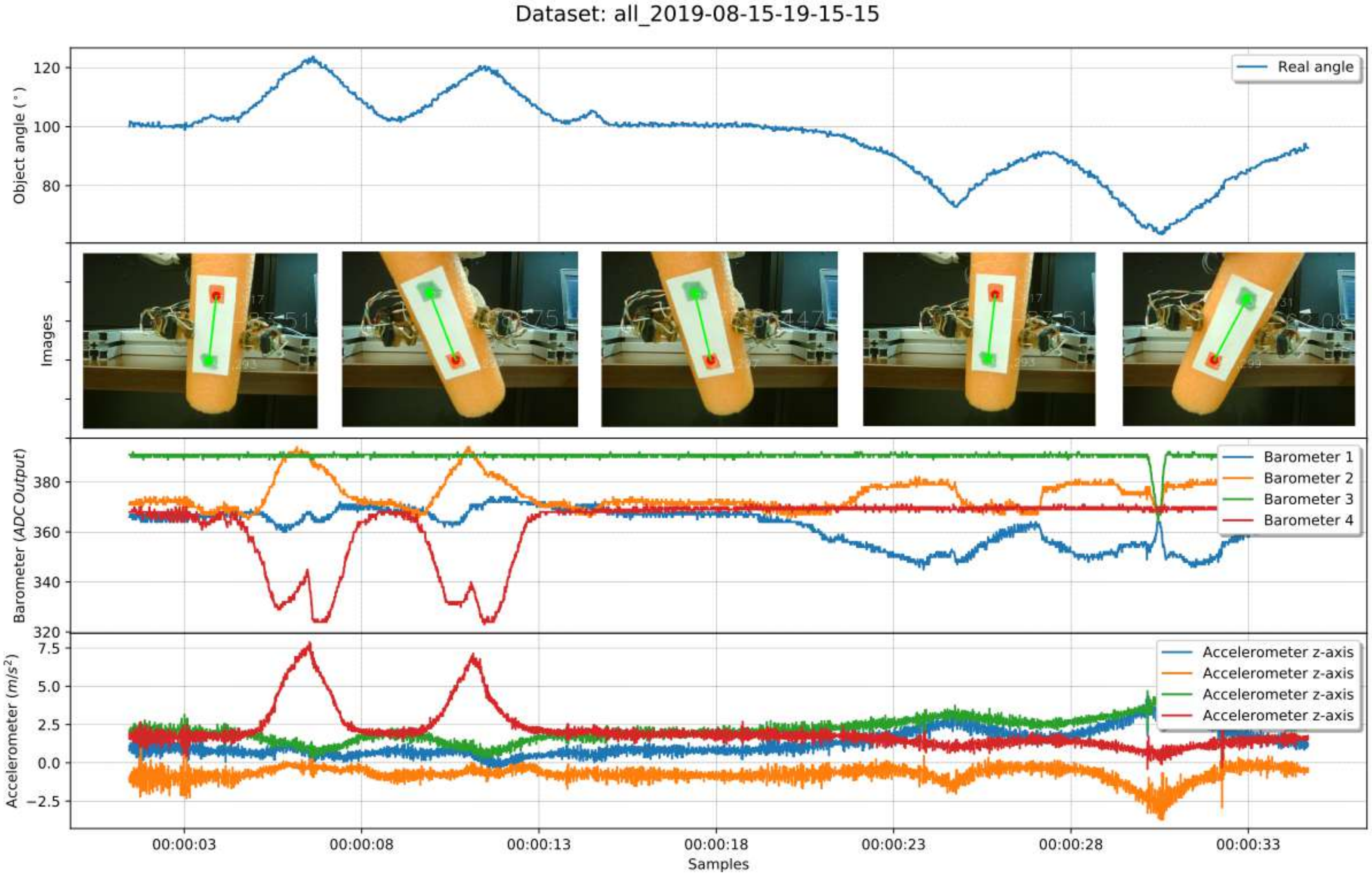

Figure 5.8: Example of data collected during teleoperation experiments.

Figure 5.8 shows one example of data collected during the telemanipulation experiment. The first row of shows the disturbance on object angle detected by the camera and further used to teach the pose variations on sensor data. The second row shows camera images of the object under stable grasping with the marker detection. The following rows of Figure 5.8 shows pressure and accelerometer (z-axis) data during object exploration.

Exploratory Feature Investigation

This section investigates which features of the sensor fits best the problem of pose estimation. During the experiment, the robotic hand holds a medium-sized object in a stable grasping. The same dual fuzzy controller as the one used in Chapter 4 is now used to for autonomous grasping control. After reaching a stable grasping position, the teleoperator executes two rotations (clockwise and counterclockwise) using the *Leap Motion* controlled robotic thumb.

Post-processing also provides a platform to evaluate different machine learning algorithms. The Table 5.1 presents the best results for all 31 combinations of sensor features possible.In total, the experiments provided 279 results evaluated here using r^2 score.

Table 5.1: Feature comparison during telemanipulation experiments on object angle estimation.

Model	Best features	Best r^2	Worst features	Worst r^2
MLPR	acc - motors - mag	0.916364	motors	-6.85777
RIDGECV	acc - mag	0.892338	gyro - motors	-8.00433
RIDGE	acc - mag	0.892333	gyro - motors	-8.00572
LR	acc - mag	0.892327	gyro - motors	-8.0058
KNN	acc - mag	0.766531	motors	-6.00931

The Table 5.1 are ordered in descending order of best r2 score. The first row shows the multi-layer perceptron results with $r^2 = 0.916364$ when using only data from accelerometer, motors and magnetometer. The worst results for the MLP is when machine learning is presented only with motor data. Other best results from the machine learning algorithms show that the accelerometer, in addition to the magnetometer, presents the best results in all machine learning algorithms. Motor data alone or in some cases, in addition to gyroscopic data provided the worst results on the algorithms studied.

Figure 5.9 shows MLP regressor's best results. The Figure 5.9 presents the estimated angle in orange following the real angle in blue. The plotted results confirm that accelerometer data in combination with other sensor data provided the best results.

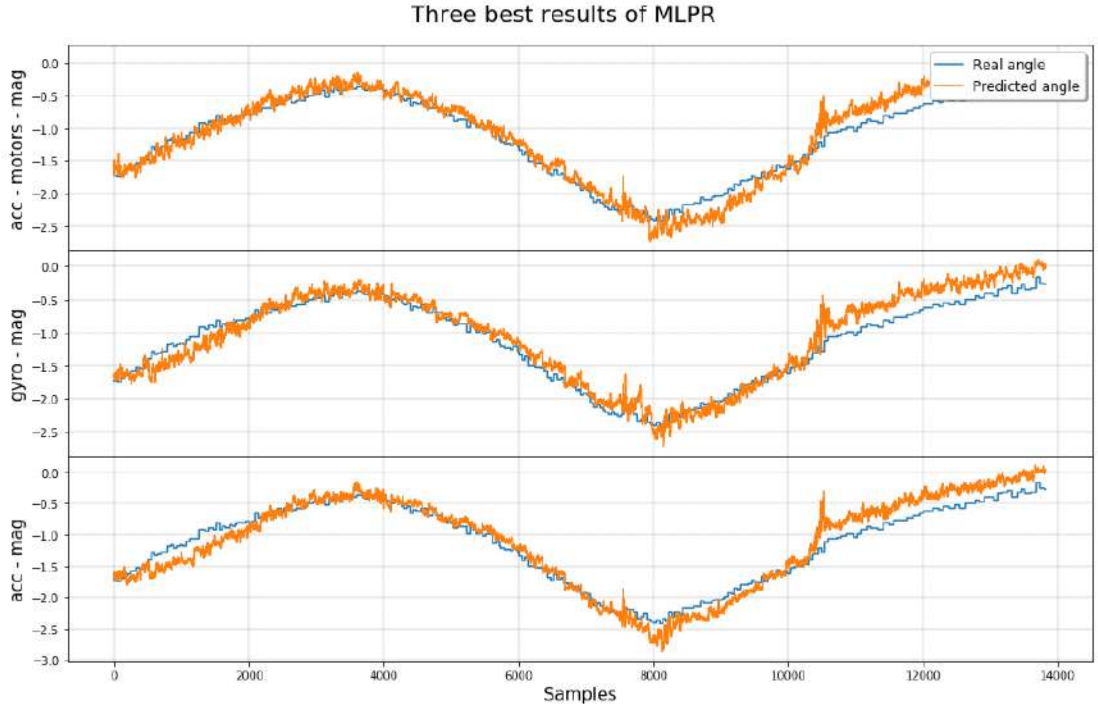

Figure 5.9: MLP regressor results under telemanipulation experiments.

5.5.2 Object Identification During Robotic Exploratory Manipulation

This section presents a second experiment of exploratory in-hand manipulation. During this experiment, different machine learning algorithms are compared when useing tactile sensing data gathered during the exploratory robotic manipulation in order to recognize the manipulated object. Similarly as done in Section 5.5.1 a prerecorded thumb movements is used explore seven different objects.

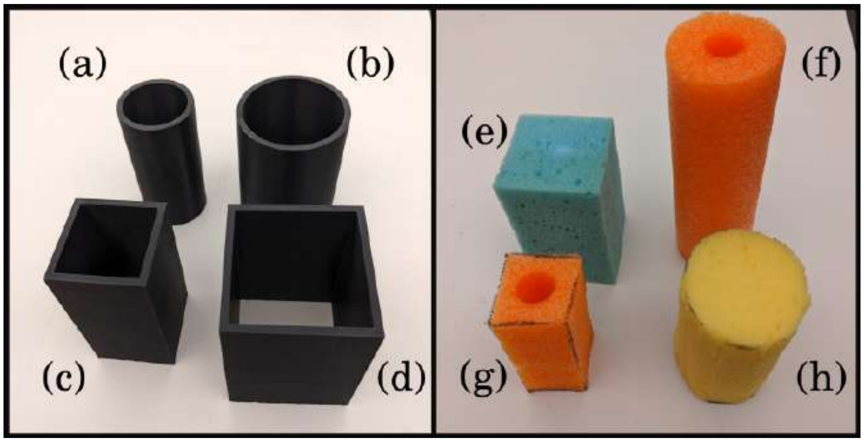

Figure 5.10: Object set used on this experiments.

Figure 5.10 show the object set used for this experiment. The left image shows 3D printed rectangular and cylindrical PLA objects used (a, b, c and d) in versions 50 mm and 70 mm, (squared sides, cylinder diameters). In a different approach of chapter 3 , we also included in this case soft materials in addition to the the 3D printed objects based on [26], but having the same sizes (the objects e, g and h), while the object f is only used in the previous section.

Expanded the idea from 3 where the machine learning algorithms only use points in the start and end of the grasping attempt to test the concept of “haptic glance”, in this case if a first classification is not possible an exploratory procedure has the potential to increase the object recognition chance through a more thorough object exploration.

To investigate the use of exploratory procedures, the input data used in this section contain ten points in the objects trajectory. Figure 5.11 shows the data points used for this task.

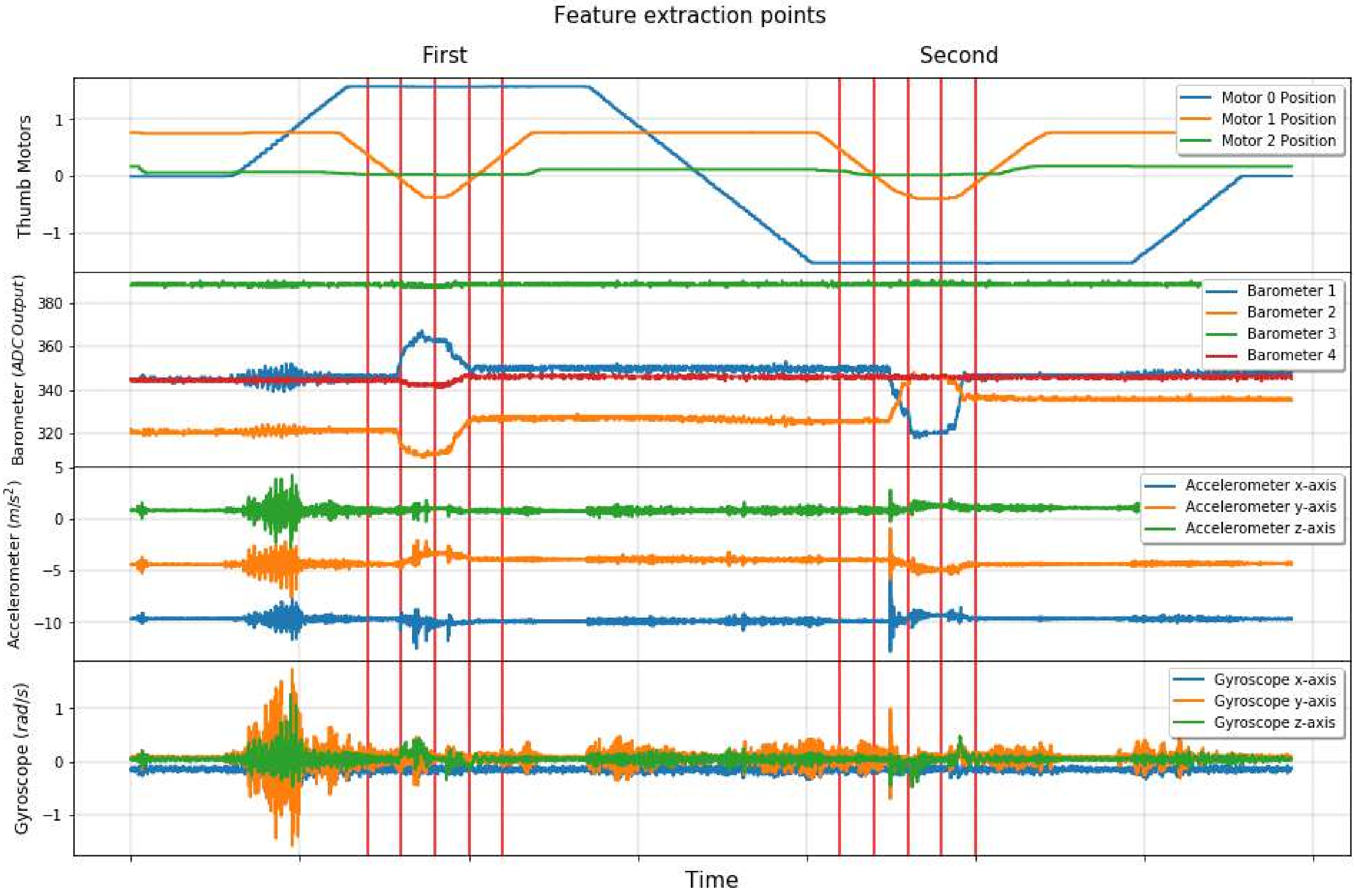

Figure 5.11: Data points used for object classification.

In Figure 5.11, the red lines indicate the ten points used for classification. The first row shows thumb motor positions during the exploration procedure. Pressure, accelerometer and gyroscope sensor data are presented in the second, third and last rows, respectively. In total, the dataset contains thirty trajectory repetitions for each object.

Table 5.2: Score mean and standard deviation for machine learning algorithms in object classification.

Model	Score mean	Score std
Random Forest	0.988571	0.0146308
Extra Trees	0.985714	0.019749
Ridge	0.968571	0.0251255
K-NN	0.887619	0.0169299
MLP	0.83619	0.0431839

Table 5.2 presents results of correct classification by five different machine learning algorithms using 70% of the repetitions for training and 30% for testing. Table 5.2 is ordered in the descending order of the average of scores for classifications of a 10 fold cross validation. The table also include the standard deviation for each of the five machine learning algorithms tested.

Figure 5.12 shows the confusion table for the Random Forest Classifier that used 100 estimators and a max depth of 30. The Ridge Classifier started with alpha of 40.0. The Extra-Trees Classifier used 50 estimators without depth. K-Neighbors Classifier used k equals to 5. Finally, Multi-layer Perceptron Classifier used two hidden layers of 100 each. The Random Forest Classifier was the best with 0.988571 average correct classification, while the Multi-layer perceptron was the worst average with 0.83619 average score.

5.6 Discussion

This chapter presented the experimental setup and results of a three-fingered robotic hand performing pose estimation and object classification. Based on complex somatosensory

Figure 5.12: Confusion matrix for Random Forest results during object classification.

processes involved in the in-hand manipulation, the humans are able to detect several characteristic using exploration and gathering redundant information for a fast and cost efficient manipulation.

In this chapter we discussed two experiments covering angle estimation and object classification using a similar trajectory and object rotation. Machine learning algorithms were able to classify and estimate object angle variations during stable grasping. Tactile sensor data from bio-inspired modules provided information about the pressure and inertial movements of the object which were then used by machine learning algorithms.

On the first experiments where the robotic thumb was teleoperated, the Multi-Layer Perceptron using accelerometers, motors and magnetometer data achieved a 0.916364 r^2 score. On the second experiment, where a trajectory executed explorations on the object, the Random Forest classificator achieved a 0.988571 average of correct results.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

There are a wide range of approaches to the development of practical applications of tactile sensing to the in-hand manipulation problems, especially the development of new sensing devices and tactile data interpretation techniques.

This thesis focuses on the application of bio-inspired tactile sensors to in-hand manipulation in order to solve problems commonly encountered in practice, such as object identification and pose estimation, using the human somatosensory system as a source of inspiration [25].

Multi-modal tactile object identification and pose estimation under autonomous stable grasping was possible following a bio-inspired approach based on the understanding of the somatosensory system and its subdivisions in human intelligent control and perception. These “What” and “Where” subsystems were used as inspiration for the development of a tactile object identification solution in addition to the visuotactile pose estimation,. They were also used as inspiration for after grasping object pose estimation combining visual and tactile sensing information. A visuotactile approach was used to reduce the uncertainty of recovering the orientation of the manipulated objects. Two sets of experiments achieved accurate angle estimation using tactile data under external forces and in-hand manipulation.

External stimuli promote learning of some representations between tactile sensing inputs an object poses, which sometimes are not achieved by a robot's finger workspace. After an initial visual exploration, angle change estimation uses tactile data from bio-inspired sensor modules.

This thesis also discusses object identification using tactile sensing data. Human perception concepts of "haptic glance," and the presence of a "What" pathway system were used to improve robotic in-hand manipulation during the early phases of manipulation. A robotic gripper could use object recognition while grasping unknown objects, which is a behaviour similar to that shown by humans. We evaluated a new approach for non-exploratory object classification during early-phases of robotic manipulation. Results confirm that it is possible to use multi-modal tactile-sensor enabled underactuated hands in addition to multi-modal tactile data for single grasping object recognition.

Humans are also able to detect several object characteristics collecting redundant information for a fast and cost-efficient manipulation. Following this human-based approach, we conducted two experiments covering the angle estimation and object classification. We used machine learning algorithms which were able to recognize and estimate object angle variations during the in-hand exploratory procedures. Pressure and inertial sensor data collected during the object manipulation provided the information used by the machine learning algorithms.

Our most recent improvements published in [39], are the result of an incremental development previously published in [21, 1, 36, 37]. The prototype developed, as well as the machine learning results, are suitable for in-hand manipulation in structured and unstructured settings. The system developed can be used for object identification and pose estimation during in-hand autonomous grasp tasks. The experiments used a fuzzy controller stable grasping system. The research also incorporates compliant bio-inspired multi-modal sensing on the feedback loop of the fuzzy system. This development is essential to reduce the gap between intelligent robotic control and human perception to action for tactile data interpretation techniques.

This thesis does not claim for the total substitution of fully actuated hands or several other types of object sensing. The findings on this thesis are an addition to such systems, serving as an alternative when using underactuated fingers and when video camera and tactile sensors are available for in-hand object manipulation operations.

6.2 Future Work

This thesis is part of the ongoing research program carried out in the Biology Inspired Robotics Lab at the University of Ottawa, aiming to contribute scientific knowledge and technological innovation to the development of a new generation of intelligent robots with advanced, human-like, tactile perception capabilities, enabling them to perform complex in-hand telemanipulation operations under poor or nonexistent visibility conditions.

The results presented in this thesis aim to bridge the gap between the conventional and the intelligent robotic in-hand manipulation using underactuated hands. Such achievements could be possible only by getting inspiration from the human somatosensory system operation for the development of new grasped-object recognition and pose estimation techniques.

Many opportunities remain open, in terms of applications as well as in the integration into robotic platforms. The methods developed here can start to being investigated in anthropomorphic robotics, which will enable it in prosthetics. The advantages of intelligent integration of robotic prostheses and tactile sensing are limitless.

Future research should focus on integration with the system in real-time object recognition and pose estimation. Robots that achieve a reasonable level of dexterity using the allocation of attention will improve the efficiency of the use of its resources to perform a broader range of tasks in unstructured environments.

Future improvements may also include adapting tactile sensing to an anthropomorphic hand. A five-finger approach using similar tactile data and fuzzy sets could adapt our dual fuzzy controller. This work is already ongoing in our lab by a subsequent group of researchers.

APPENDICES

Appendix A

Distributed System Nodes

This appendix shows a ROS graph with all nodes running during telemanipulation tests. Figure A.1 in the next page shows: Motor modules (dynamixel_controller), Leapmotion (LeapSDK), Camera (obj_angle), fuzzy (baro_fuzzy_control_dynamixel) and sensors (baros_node and imus_node). Some extra nodes are pre-processing and demultiplexer nodes.

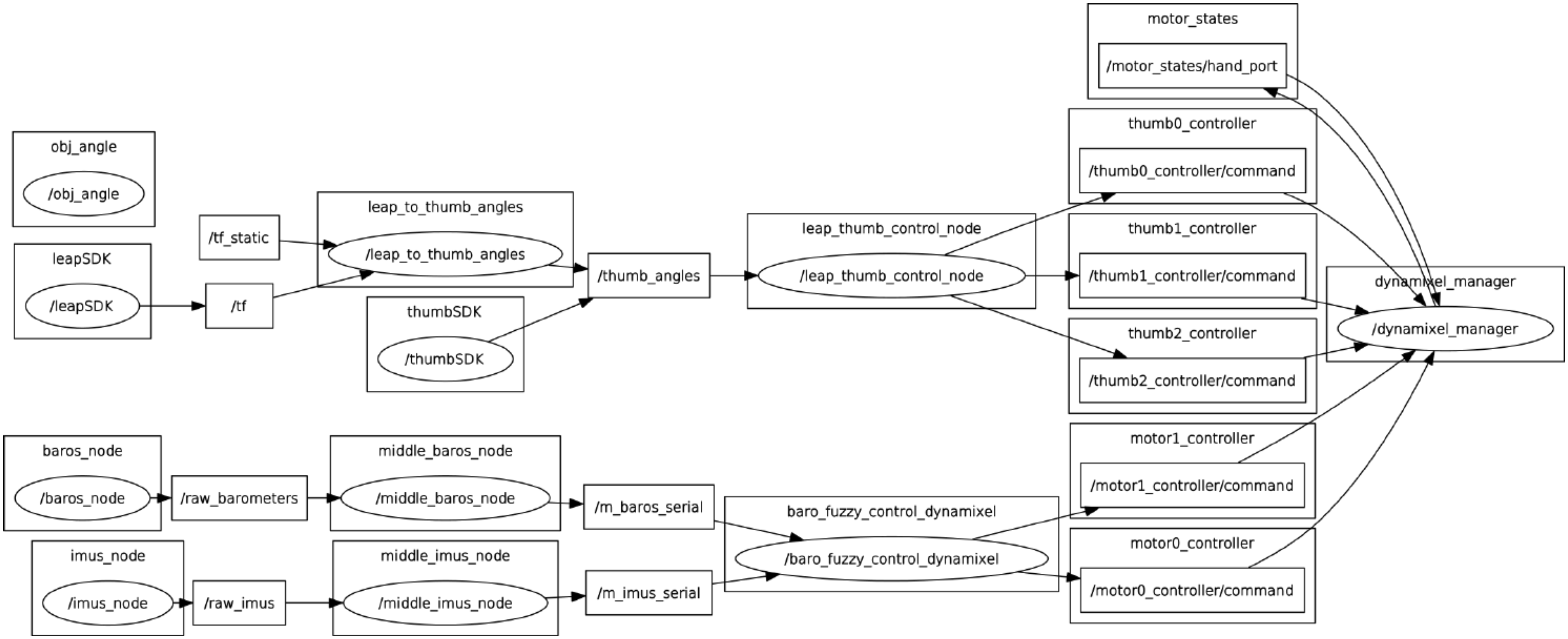

Figure A.1: All nodes developed for the ROS distributed system

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