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SUPERVISED LEARNING FOR HAPTICS TEXTURE CLASSIFICATION USING FOURIER ANALYSIS

THESIS

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE ACADEMIC DEGREE OF:

MASTER OF SCIENCE WITH SPECIALITY IN INTELLIGENT SYSTEMS

BY

GERARDO ALBERTO HIDALGO VAZQUEZ

MONTERREY, N. L. DECEMBER 2011

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To my parents

Acknowledgements

Two years ago I could not believe that today i will be completing my M.Sc. Firstly, I want to thank my parents, brother and sister for offered me unconditional support during the course of my undergraduate and graduate studies and constantly reminding me what really matters in life, even in my own moments of doubt when I needed to get back in track. My deepest thanks to God for being next to me every day.

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Supervised Learning for Haptics Texture Classification using Fourier Analysis

Gerardo Alberto Hidalgo Vázquez, M.Sc.
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Human sense of touch is used to explore the environment that surrounds us, and to identify and learn about objects through the surface properties. In the design of a robotic system that is able to analyze and identify textures, it is essential to understand the perceptual factors of the human sense of touch, which presents a significant challenge in control, sensing and learning. However, recent developments in haptic sensing have made it possible to explore surface textures and classify them through a learning algorithm.

This thesis investigates the use of *Haptic feedback* as an approach to improve and classify surface textures by a robotic system. A review of haptic interactions indicated that haptic information provided by the sense of touch, are used successfully to convey important data of the surface texture properties.

Haptic feedback, expressed through the kinesthetic measurements of the surface waveform that arises when prescribing a predefined motion over the surface texture, was collected from four cardboard samples with different surface properties. The motion trajectory traced by the spherical probe shows some intrinsic properties that facilitate the data extraction and that reproduce the way humans identify the texture of a surface. Features were extracted from this data through frequency spectrum by Fourier analysis and used for training and classification by a supervised *k-NN* machine learning algorithm.

The results from this work, obtained in a controlled environment test rig, shows that the algorithm could correctly classify 100% of the surface texture samples and confirm that the information provided by the haptic sense has the potential to improve the performance of many activities that require surface texture classification.

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Chapter 1

Introduction

In robotics, the sense of "touch" is not well understood by the majority of people, including those who specialize in this area of research. According to Salisbury et al. [7], in the early 20th century, the word *Haptics* (from the Greek *haptesthai*, meaning to touch) was introduced to label the subfield of studies that addressed human touch-based perception and manipulation.

Further research in the field of robotics focused on the manipulation and perception of touch (See section 2.4.2). At the beginning concerned with the development of autonomous robots, researchers such as Okamura et al. [8], Johnsson et al. [9], Payeur et al. [10], and Natale et al. [11] soon found out that the development of robots with a sense of touch similar to that of humans, was more complex than their initial thoughts suggested. This complexity is understood by the researcher and describes the haptic sense in terms of forces, friction and frequency. The Haptic sense, however, is much more complicated and detailed than the aforementioned explanation.

Salisbury defines *Haptics* as the "touch interactions (physical contact) that occur for the purpose of perception or manipulation of objects. These interactions can be between a human hand and a real object; a robot end-effector and a real object; a human hand and a simulated object (via haptic interface devices); or a variety of combinations of human and machine interactions with real, remote, or virtual objects" [7].

Citing Aristotle, "if touch is not a single perception, but many instead, its purposes are also manifold" [12]. Hence it is noted that its versatility describes the functionality and complexity of the structure contained in the sense of touch.

Thus, subsequent research was divided into a variety of disciplines that have been focused on different aspects of the haptic sense, however for formal methods the investigation will be focused in two directions: (i) the development of robotic hands and (ii) the creation of devices that enable users to be able to get the feeling of touch while manipulating objects. Development in these areas led to the creation of another subspecialization of computer science called "computer haptics" [7].

Srinivasan and Basdogan [13] describe computer haptics as a science that displays simulated objects to humans in an interactive manner. Computer haptics uses a display technology through which objects can be touched and palpated. One of the major advantages in a user-haptic interaction is that the flow of information and energy is a two way process between the user and the device. Incorporating the haptic component into environments facilitates the tactile sensation and imparts a more realistic experience to the user.

Although Knoll demonstrated haptic interaction with simple virtual objects in the early 1960s [7], haptic interaction is nowadays possible due to the technological developments with complex computer simulated objects. Furthermore, Salisbury [7], and Srinivasan and Basdogan [13] stated that since 1990 there has been noteworthy progress in the potential to simulate haptic interactions with 3D virtual objects in real time.

Current research trends, in contrast with the construction of robotic hands and the overall implementation of the sense of touch for autonomous robots, requires a set of both cognitive and motor characteristics of human tactile perception. This work considers the combination of high-performance force-controllable haptic interfaces, computational techniques, cost-effective processing and memory, and an understanding of the perceptual needs of the human haptic system, and proposes a computer haptic system that can recognize and classify surface textures extracted not from the virtual environment, but from the real world.

Within the thesis, the aim of this work is to gather the textural properties that can be extracted from the tactile feedback through a simple exploration strategy performed by a haptic device. Textural properties that will construct a representation of the texture under study and classify it by analyzing differences on their patterns through the spectral analysis given by the discrete Fourier transform.

It is also important to mention the importance of texture sensing in robotics, since it provides physical properties such as surface roughness, hardness, softness and orientation that cannot be acquired by other senses, e.g. sight.

According to Zhou [14], textures can be divided into two categories, tactile and visual. While tactile textures refer to the immediate tangible feel of a surface, the visual textures refer to the discernible impression that textures produce on the human observer.

This thesis focuses only on tactile textures, henceforth the term "texture" is referred to tactile texture, i.e. those surfaces which can be extracted through the sense of touch. Also, whereas the primary goal of the haptic system is recognition and texture classification based on surface properties, it also seeks to provide a deeper insight into human perception of textures.

1.1 Motivation

According to Grunwald [12], the sense of touch is *sine qua non* for thought, action, and consciousness. In view of this fascinating thought, it is worth mentioning that no other sense exhibits properties that allow awareness of the surrounding and ourselves to the same degree as our ability to touch. Given the technological developments in recent decades, it is possible to study this field of knowledge.

As said before, the haptic sense is gaining importance within the academic community, and this can be noted through the increasing number of publications in recent years, and the development of new devices that allow a better understanding of haptic research. At this point, it is obvious the reason about why the sense of touch is vital and why the interest of this thesis to seek and study the human sense as a channel for information acquisition.

In addition, the recent developments in force feedback devices that enable users to touch and feel objects have given rise to not only see objects, but also to feel the tactile sensation of those objects, and let one to obtain information like the sense of human touch. In this context, it becomes necessary to understand how this technology could be used to extract the textural information of a given surface to recognize and classify it.

Nevertheless, despite the wide variety of projects in industry and academics, few have been focused on the development of a robotic system with the sense of touch that is able to acquire information from its surrounding environment and generate a decision based on the analyzed objects.

As described above, the particular interest of human haptic perception in robotic systems results from the need to provide the robots with the sense of touch that allows humans to perform many tasks in their natural environment when combined with senses such as sight and hearing.

Current research on artificial perception has focused on texture analysis by vision systems. Considering the perspective of how human vision allows us to analyze the textured world surrounding us, without emphasizing the natural way humans perceive surfaces that leaves a detrimental void in the study of the human condition.

Within the context of this research work, we ask ourselves "Do we find similarity between two textures using touch or vision?" It can be mentioned that the visual texture classification is a widely-researched topic in image analysis, however, little is known of its counterpart, i.e. the haptic texture classification. Also, surface texture is among the most important haptic characteristic of objects, which helps in object identification.

On the other hand, integration of haptic sensors appears to be a very promising approach in the development of autonomous robotic systems because it reproduces the multiplicity of sensing sources used by humans.

Also, it is indeed natural for humans to touch objects in order to get a more precise idea of their shape and texture when visual perception does not provide enough information, like in dark environments.

Finally, this work is aimed to tackle the need for haptic perception in robotic systems. Particularly on service robots, where careful and precise handling of objects is required, in order to make-decisions similar to the way a person will do it.

1.2 Problem Definition

Despite the valuable work done in recent years by the research community in the field of haptic-related technologies, many problems still prevent wide spreading of haptic enabled applications and devices. Surprisingly enough, one of these problems is the access to haptic devices for software developers [15]. In the same context, it would seem that as the computing technology progresses, so would the number of haptic algorithms examined and created.

Given these considerations, we must ask why there is so little research in a field that can change the way a running computer system is able to provide a realistic sensation of touch to a robot. There are many possible approaches to answering this question, but the two main reasons are: (i) good and cheap quality haptic technology is not widely available, and (ii) knowledge on the use of this technology is limited.

Further exploration into the sense of touch is imperative in order to maximize the potential of humanoid robots ability that unlike all other senses is not directly connected to any organ.

Note that the sense of touch specializes not only on the perceptions of the boundaries of the body, but on the analysis of surface properties as well. These properties serve as a way to discriminate against all structures and provide a unique and unparalleled ability to differentiate among the acquired information.

Consequently, the sense of touch allows the discrimination of surface properties and structures, process in which humans have developed a very common but effective way to interact with the surfaces, enabling the ability to draw conclusions based on this mechanism. This method consists of moving the finger along the surface (Lateral motion, See Fig. 1.1), allowing shear-forces to interact with the skin, and will be the starting point for solving the problem proposed in the development of this thesis.

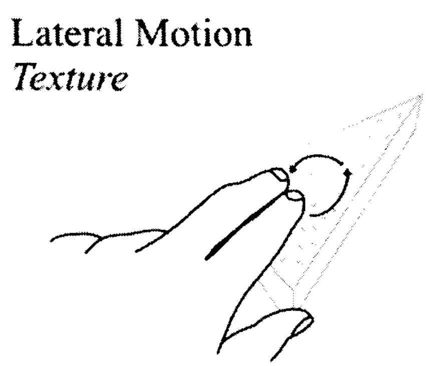


Figure 1.1: Klatzky and Lederman exploratory procedure to determine texture. Adapted from [1].

To address these challenges, this document examines the haptic texture classification in order to investigate how well it could be used to extract information that allow us to generate a descriptor that recognizes and classifies a given texture, descriptor that will be the discrete Fourier transform coefficients.

Finally, this research tackles the problem of texture recognition and classification using a robotic haptic system, which will calculate the required information based on the real world measured data.

1.3 Hypothesis

A haptic texture recognition system will provide the robots the ability to recognize and classify textures. Feature extraction will play an important role in the recognition and classification process. The effectiveness of such a process relies greatly on the choice of this feature and the motion pattern that will simulate the way that humans use to interact with the surface properties. In this case, a suitable extraction method will be used to achieve the goal.

In order to guide the development of the theoretical framework for solving the research problem and achieve the hypothesis described above, the following research questions have been identified:

- Can force feedback and motion be created through implementation of force models in the haptic device?
- What kind of haptic device will be used to implement the haptic system for surface texture classification?
- What kind of end-effector will be implemented on the haptic system to gather the surface texture properties?
- Will be suitable the use of the discrete Fourier transform as a feature for texture recognition and classification?
- How to compare the efficiency of the implemented haptic system for surface texture classification?

1.4 Objectives

As part of the research work, the following of objectives are set to demonstrate the veracity of the proposed hypothesis:

- Develop a prototype system for surface measurement and mapping. The development of an automatic haptic system capable of surface measurement will be a starting point to acquire the information necessary for the feature implementation. In order to achieve a full control of the system, its basic functionality has to be tested.
- Determine the appropriate design of the haptic system end-effector to allow the acquisition of the surface properties by mapping its waveform using the motion pattern performed by the system.
- Provide an approach for texture classification using Fourier coefficients as a suitable feature of a given surface and obtain parameters for its classification, feature that has to be able to differentiate between different surfaces textures.

Additionally, this methodology seeks to provide a first approach for texture classification by the sense of touch. Furthermore, this work proposes a robotic system that reproduces the way humans identify and characterizes the textured world that surrounds them.

1.5 Methodology

This section presents the required steps for the implementation of this proposal. Steps that will be needed to achieve the proposed objectives and will provide foundation for the next step.

1. Review the state of the art for texture classification to justify the proposed approach based on human tactile perception.
2. Select a proper haptic device that allows us to interact with the surface textures for purposes of implementing the robotic haptic system for texture classification.
3. Test and implement motions in the haptic device to validate its properties. Ensure that you can have precise control of the device.
4. Select the appropriate surface texture stimuli.

5. Test the end-effector interaction with the surfaces. Such test will be a starting point for making adjustments to the end-effector and ensure its proper operation.
6. Decide a motion path that allows us to generate a data map of the surface.
7. Select a classification algorithm that allows us to validate our approach.
8. Select the appropriate feature from the haptic feedback device information to use as input into the classification algorithm.
9. Test and implement the overall system automatically to prove that the results are conclusive.

This methodology seeks to prove that it is possible to recognize and classify textures through the haptic sense generated by a haptic device and feature extraction using a mathematical transform. Also, based on the experiment, it seeks to demonstrate similarities in the analysis of the same texture and differences between different textures.

1.6 Organization

The research thesis is divided into five chapters. Chapter one introduces the problem. In order to solve the problem the hypothesis and the research questions are presented and will become the foundations that support this thesis. Also, the objectives proposed and the methodology for solving the problem is presented. In the organization, a brief description of the following chapters is included.

Chapter two presents the state of the art related to this work. This chapter presents the theory concerning haptics, haptic systems, some commercial haptic devices, and describes the vision and haptic texture classification systems. Subsequently, emphasis is placed on pattern recognition, learning and classifying systems.

Chapter three presents the proposed methodology for the generation of the system that allows texture learning, detailing the use of the haptic device, sampling mechanism and the feature extraction for pattern recognition, classification, and the learning process.

Chapter four describes the tests and scenarios that were designed to evaluate the performance of the system and will discuss the results of the examination performed on the machinery. It is worth mentioning that the implementation of the proposed system is performed in a controlled environment.

Finally, conclusions are presented in Chapter five which summarizes and discusses the tests results. It also emphasizes the contributions made and determines the future work aimed at complementing the proposed system.

Chapter 2

Theoretical Background

This section presents the fundamentals concepts of haptic perception, vision and haptic systems for texture classification. These general concepts build a theoretical perspective for the further development of the technical part of this investigation. In the previous section a number of terminologies originating from the context of haptic science were introduced. In this chapter a systematic introduction into the state of the art will be presented.

2.1 Haptic perception

In the design of a robotic system that is able to analyze and identify textures, it is essential to understand the perceptual factors of the human sense of touch. Human tactile perception is used to explore the environment that surrounds us, and to identify and manipulate objects (See Fig. 2.1).While humans depend on the sense of touch to carry out many activities, the real potential of this interaction is undervalued. The sense of touch perception allows the discrimination of surfaces that come in contact with us, which is astounding considering that the properties of such surfaces range from smooth to rough. Note that these categories lead to an infinite number of intermediate ranges.

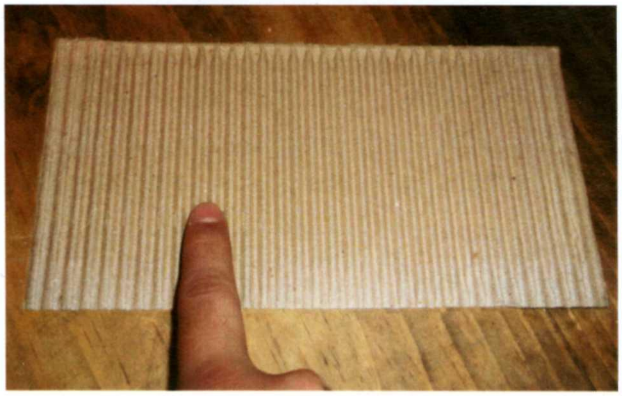


Figure 2.1: Illustration for the interaction of movements between the finger pad and a frictional surface.

Although the reader might believe that the sense of touch is only present in the skin, this is not the only system in the body capable of haptic perception. Klatzky and Lederman proposed three sensory systems within the sense of touch: (i) cutaneous, (ii) kinesthetic and (iii) haptic systems, based on the underlying neural inputs [16]. The cutaneous system receives inputs from the receptors embedded in the skin, the kinesthetic system employs receptors located within the muscles, tendons and joints while the haptic system is associated with active touch and uses combined inputs from both cutaneous and kinesthetic systems (See Fig. 2.2).

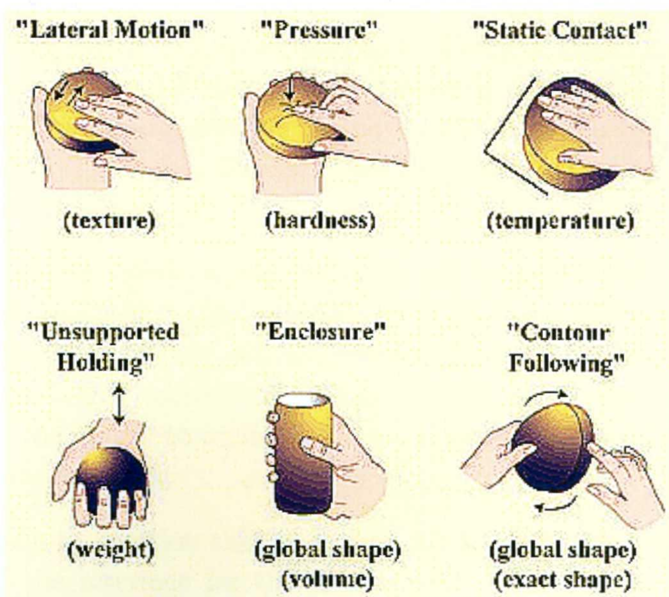


Figure 2.2: Exploratory procedures described by Lederman and Klatzky [2] and the object properties with which is associated.

In order to identify the difference between passive and active touch, the author proposes the example of the cutaneous tactile system. While the passive perception occurs between the movements of the fingertip in a static state with a moving surface, the active perception occurs between a static surface and the fingertip on motion. With this in mind, the overall difference between active and passive touch will be considered as the presence or absence of motor activity.

2.2 Haptic devices

At this point of the thesis, it has been insisted about the importance of the sense of touch for understanding the environment around us. With the increase in human-computer interactions, the use of force feedback haptic sensations to replicate a virtual environment through a haptic interface has been studied intensively.

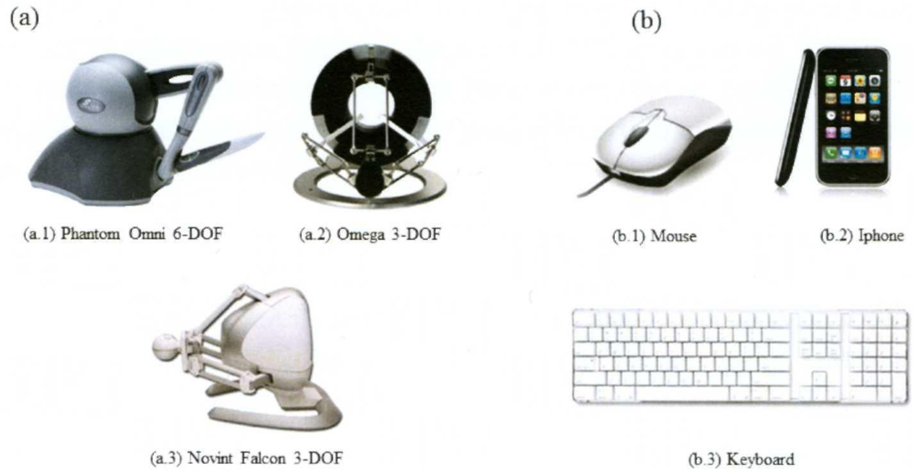
On the other hand, unlike the information acquired by the other senses that have a well-located organ, reproducing the sense of touch through a mechanical device is a task that involves many technical difficulties.

Hence, it becomes of interest to investigate the haptic perception and related phenomena. Within this scope, the importance of haptic technology becomes the basis for new applications not only within the area of scientific research, but also commercial.

Current advances in haptic technology, allow exerting considerable control over important variables in haptic perception mechanical experiments. According to Grunwald [17], haptic devices can be classified as passive or active (See Fig. 2.3). Passive devices include those where the user applies power to the device and the dissipation of energy is generated in the device. On the other hand, active devices provide energy to the user in the form of forces.

For purposes of this thesis, a haptic device will be defined as a system that can transmit and/or acquire information through force feedback and position. Also, there is a particular emphasis on the use of haptic devices for force feedback and its ability to generate haptic signals that correspond to user actions. In all, the capacities of haptic devices range from the ability to replicate virtual textures to reproducing motions that generate haptic force feedback.

It is noteworthy to mention that in section 3.1.2 the Novint Falcon haptic device is used as part of the interface for the development of the texture classifier system corresponding to the active haptic devices that will be analyzed in this thesis.



(a) (b)

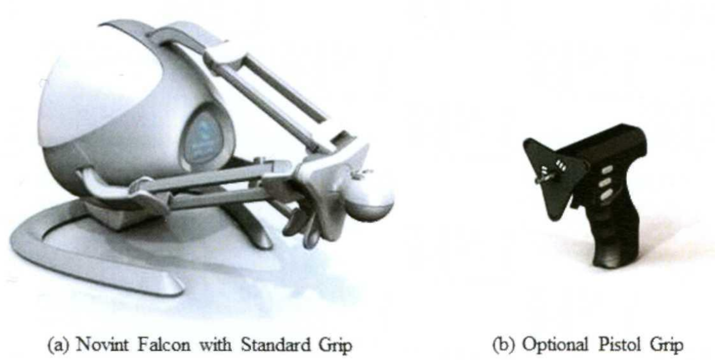
(a.1) Phantom Omni 6-DOF (a.2) Omega 3-DOF (b.1) Mouse (b.2) Iphone

(a.3) Novint Falcon 3-DOF (b.3) Keyboard

Figure 2.3: Active Haptic Devices (a). Passive Haptic Devices (b)

2.2.1 Importance of Haptic devices on perception experiments

In the 1990s, commercial desktop haptic devices that cost thousands of dollars emerged, bringing high-fidelity and three-dimensional force. Most recently, Novint Technologies has introduced the Novint Falcon (See Fig. 2.4) which offers an invest-cost alternative and enables realistic-force feedback for entertainment and training applications.



(a) Novint Falcon with Standard Grip (b) Optional Pistol Grip

Figure 2.4: Novint Falcon Haptic Device and Pistol grip

Furthermore the haptic interaction with real world environment is complex and wide in terms of information gained. As a result, a haptic device that can play all aspects of real haptic interaction has not been affordable or possible until recently. Therefore, the current haptic devices only generate certain signals or forces that represent the current interactions.

However, the fundamental limitation of haptic virtual reality devices consists that the users cannot simply interact with virtual objects in the same manner as with their real counterparts. This is explained by considering that the device used to relay the haptic sensation to the user dictates the nature of the virtual object tactile sensation. This tactile sensation equals to touch the object surface through a probe and not directly with our skin.

2.3 Perception of surface texture properties

The perception of surface texture properties is a task of the sense of touch; this system refers to the identification and discrimination of surface features being analyzed. A majority of the activities that humans perform requires the identification of objects through its surface, with this in mind, Katz [3] identified the importance of determining the movements for optimal identification of surface properties through haptic exploration. To accomplish this, Katz conducted an experiment where the purpose was to identify the different surface properties of several types of paper (See Fig. 2.5).

Also, Klatzky and Lederman explained two methods of identification of textures using features. In *contour following* [16], the contour of the surface is followed in lateral motion producing shear forces that are informative about the pattern texture. On the other hand, in *haptic glance* [18] the object identification is performed from initial contact, this refers to a space of contact that involves little or no fingertip movement; additionally it is worth mentioning how through this latter method of identification great accuracy was achieved in small areas of contact that resulted in the recognition of patterns textures. Besides, the use of contour following for shape determination was not only optimal, but necessary in order to achieve high performance.

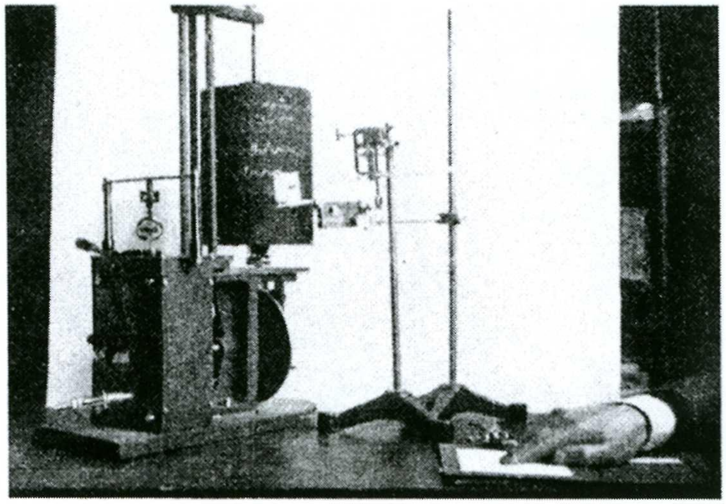


Figure 2.5: Device for recording finger movements during the finger exploration of various types of paper [3].

The experiments conducted by Klatzky and Lederman show an interesting relationship between feature size and contact area during the perception of the surface. Studies on the identification and detection of texture parameters are of particular interest for the development of this thesis. However, for the purpose of designing the recognition system proposed for this thesis, the kinesthetic perception for the interaction of the haptic device end-effector and the texture surface will be of interest (See Section 3.1.3).

Regarding the roughness texture perception, Lederman et al. [19], [20] have conducted extensive research on real surface textures. In these experiments the stimuli were metal plates with equally spaced grooves. The depth profile of these plates is a periodic rectangular waveform. The textures provided by the grooves can be defined by the groove depth, groove width and spacing between the grooves, where the groove width was the most meaningful for the roughness perception (See Fig. 2.6).

Katz [21] suggested that the roughness is perceived by the combination of vibrations directly through the skin. The evidence shows that the static pressure distribution plays an important role in the textures with features larger than 1 mm [19], but in order to perceive fine textures it is necessary to acknowledge the vibrations generated by the movement.

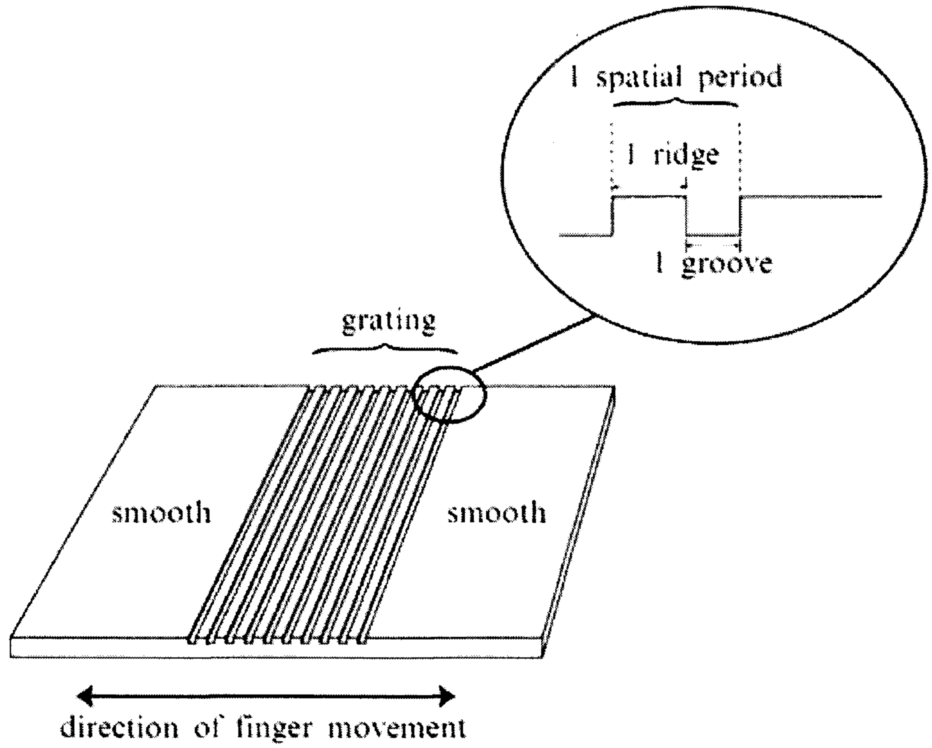


Figure 2.6: Stimulus grating with relevant physical parameters indicated [4].

On the other hand, the identification of textures using a robotic system involves the interaction between two objects; in this regard it is worth mentioning the studies related to the object-object perception of textures transmitted to the subject. These studies consider the factors that affect the perception roughness through a rigid probe; however, for the design of the robotic system for haptic texture classification, the focus is centered in the factors related to the interaction between objects: object geometry, applied force and speed [22].

Klatzky and Lederman [23] concluded that when a texture is perceived through a rigid spherical probe, the roughness increases with higher width of the spaces in the texture up to a maximum value which decreases again. Considering this finding, the roughness of a surface can be considered in relation to the length of the spacing that is in the texture.

Furthermore, it was showed that the diameter of the spherical probe plays an important role in the perception of roughness as the latter increases with smaller spacing. In relation to the applied force, it was concluded that the roughness of the texture increases as the force is greater. Finally, it was determined that at higher speeds the texture is perceived softer in small spaces and rougher at larger spacing [22]. In Section 3 its described how these factors are addressed in the robotic system design for texture identification and classification.

2.4 Systems for Surface Texture Classification

When a subject is in contact with an object, the sense of touch gives him the ability to extract information that allows the object identification, this information is based on their shape, size, weight and temperature to name a few. However, to determine the properties of smoothness or roughness, the human being recurs to texture identification.

According to the Oxford Dictionary, texture is defined as "the feel, appearance, or consistency of a surface or a substance" [24]. However, this definition is quite general and does not consider that different texture definitions appear in different contexts. For the purpose of this thesis, the meaning of texture in vision and haptic systems will be explored. The foregoing, in order to sustain the background that will differentiate the way surface textures are classified. Both scenarios are discussed in Section 2.4.1 and 2.4.2 as part of the theoretical framework of this thesis.

2.4.1 Vision Systems for Surface Texture Classification

In vision systems, surface texture can be perceived at different resolution scales and in many contexts is defined as the variation of pixel intensities. For example, consider the texture represented on a brick wall. The texture is represented at low resolution by the individual bricks, losing the interior details of the bricks, while higher pixel intensity allows us to appreciate the details of them and this affects the smoothness or roughness of the surface texture [25].

Computer vision pattern recognition has evolved over the last decade and now appears as standard approaches in robotic applications where objects or textures have to be recognized. According to Zhou [14], a fundamental goal of research in computer vision texture is the development of methods for the acquisition of visual information and understanding of the image based on textural properties. The primary focus of his research is the development of a generic structural identification of a Markov-Gibbs random field model of textures. The idea behind the Markov-Gibbs random field is to incorporate prior information about the image model for the Bayes decision theory, which can be applied to the problem of image segmentation. Additional information about this model can be found in [14].

Targhi has developed research in the area of classification of textures from one image by taking this as a problem of statistical learning [26]. In general, the classification of textures from images has been extensively investigated theoretically and experimentally by Caputo et al. [27], Cula et al. [28], and Varma et al. [29] resulting in a large number of databases. However, in order to accomplish true recognition of the texture, prior knowledge of the tactile sensation of the texture image being analyzed is necessary to determine its roughness or smoothness.

2.4.2 Haptic Systems for Surface Texture Classification

Kern defines haptic texture as the properties of objects which can be exclusively felt by touch [30]. With this statement as a starting point, it is important to mention that haptic perception is characterized by its ability to feel textures through direct stimulation of forces when the surface of an object comes into contact with the human body. Considering the above, this section mainly focuses on texture classification via tactile sensing of a robotic system, illustrating the working principles and giving an insight into the current state of the art.

Before proceeding to detail in this section, it should be emphasized that the research presented will be part of the state of the art corresponding to those methods of haptic perception that has been done on real textures and not in virtual environment like many other investigations characterized by using haptic devices for feel or analyze virtual textures like the research works presented in [13], [31], and [32].

A number of studies has addressed the problem of using robotic fingers in exploratory procedures. Okamuta and Cutkosky [17] analyzed the feature detection in robotic exploration. The analysis consisted in detecting surface features of an object such as ridges and bumps. They observed that during the process of haptic exploration, the detection of some properties depends on the size of the fingertip, e.g. if the contact area is very large, detail can be lost. It also showed that the path traced by the fingertip has intrinsic properties that facilitate the detection of certain characteristics. Similar research has been conducted in [33], [9], and [11].

In the context of surfaces classification, Hoepflinger et al. [34] present a method for classifying natural terrain using haptic feedback, via the acquisition of properties through contact forces and joint angles.

Payeur et al. [10] provide an approach for the refinement of information gained through a vision system for the design of autonomous robots by integrating a tactile sensor that plays the skin component, providing the geometry of the sensed object. Under the same concept of using the sense of touch in conjunction with the sense of vision, Natale et al. [11] explored the possibility of extracting the properties of an object to understand the type of parameters that could be extracted through the tactile perception.

2.4.3 Fourier Analysis

As a part of the classification process is worth mentioning the related work that has used the frequency spectrum provided by Fourier analysis as a proper feature for pattern recognition.

A number of studies in perception of surface textures have used Fourier analysis as a reference point for simulation models in virtual environments and detectability of surface textures in [35], [36], [37], and [38]. According to Cholewiak, the implicit reasons behind this fact is that (i) the human sensory system might be able to perform a spectral analysis of a stimulus derived from the interaction with the surface texture, and (ii) the perception of individual spectral components can be combined linearly from a overall approach [38]. Validation of these assumptions was first suggested in the study of visual grating perception [39].

It is worth mentioning a similar work to the visual gratings used in the Campbell and Robson study [39], but implemented as a tactile analog in surface height gratings at the micro-scale (i.e., surface texture) proposed by Cholewiak [38]. In the given study, Cholewiak et al. used virtual surfaces with sinusoidal and square-wave gratings to analyze the detectability of the gratings in the frequency domain.

Similarly, Wall et al. [36] proposed a method which employs Fourier analysis to describe the surface profiles of several stimuli surfaces. The obtained results suggest that a limited band of Fourier series can be used to provide a realistic approximation to the amplitude of the profiles.

Considering the related works that have employed the use of Fourier analysis, its worth to mention that to the best of our knowledge, the research developed in this thesis differs not only in the acquisition of real environmental data instead of virtual textures simulation, but also in the process of classifying them via the data provided by Fourier analysis.

2.5 Summary

This chapter deals with the spectrum and influence that Haptics has on the human begins beyond technological descriptions. It is also a hint for the development engineer, to be responsible and conscious when considering the capabilities of the haptic sense. Furthermore, this section shows how the sense of touch is specialized on the perception of the physical boundaries of the body and also on the analysis of surface properties.

Based on the above statement, a number of studies related to the texture analysis from the point of view of vision and haptics have been conducted, and the two streams of analysis for the classification of textures have been presented.

Finally, although haptic feedback is often taken for granted in real life, it is still not common when interacting with computers; this chapter discusses that by using a haptic device, it is possible to feel and to acquire some characteristics of a material such as smoothness, roughness, and viscosity, among others.

Chapter 3

Haptic Texture Classification Methodology

This chapter covers the methodology developed for the robotic haptic system design for texture classification. The system consists of the following subsystems: (i) control sampling overview, (ii) the experimental methodology and (iii) the classification process. The control sampling overview explains the main hardware components and the task they perform as well as the GUI (Graphical Unit Interface). The experimental setup covers the validation of the stimuli and the working interface for the research development. Additionally, the classification process covers the feature selection and the learning process.

Before proceeding with the subsystems description, it is important to note that the software design is divided into two parts: C++ and Matlab. The communication interface to the Novint Falcon via the SDK (Software Development Kit) of Novint Falcon Technologies [6], the GUI, the learning algorithm, a simple signal filtering and segmentation, and the kinesthetic position measurement cycle logger are implemented in C++. On the other hand, Matlab is used for feature extraction (See Section 3.3.3).

3.1 Control sampling overview

The control sampling integrates four main components. Controlling computer GUI (CCG), the haptic sensing element Novint Falcon (NF), the End-effector (EF) and the Position Measurement Cycle (MC). The perpendicular motion across the surface and logger of the surface map data is generated by their interconnection. In Fig. 3.1 the components are illustrated.

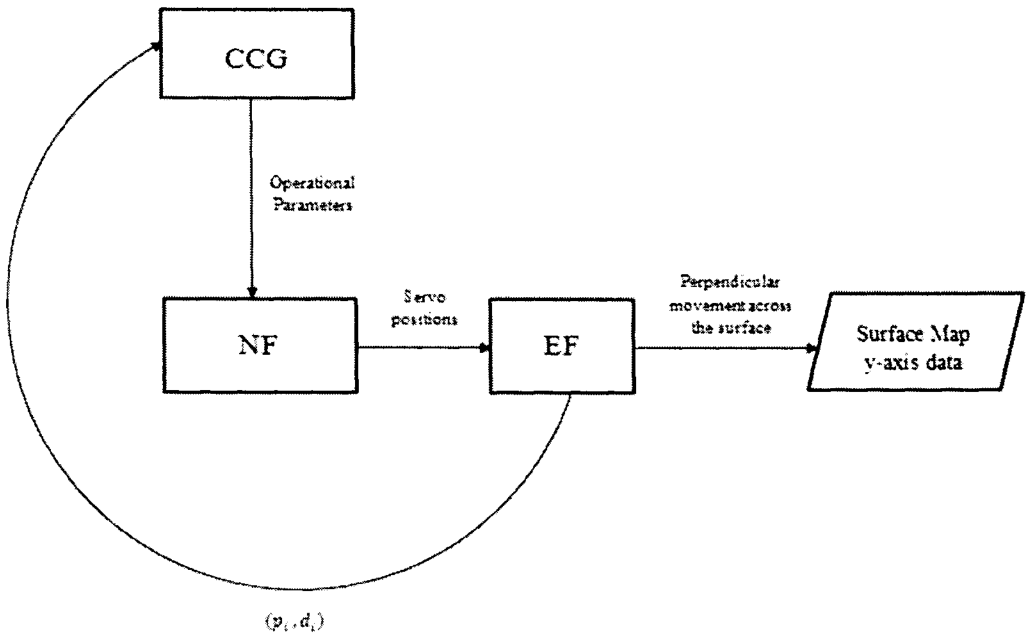


Figure 3.1: Control sampling overview. Integration of the distinct components of the system required for the y-axis data acquisition.

First, the haptic sensing element NF receives a predefined motion trajectory from the CCG; this is done in an update cycle of positions once per test. After the NF has its configuration via the operational parameters, it proceeds to compute the servo positions to move the EF through a perpendicular path to the contact surface and record the surface map data.

For more information about the update cycle of positions see Section 3.1.5. The initial conditions are that the NF motors are at homed position (See Section 3.1.1, Operational modes) at the start of the test cycle.

3.1.1 Controlling Computer GUI

The Controlling Computer GUI is used to provide visual feedback and control over the texture classification system. This was made in order to have control over the operational mode of the NF as a robotic system. In this case, users need to know the mode in which they are currently operating in or switch between modes to perform the different tests to identify textures.

It also features the output fields of *Actual position* and *Force* that respectively provide information about the EF current position and the force generated to bring the EF to the desired position. These issues have been addressed by providing all necessary information in an understandable GUI. (See Fig. 3.1a). Additionally, it has a graphic display developed with OpenGL and OpenGLUT in conjunction with the SDK provided by Novint Technologies, which shows the current position of the EF by a blue sphere in a 3-D space (See Fig. 3.1b).

Once the analysis to predict the texture is performed, Matlab plots the different data. These plots can be used to get an overview of the measurement data of that specific sample or just to see if the measurement delivers meaningful results.

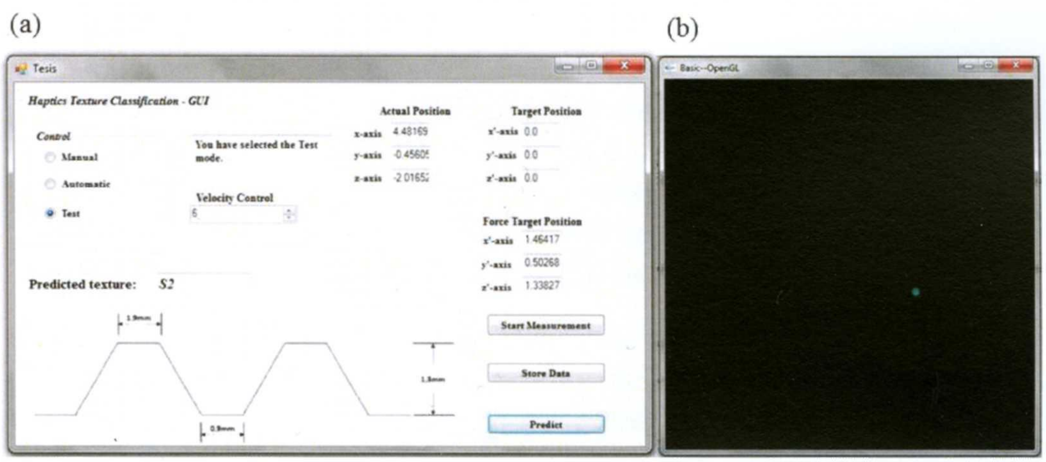


Figure 3.2: GUI screenshot with a measured S2 sample (a). Graphic display (b).

Comprehensively, the GUI components can be divided into (i) Operational Modes, (ii) Output / Input Fields and (iii) Buttons; each of them will be explained in detail as part of this section.

Operational modes

There are three principal operational modes represented in the Control Box, (i) Manual/Initialization, (ii) Automatic/Target position and (iii) Test; each of one performs the following functions:

- **Manual/Initialization:** Allows the EF motion to the desired position by applying an external force e.g. move the EF to the desired position via the hand user force. This was done because it was necessary the initialization of the NF once the system is started and each time the test is preformed (See Fig. 3.3).

Figure 3.3: Novint Falcon Manual Initialization

The Novint Falcon has its own initialization functions which have been supplied by the SDK. The main functions checked are the servos for each pair of motor and encoder, and that the device is homed (meaning by this that the x, y and z-axes are fully opened and then fully closed). If the device is not homed then the LED lights at the center of the NF will be red and a dialogue appears asking to move the grip in and out until the LED lights turn to blue.

- **Automatic/ Target position:** This mode was designed in order to move the NF to an arbitrary position by indicating the desired position in cm in the three coordinate axes as long as they do not exceed the limits of the work of the NF area hovering around 10 cm in the x, y and z-axes. For more information about how to specify input values for that field, see *Output/Input Fields* in this section.

- **Test:** An extension of the automatic mode, developed in order to have a predefined motion path that was perpendicular to the contact surface texture analyzed. Figure 3.4 illustrates the motion path of the EF according to the indicated points in the space and coordinated system. Note that all units are in cm.

Output/Input Fields

The output fields provide information about the current position and force exerted, while the input fields provide a space to put the target position for the EF.

- The **Actual position** fields of the GUI provide visual feedback of the current position on the EF, this position register and display any motion along the coordinate axes in the output fields in an update rate of 1 kHz.

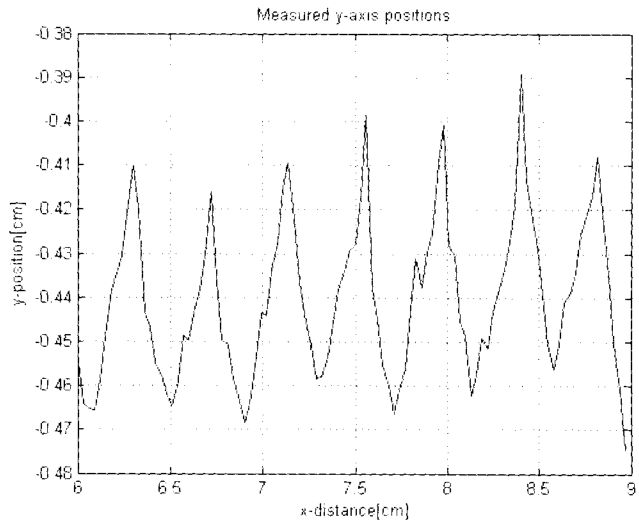


Figure 3.4: Motion path of the S2 sample measurement.

- The **Target position** provides an input field for each one of the three coordinate axes to indicate the position you want to set the EF. The Position value has to be on cm.

- The **Velocity** input value provides an arbitrary factor to move the EF faster or slower, however it was determined by experimentation that the motion with a value of 6, which refers to the change of value between one position and another, is similar to the velocity that humans use to feel a texture.

- The **Force target position** section offers output fields for the generate force in each of the three coordinate axes, this force is necessary to set the EF in the required position. Note that the value of this force is not expressed in Newton but in some internal units used by the Novint.

- **Predicted texture** field conforms the texture class predicted by the classification algorithm (See Section 3.3.1) and the image of the frontal view with its parameters.

Buttons

There are three principal buttons modes in the GUI, each of one performs de following functions:

- Pressing the **Start Measurement** button (considering that the user is in the Test mode) will start the automatic motion of the EF.

- Pressing the **Store Data** button is an alternate function that was built to save the position data of y-axis to a text file which is then used, preprocessed, and plotted (See Section 3.1.5).

- The **Predict** button is used in order to start the feature extraction, classification process and, display the graphic results.

3.1.2 Haptic Sensing element

The haptic element used in this research is the Novint Falcon (See Fig. 3.5) and a modified version of the gripper (See Section 3.1.3) provided by Novint Technologies Company, Inc. [6] for the force measurement, in order to trace automatically various real world surface textures. See Appendix A for the Novint Technical Specification and the Recommended System Requirements.

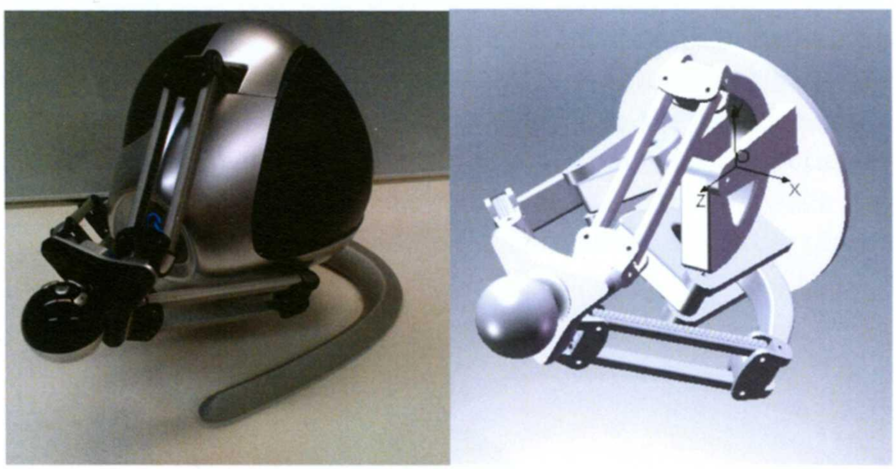


Figure 3.5: Novint Falcon CAD model with its axis coordinated system[5].

The Novint Falcon is a haptic device of 3-DOF (Degrees of Freedom) relatively inexpensive with a similar configuration to the delta robot proposed by Tsai [40], in which the ball joints from the Clavel design [41] are replaced by rotational joints. Also, the Novint Falcon design incorporates an end-effector that can be replaced with the pistol grip or the default grip offered by the commercial version of the system.

The Falcon devices communicate via the USB interface with information and commands to provide actuation commands sent from the computer. Furthermore, the encoder information is transmitted to the computer from the Novint Falcon; such transmission is done via the SDK provided by Novint Technologies, Inc.

The interface uses an update rate of 1 kHz, however in accordance with Martin et al. [5] the update rate varies between 800 Hz and 1 kHz. Furthermore, the authors discuss that the variation in the update rate is due to the USB interface that is unable to sustain the communication and is prone therefore to miss commands or data acquisition. Also, it was noted a delay between force commands and encoder measurement. To the best of our knowledge, it is noted that these facts coupled with the significant non-linearity of the system kinematics and dynamics can cause unexpected vibrations and oscillations that affect the motion control of the device. Additional information about the position control can be found in the Haptic Device Abstraction Layer (HDAL) on Appendix B.

3.1.3 End-effector

The prototype of the EF haptic system consists of a spherical tactile probe mounted on the default Falcon grip (See Fig. 3.6). The EF device will have a limited range of motion of approximately 10 cm on the x, y and z-axes within the working area of the Novint Falcon, which will make the kinesthetic measurements highly dependent on the position and orientation of the system in relation to the surface texture analysis. Moreover, direct measurements with the tactile probe imply that the orientation of the EF will be perfectly perpendicular to the surface in lateral motion while the force and position information are acquired. Additional information about the range of motion of the NF can be found in [5].

Figure 3.6: End-effector

Considering that the Novint Falcon does not work without the default gripper connected to the haptic device, it was necessary to modify the gripper through the steps shown in Fig. 3.7.

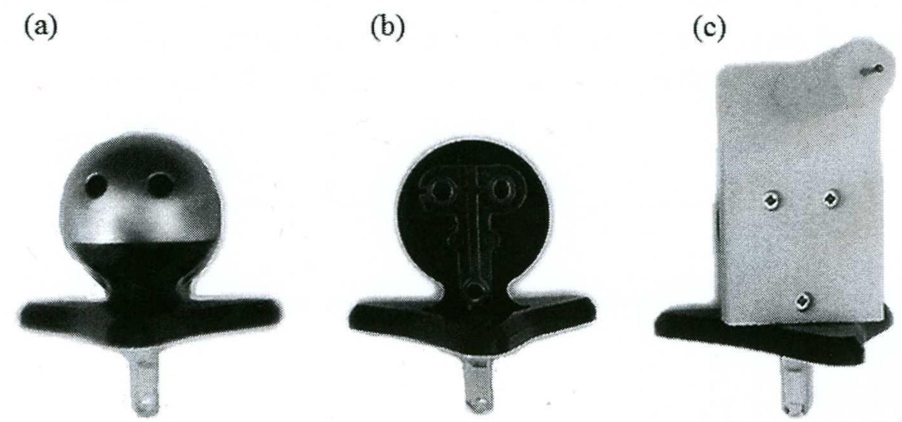


Figure 3.7: Modification of the Falcon grip. (a) The original grip. (b) Mounting plate after removing the lower hemisphere. (c) Modified component placed in the mounting plate.

A fundamental part of the EF is the spherical tactile probe of 2 mm in diameter and 12.53 mm length (See Fig. 3.8), which consists of a tungsten carbide ball for a proper motion on the surface test and the application of force in an uniform manner at a constant speed. Similar work in this field can be found in the work of Klatzky et al. [23], where a spherical probe is used to test the textures.

Figure 3.8: Spherical Tactile Probe.

The blueprints of the additional component mounted on the Novint Falcon gripper can be found in Appendix C.

3.1.4 Kinesthetic position measurement cycle

To obtain meaningful data from the sensors and achieve the surface texture classification, the end-effector moves automatically perpendicular to the surface (motion along the + x-axis) with a frequency of approximately 1 kHz. Fig. 3.9 shows the end-effector position when the latter moves across the surface. This information was stored and later used for the feature space generation (See Section 3.3.3).

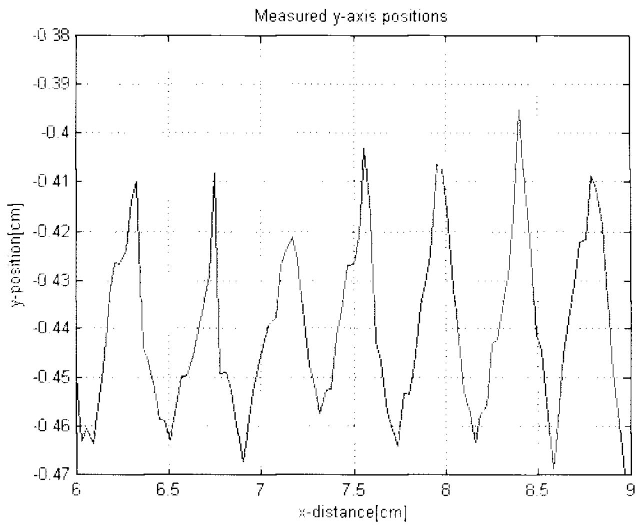


Figure 3.9: Plot of the S2 sample referring to the y-axis position mapping.

Ideally, the signal would be identical to the shape of the texture (trapezoidal waveform or planar form depending of the texture), but effects such as nonlinearities of the Falcon, the frequency variation in sampling , surface deformation, and the error of 1 mm from the EF in Cartesian space [5] cause signal degradation.

On the other hand, Fig. 3.10 shows the motion path by the EF in order to perform the surface mapping automatically. Similarly, Table 3.1 shows the distances achieved in the three coordinate axes according to the limits of movement marked.

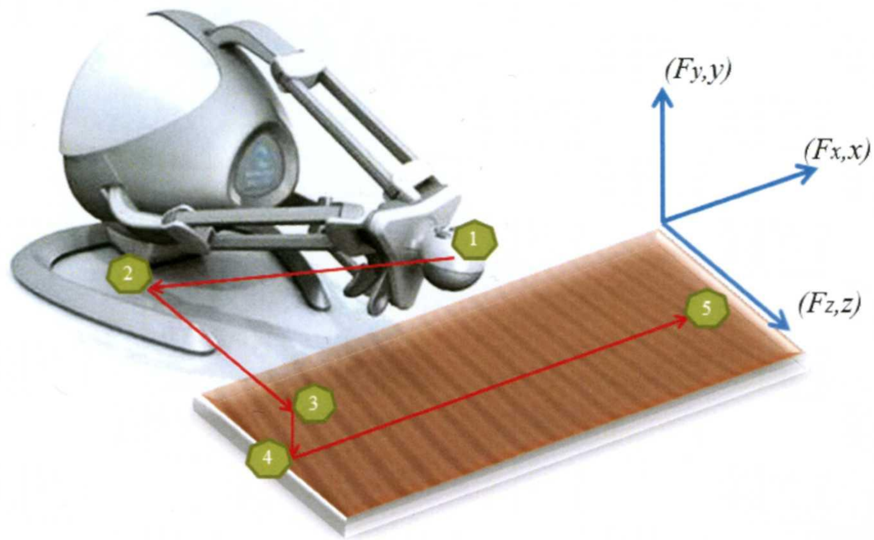


Figure 3.10: Motion path perform by the EF.

Table 3.1: Motion path parameterization

Position label	(x, y, z) **cm**
1	(0,0,-6)
2	(-4.5,1,-6)
3	(-4.5,1,-2)
4	(-4.5,-0.48,-2)
5	(4.47,-0.48,-2)

3.1.5 Position Control overview

To move the EF to an arbitrary position automatically, it is necessary to maintain the EF position in a particular position while keeping the force through Hooke's law (See Eq. 3.1) that simulates the mass-spring-damper force model (See Fig. 3.11) and is presented below:

$$F_i = -K(p_i - f_i) + D\frac{(p_i - f_i) - (p_{i-1} - f_{i-1})}{\Delta t} \tag{3.1}$$

where i is the update counter in the haptic process, p is grip position, f is the keeping position and K is the spring constant, D is the constant of damper, Δt is the update rate of the haptic process. It is possible to move the grip to an arbitrary position by changing f.

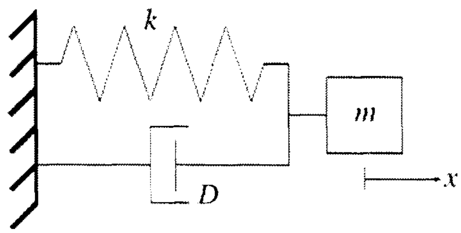


Figure 3.11: Mass-Spring-Damper Model

It is noteworthy that the force model used is a second order system (See Eq. 3.2), whose transfer function is shown in the following equation:

$$\frac{k\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{3.2}$$

where ω_n is the natural frequency of the system, ζ is the damping ratio and k is the steady-state gain.

In order to obtain an under-damped system behavior, it was necessary to modify the value of D so that the ζ value was maintained between $0 \leq \zeta < 1$. The relation between D and ζ is shown in Eq. 3.3.

$$\zeta = \frac{D}{2m\omega_n} \tag{3.3}$$

In order to perform a successful feature extraction necessary for the classification process (See Section 3.3), and considering that the significant nonlinearity of the system kinematics and dynamics can cause unexpected vibrations and oscillations that affect the motion control of the device, a filtering and segmentation process has been applied to the data.

Filtering

Considering the update rate of 1000 Hz, it has been observed by experimentation that the signal was too noisy compared with the known waveform of the original smooth surface. To correct this situation the sampling process was decreased to a sampling position interval of 0.3 mm on the stable area (See Fig.3.12).

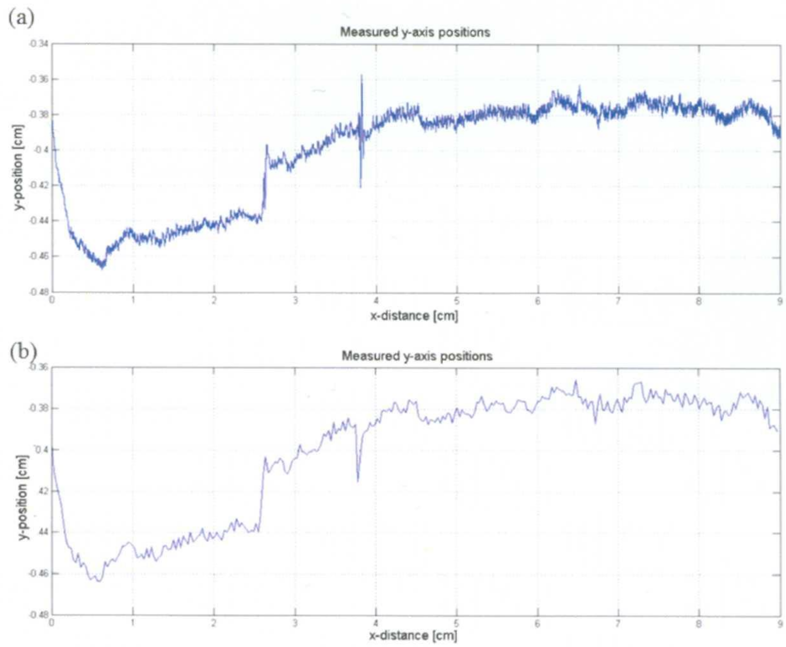


Figure 3.12: Filtering process plot. Before the filtering (a), and after the filtering (b).

Segmentation

Given the Delta configuration of the NF, it is well known that serial singularities occur on the boundary of the workspace of a parallel manipulator (Simaan, 2009). Since the under-damped system that controls the position is capable to produce a significant velocity, it has been determined to reduce the analysis area of the surface texture mapping. As a result, the first 6 cm were removed from the area, remaining a stable and effective dimension of 6-8.97 cm (See Fig. 3.13).

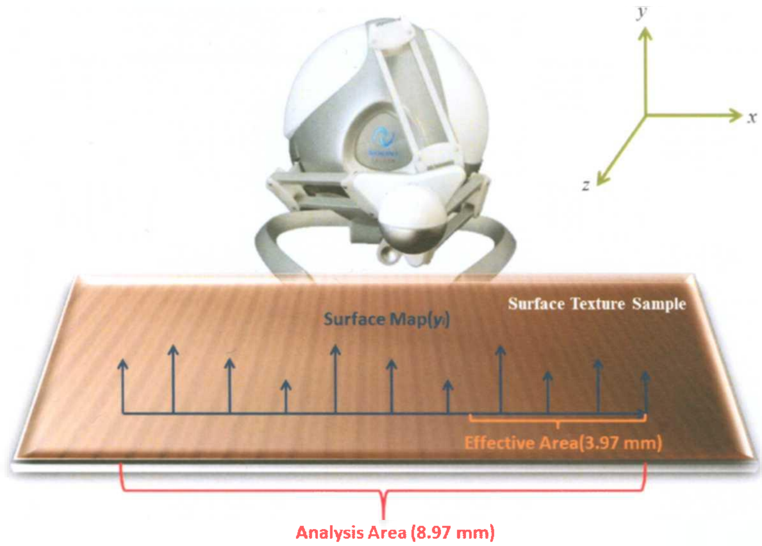


Figure 3.13: Sampling area

Furthermore, the segmentation process results of the data obtained by measuring the position of EF while controlling it automatically are shown in Fig. 3.14.

3.2 Experimental methodology

The research includes one main experiment for the surface texture classification performance by haptic perception. The experimental methodology is the following:

1. Set the surface texture on the workspace interface according to the proposed setup that can be consulted in Section 3.2.1.

2. Place the end effector of the haptic device at home position (See Section 3.1.1, Operational Modes / Initialization).

3. Perform the automatic motion of the EF to acquire the surface texture data mapping.

4. Preprocess the collected y-axis position data to apply the spectral analysis using the DFT.

5. Use the Discrete Fourier Coefficients as the input feature for the classifier system.

6. Verify the analysis accuracy and determine whether the results are conclusive according to the proposed hypothesis in this thesis.

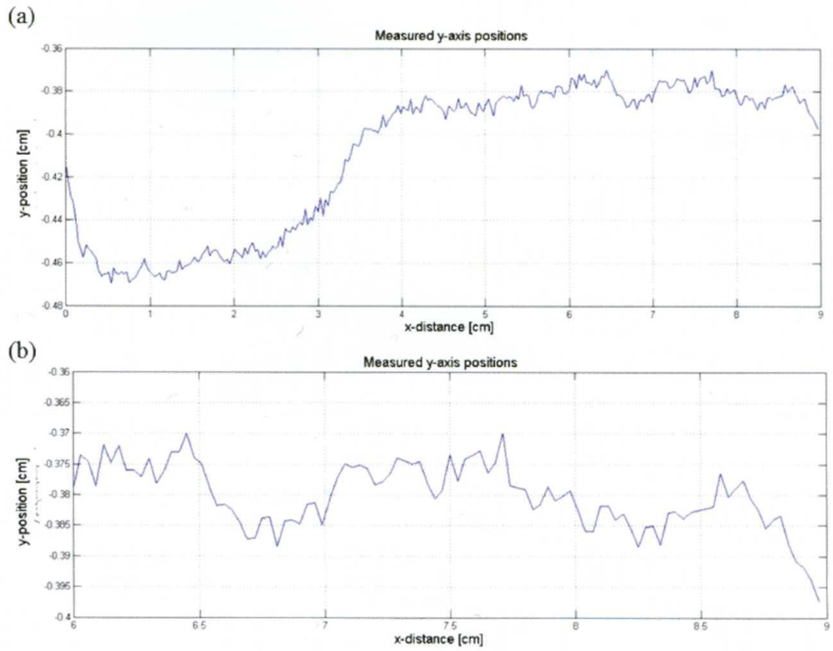


Figure 3.14: Segmentation process plot (a) before the segmentation and (b) after the segmentation.

3.2.1 Experimental setup

For the experiment, a set of surfaces has been selected. The full set of texture surfaces is listed in Table 3.2 and Fig. 3.15. In these experiments the surfaces were corrugated cardboard plates with different spaced grooves (See Fig. 3.15b.1-3). The depth profile of these plates is roughly a periodic trapezoidal waveform with some degree of deformation by exerting a force on the material because is not completely rigid (See Fig. 3.15b). Furthermore, it is included a flat cardboard surface texture as a part of the stimuli (See Fig. 3.15a).

Table 3.2: Surface Texture parameterization

Surface Texture Class	A	B	C
S1	NA	NA	NA
S2	1.9 mm	0.9 mm	1.3 mm
S3	1.7 mm	1.9 mm	1.8 mm
S4	2.1 mm	2.2 mm	3.5 mm

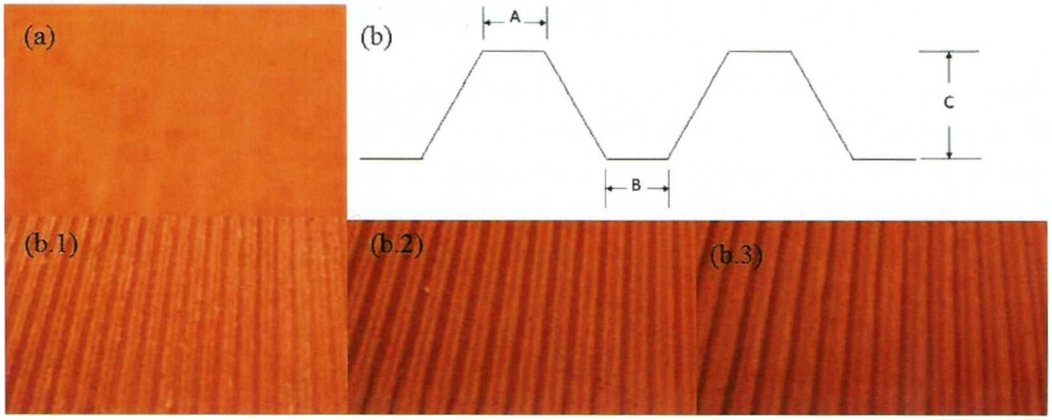


Figure 3.15: Cardboard surfaces used for the experiment. (a) S1-smooth cardboard, (b) Corrugated cardboard trapezoidal waveform (b.1) S2-corrugated cardboard, (b.2) S3-corrugated cardboard, (b.3) S4-corrugated cardboard.

In order to get repeatable results and to easily mount the stimuli on the test bed, the surface textures were placed on the working interface properly equipped for research development (See Fig. 3.16).

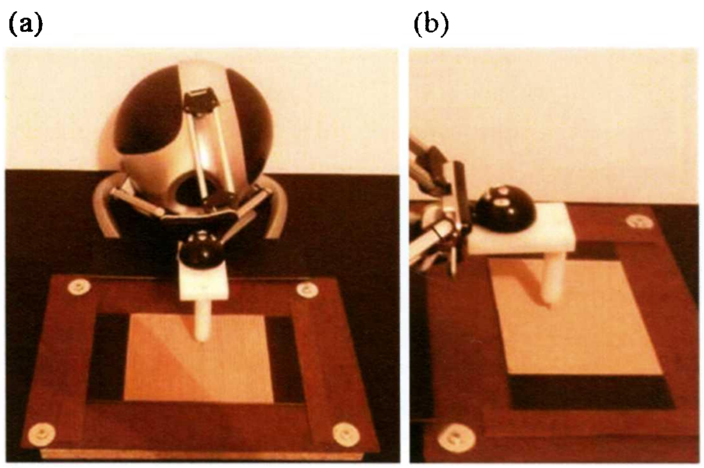


Figure 3.16: Different surface textures samples could be mounted in this setup, which is shown as an overview in (a). The detail of the EF placed on a texture is shown in (b).

3.3 Classification framework

The objective is that the implemented haptic robotic system can distinguish between different surface textures. For this task, the haptic system automatically draws a path of 8.97 cm perpendicular to the contact surface. The measurement of the position in the y-axis will allow the acquisition and observation of the surface map. Fig. 3.17 shows a plot example of the surface map generation and a representation in the frequency domain.

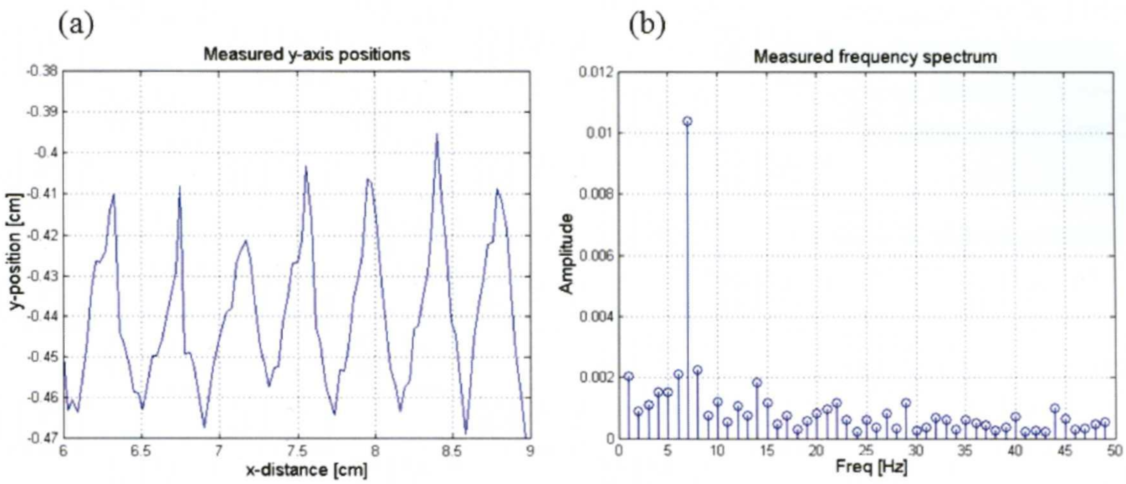


Figure 3.17: S2-sample measurement, the y-axis mapping (a) and the corresponding frequency domain representation used as a feature for the classification process.

3.3.1 Classification overview

Fig. 3.18 shows the classification process schematic. A C++ program performs the execution of the measurement cycle and records the position information provided by the sensors. These files are used afterwards by Matlab for preprocessed the data using a segmentation and filtering process (See section 3.1.5.1-2) to reduce noise and generate the feature extraction using the Discrete Fourier Transform (See section 3.3.3).

In further steps, the feature extracted information was then used either to train the classifier or to evaluate the performance of a set of different tests. The difference between training and prediction files can be changed easily because both files contain the same structure.

Considering the above, a C++ program reads the data from all the previously generated logs files and use this data for the training. At the end, once trained the system, a classification algorithm (See section 3.3.2) is used to evaluate the output of the classification. Additionally, Matlab plots different data from the test that has been performed. These plots can be used to get an overview of the measured data of that specific sample or just to see if the measurements deliver meaningful results.

For the learning algorithm, the texture classification samples consisted of 20 training samples and 10 test samples for each of the 4 classes (120 samples in total.). The number of training samples used was defined based on the number of samples that are considered necessary to actually get good results with the least amount of files by just removing training samples, even with the consideration of knowing that the learning algorithms tend to perform better with a higher the number of training samples, however, experimentally the number of training samples used led us to positive results (see Section 4.5).

In addition, 10 test samples were used, consider this number as a representative function of the number of samples needed to test the classification process taking into account the specified number of training samples.

3.3.2 Classification method

To confirm the validity of the thesis proposal, it was employed the k-Nearest Neighbor (k-NN) classifier, provided by OPENCV, to identify the surfaces textures samples. k-NN is a supervised classification algorithm based on training examples in feature space. This is the one of the simplest classifier, but it is used in many applications.

The k-NN predicts the response to a new sample by analyzing a number of nearest neighbors (k) and the voting by its majority class. In pattern recognition, it is needed to train the system before the input element can be classified. The algorithm input is a set of labeled training data (f_i, c_n), $i = 1, ..., 20$ and $n = 1, ..., 4$ where each f_i is an example and c_n indicates the training data class.

An appropriate value of $k = 10$ is assigned to classify a surface texture sample among multiple classes. Therefore, a multiclass classification problem is faced for which the prediction looks for the feature vector within the training data with a known response that is closest to the given vector.

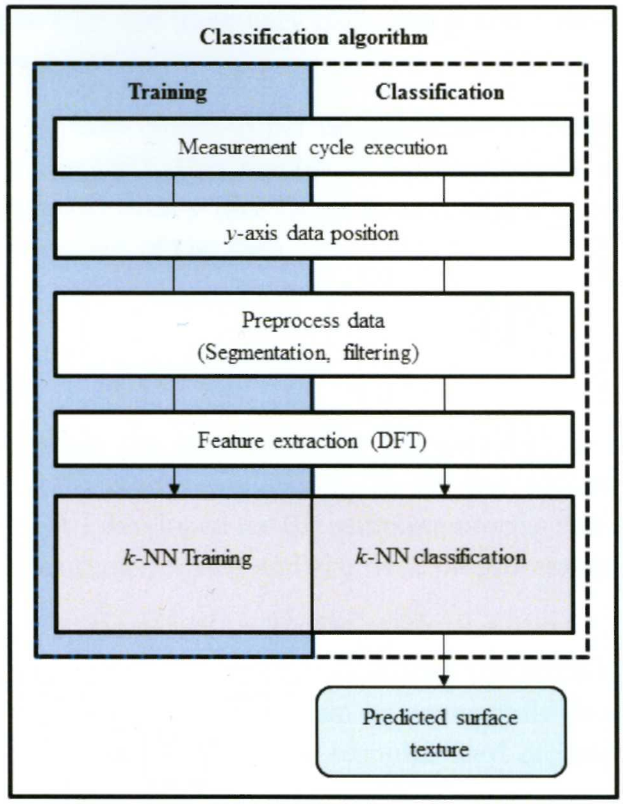


Figure 3.18: Overview of the surface texture classification process.

3.3.3 Feature Space

A feature space is proposed consisting on the spectral analysis by identifying component frequencies in the sampled data. For discrete data, the basis of the spectral analysis is the Discrete Fourier Transform (DFT) which was performed by the Fast Fourier Transform (FFT) which has computational complexity $O(nlogn)$ instead of $O(n^2)$ on the preprocessed sample vector x (consisting of the y-axis position measurement).

According to Matlab documentation [42], the DFT of vector x of length n is another vector y of length n:

$$y_{p+1} = \sum_{j=0}^{n-1} w^{jp} x_{j+1} \tag{3.4}$$

where w is the complex n^{th} root of the expression:

$$w = e^{2\pi i/n} \tag{3.5}$$

This notation uses i for the imaginary part, and p and j for vector y parameter that run from 0 to $n-1$.

In total, 49 features were collected per sample of the 50 corresponding to the cc efficients extracted by the DFT, this number of features results considering that th DC component was removed from y (See Eq. 3.4) so that it does not obscure/interfer the positive frequency content of the data.

3.3.4 Summary

This chapter describes the series of steps followed for the development of th robotic haptic system for texture classification. In the first section of this chapter th hardware used and the GUI developed for the sampling process and control is describec It also justifies the measurement cycle and the data preprocessing for later use in th classification process.

Subsequently, the methodology section describes the stimuli validation and tl working interface so that research preform can be successfully developed under a coı trolled environment. Note that the surfaces stimulus used are parameterized in ord to have a comparison between them.

The last section of this chapter refers to the classification process, feature extra tion method, training and the type of classifier used. Finally, the following chapt describes the preformed experiments for surface texture classification and the perfo mance achieved by the classifier considering the selected feature.

Chapter 4

Experiments/Results

Several preliminary experiments were required to ensure the quality of the results of this work. This section explains the nature of these experiments and the results obtained from them.

4.1 Measurements cycles

One measurement consists of one cycle placing the EF perpendicular to the surface of analysis. During the measurement, the y-axis position data is recorded and saved for later processing, feature extraction, and classification.

To achieve the perpendicular motion, it was sought to chart a course as straight as possible on the y-axis, achieved by controlling the position as explained previously in section 3.1.5, obtaining the results shown in Fig. 4.1. Note that the data generation presented in this figure was not in contact with any surface, but is the result of the motion of the EF avoiding any perturbations.

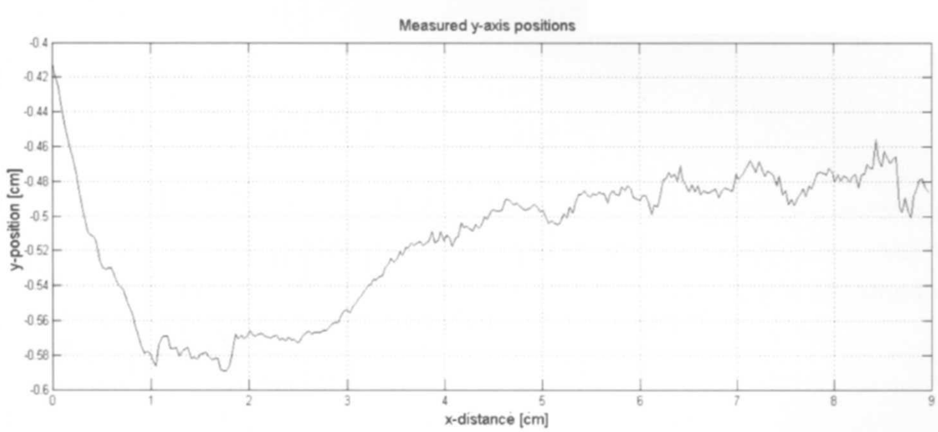


Figure 4.1: y-axis position control

It is noteworthy that the EF must have reached a position of -4 mm in the y-axis according to the position indicated previously as pre-set parameters for the development of the test. The establishment period occurs in -0.48 mm as a result from the extra weight that involve the modifications made to the EF. These positions are taken considering the Novint Falcon Cartesian plane shown in Fig. 3.10.

From Figure 4.1, we see that in the first 6 cm a period of oscillation occurs because the position control is carried out as a mass-spring-damper system with a damping ratio, $0 \leq \zeta < 1$, leading to an under-damped system that reaches its desired position with a significant velocity.

Result of this under-damping period, to improve the success rate it was necessary to segment the analysis area from 6 to 8.97 cm which recorded 100 position measurements on the y-axis (See Fig. 4.2).

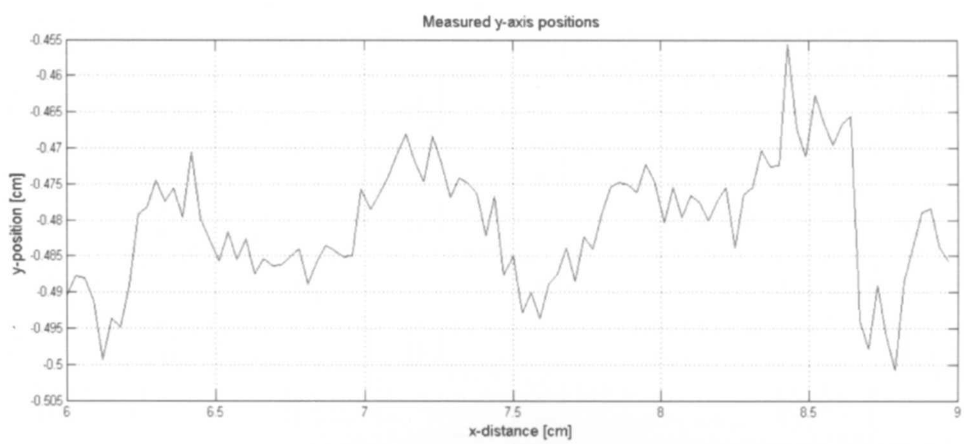


Figure 4.2: Measured y-axis position segmented

4.2 Outlier detection

Since the outlier detection in the training stage of the algorithm is an important factor for increasing the success rate of the surface texture classification, the variance of each of the features is determined in the experiment. The results obtained are considerable low, indicating by this that the dispersion of data is very low.

In conclusion, the main result of the outlier detection was that there are not severe outliers in the measurements. The reason for the low number of outliers is because the test rig allowed repeatable tests. It is worth mentioning that in the experiments for obtaining the training values, non-repeatable measurements result of the incorrect use of the test configuration were omitted in further experiments.

Fig. 4.3 shows the scattering data from a sample of five elements of the total training instances for each of the textures to graphically display the low variance involved that give as a result the demonstration of the desirability of the frequency spectrum as a learning feature.

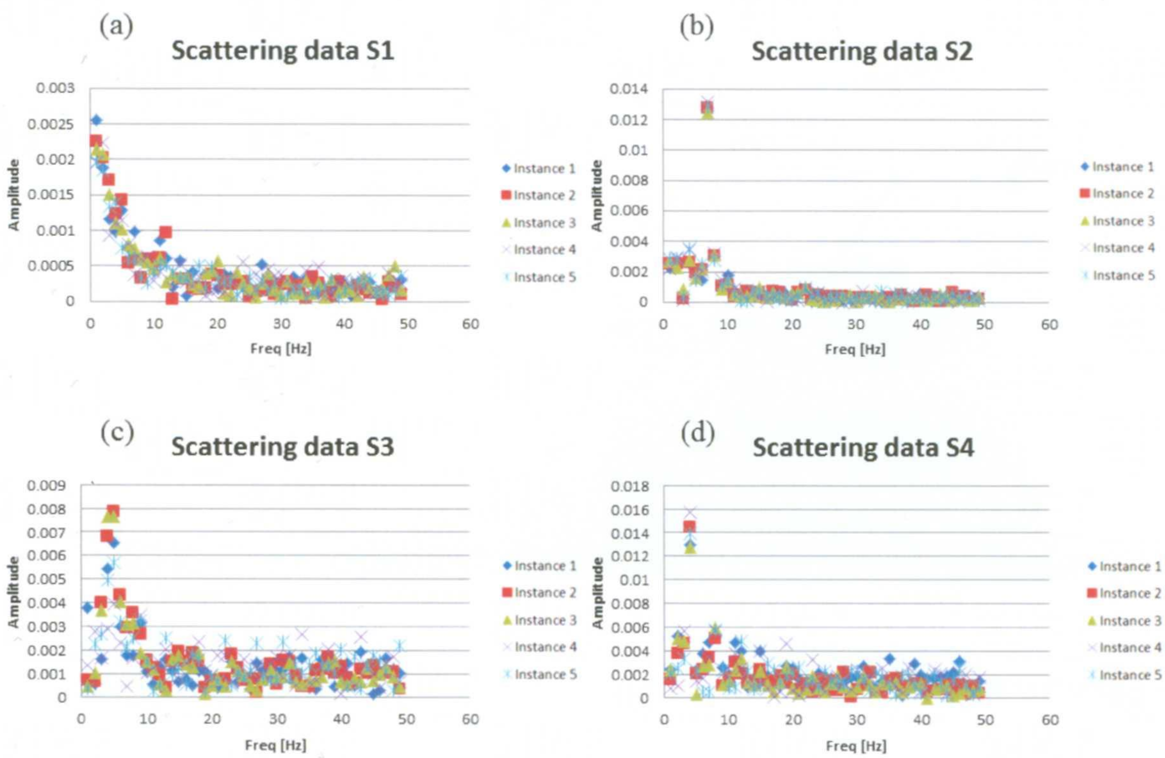


Figure 4.3: Sample scattering data of 5 instances selected randomly from de training classification data of S1 (a), S2 (b), S3 (c) and S4 (d).

4.3 Experimental operational parameters selection

By conducting preliminary tests in the experimental phase, it was determined that if a very high $K(K_y > 10)$ is maintained in Eq. 3.1 to keep the position of EF on the y-axis at -4 mm, it was difficult to move the EF spherical probe on the x-axis perpendicular to the surface texture analysis. This was because the force exerted to reach the desired position had prevented a displacement of EF y-axis in the positive sense (See Fig. 4.4). Similarly, the values of the constant K to generate the motion of the EF on x and z-axis were defined experimentally as $K_x = 80$ and $K_z = 80$.

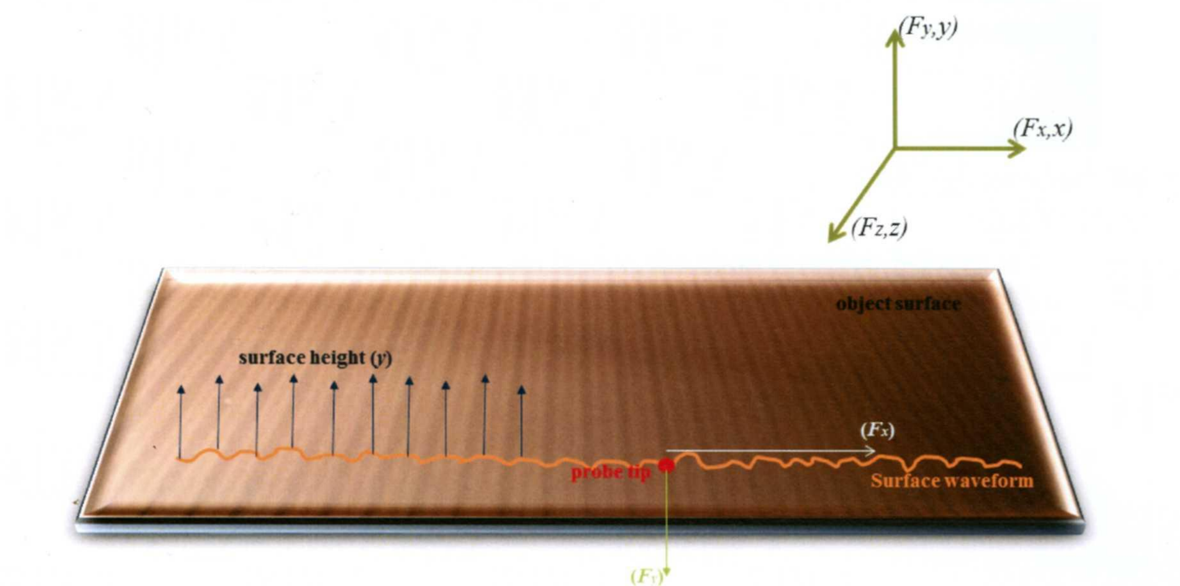


Figure 4.4: EF spherical probe on the x-axis perpendicular to the surface texture

An additional consideration that must be present on this last point, is that due to the extra weight provided by the modifications made to EF and the accuracy of ± 1 specified by the manufacturer of the Novint Falcon haptic device, is that although the reaching position of 4 mm is indicated, actually it reaches -4.8 mm.

Considering the above, the use of a value of $K_y = 9$ was considered and even though it does not offer the same precision, it allows the necessary elasticity on the y-axis to achieve the correct mapping of the surface.

In addition, a 6-speed value is chosen since higher speeds caused a poor mapping of the surface by missing details of the grooves and ridges, a similar situation is presented in the work of Klatzky and Lederman [23]. It is worth mentioning, as with speeds less than the value of 6 allowed to obtain good mapping of the surface, but took longer tests, a condition that led to the selection as the optimal value.

Another point to be considered in the selection of the parameters was that for each surface a depth penetration of 1 mm is exerted on the surface in order to map it as accurately as possible, considering all its features. A higher force exerted by F_y blocked the perpendicular displacement of the probe on the surface and a lower value prevent the correct surface features mapping.

As part of the automatic motion made by the EF, it is important to address that the values indicated in Table 3.1 from section 3.1.4 also has been experimentally defined in order to achieve the greatest possible area of texture analysis.

Finally, with the objective of achieving greater success rate in the texture classification it was necessary to optimize the value of k(nearest neighbors number) for the k-NN classification algorithm, given a predefined number of $k = 10$ and letting the majority vote will nearest neighbors decide the class to which belongs the texture analysis. The reason why it was chosen a high value of k is that the classification is less sensitive to the location of the sample.

4.4 Texture Classification

This section summarizes the results obtained by evaluating the texture classification performance using the haptic system designed in this thesis. At first instance, it provides a description of the mapping of each of the analyzed surfaces and its corresponding frequency spectrum for its classification.

It is important to note, within the frequency spectrum, that the amplitude at each frequency is the factor that is used for the surface texture analysis.

4.4.1 Surface Texture S1

According to the results of the frequency spectrum from the DFT, one can observe that the surface S1 (See Fig. 4.5) has a higher frequency range in the first 5 Hz, being this a characteristic feature of this surface.

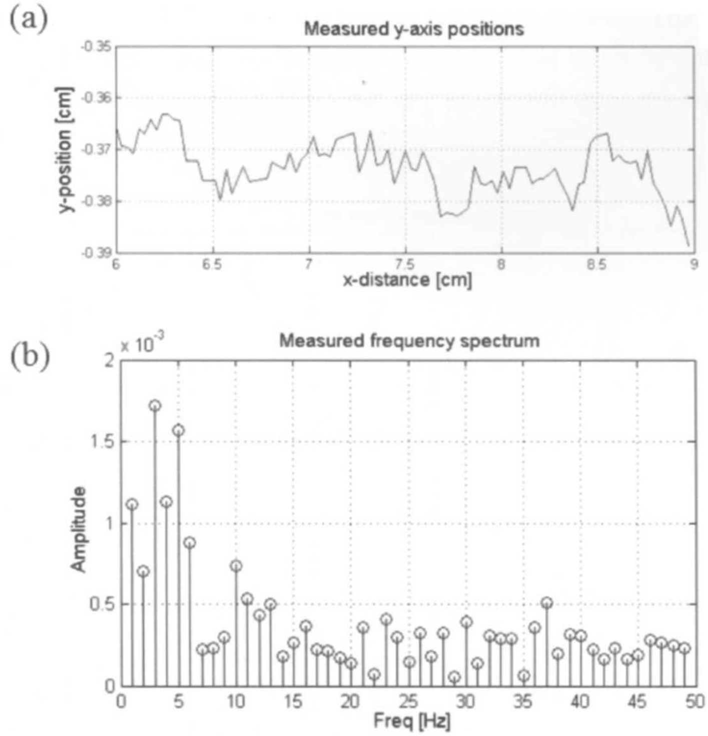


Figure 4.5: Measured y-axis position (a) and Measured frequency spectrum (b) for sample S1.

However, the most interesting factor that occurs in the spectral analysis of S1 is that it is practically being performed the DC component Fourier transformed, more commonly known as the average of the input series. Considering the above, it is observable that frequency values present are practically null as they only reflect the minimal irregularities present in the waveform of a constant function which in the spectral analysis would be reflected only as the value of the DC (Freq = 0) or Dirac delta function. Note that for this study the DC component was removed so that it could be appreciate the extent of the other frequencies.

4.4.2 Surface Texture S2

The sample S2 has a trapezoidal waveform whose surface mapping and frequency spectrum can be seen in Fig. 4.6.

It is worth mentioning that the resulting waveform is not completely similar to the trapezoidal surface geometry, this situation arises due to the deformation that occurs in the cardboard at the moment of exerting a force on it with the spherical probe. However, since the training and the surface sampling was done in similar conditions, this type of wave parameters and their frequency spectrum are presented in each test.

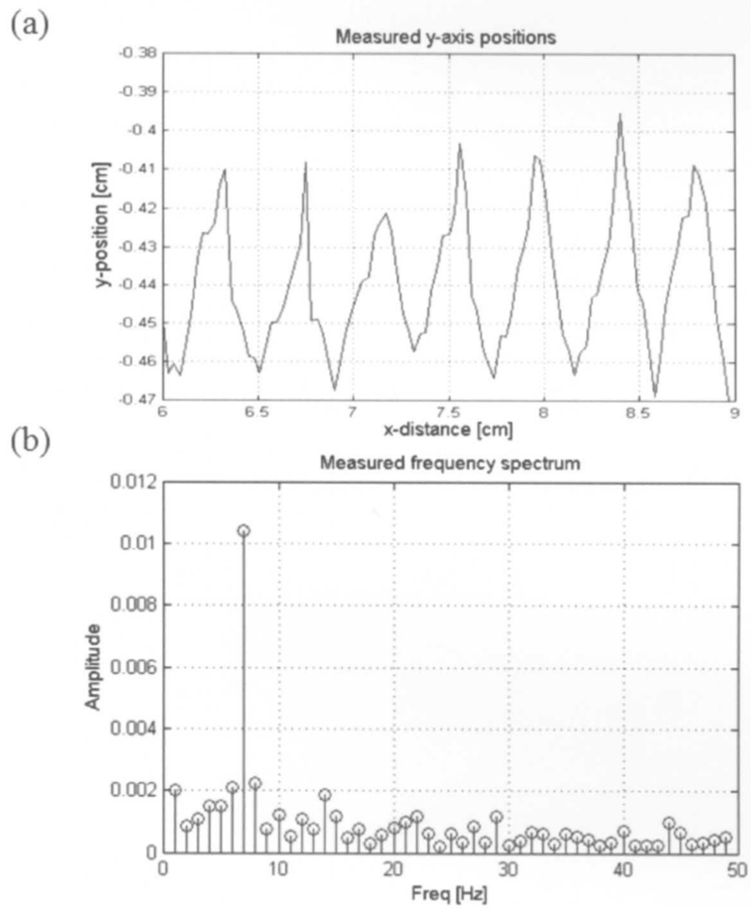


Figure 4.6: Measured y-axis position (a) and Measured frequency spectrum (b) for sample S2

From the spectral analysis of this particular case is noticeable that the frequency with larger amplitude is the frequency presented in 7 Hz, in fact, this reflects that if a signal is periodic with frequency f, the only frequencies composing the signal are integer multiples of f, frequencies that are called harmonics. However, result of the distortion considering that is not a perfect sine wave, the frequency domain is composed of the peak in 7 Hz corresponding to the seven harmonic plus other harmonics of smaller amplitude.

4.4.3 Surface Texture S3

In the case of sample S3, although the waveform (See Fig. 4.7a) is very similar to the S2 is important to note how the shape parameters corresponding to the period and amplitude are different, which subsequently generated a frequency spectrum characteristic for this surface.

In Fig. 4.7b one can observe that the higher amplitude of frequencies is located in the first five frequencies, the highest being 4 Hz, however, a characteristic part of this wave is also how the amplitude of the other frequencies behave.

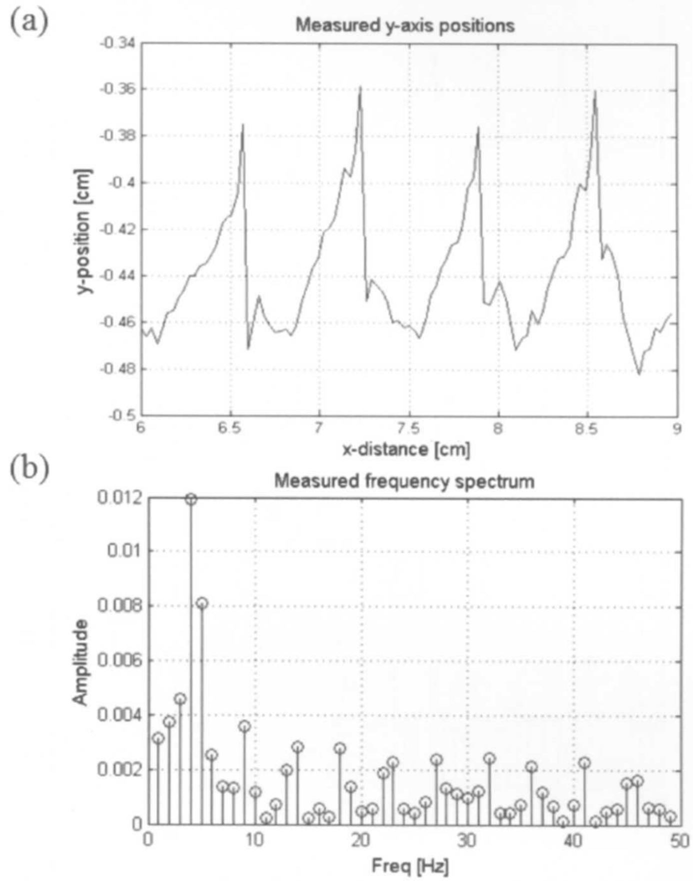


Figure 4.7: Measured y-axis position (a) and Measured frequency spectrum (b) for sample S3

The particular spectral analysis of this surface (S3), as well as the one of S2, shows that the Fourier analysis for periodic waveforms, according to the parameters of the function, has a very particular pattern composed of the fundamental harmonic (highest value) an the others which are result of the present distortion on the waveform.

4.4.4 Surface Texture S4

The S4 sample analysis resulted in the waveform and frequency spectrum shown in Figure 4.8. Characteristic feature of this type of surface was the deformation produced under the pressure exerted by the EF, as well as the greatest amplitude and period compared with the other samples.

This sample like the S3 has its highest frequency in the 4 Hz, but by supplementing their classification with the other frequencies contrast with it.

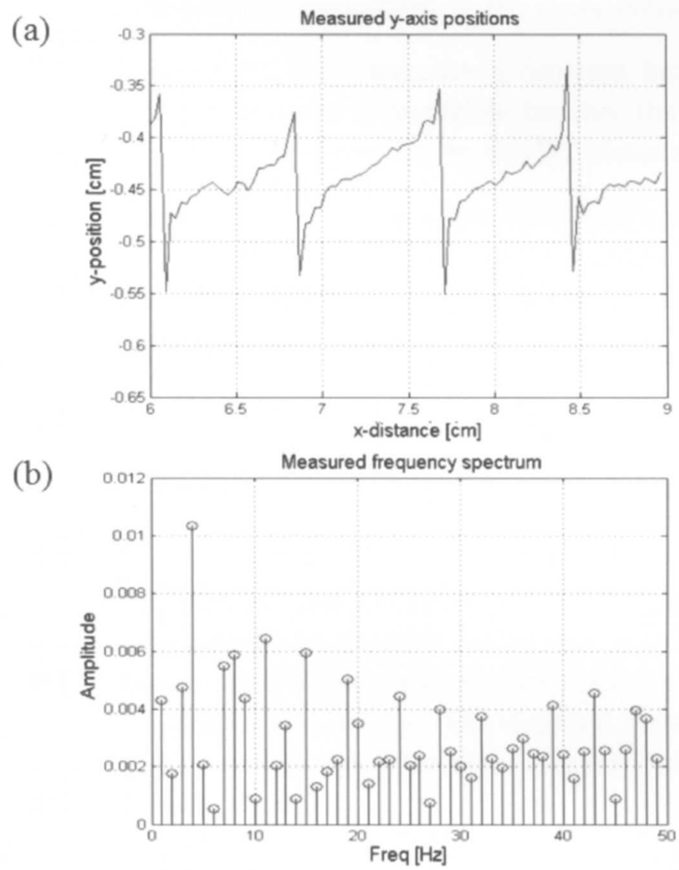


Figure 4.8: Measured y-axis position (a) and Measured frequency spectrum (b) for sample S4

Considering that S4 was the one with the less similitude to a sine wave, it is valid to think that the value of its fundamental frequency will not be as pronounced when compared with the others harmonics. The previous can be verified considering that the fundamental frequency located at 4 Hz in this sample does not differ from the other frequencies so markedly as the spectral analysis of the S1, S2, and S3 samples.

4.4.5 Discussion

For the application of this mathematical transform in haptic pattern recognition, the overall spectral analysis performed for each of the surfaces is consistent according to how behaves the DFT to periodic waveforms.

Considering the above, the fact that the resulting waveforms (S2-S4) of the surface mapping are similar to that of a perfect sine wave with some degree of distortion, consequence of the surface mapping by the spherical probe, makes possible to observe and demonstrate the behavior of the DFT and the relationship between the harmonics obtained by the DFT and the periodic component in the space domain.

Additionally, the behavior of S1, that resembles a constant function, shows that the amplitude of the resulting frequencies is negligible because the fundamental frequency is located at zero frequency corresponding to the DC component.

Finally, it is worth mentioning that the samples waveforms are the result of the dimensions of the spherical probe used to map the surface texture. The dimension of 2 mm in diameter was selected taking into account the surface with smaller ridges and grooves, (S2) so that it could be mapped correctly.

4.5 Results

The final results of the main experiment with the optimized parameters can be seen in Table 4.1 that shows the confusion matrix of the surface texture classification and that reflects the performance of the classifier for 10 test samples for each of the four types of surfaces. Shown in each column and row are the results for the different surface classes addressed throughout this chapter. The diagonal elements in this matrix represent the correctly classified samples while the other elements located in a different position represent the incorrectly classified.

The parameters of *Success Rate* (SR) and *Error Rate* (ER) are used to evaluate the performance of the classification. The SR is the ratio of the number of elements in a given class that are correctly classified with respect to the total number of elements of the class. On the other hand, the ER is the percentage of the class elements that have not been classified correctly with respect to the total elements of the class.

In the experiment, high success rates were achieved for the classification of the surfaces textures tested (100% for all the samples). This shows that the prediction of surface textures with small geometries is possible, especially bearing in mind the small variation among their parameters.

Table 4.1: Confusion Matrix of the surface texture classification

Classified as	S1	S2	S3	S4
S1	10	0	0	0
S2	0	10	0	0
S3	0	0	10	0
S4	0	0	0	10
SR(%)	100%	100%	100%	100%
ER(%)	0%	0%	0%	0%

4.6 Summary

This chapter analyzed the haptic system texture classification that use the frequency spectrum obtained by the DFT for texture recognition. At first instance, a series of preliminary experiments for the measurement cycle are presented, detection of outliers and parameter optimization. Consequently, a description of the waveform and the corresponding haptic frequency spectrum from the data acquisition system is performed, showing their distinct features.

In addition, the performance analysis of the proposed system is performed. Analysis, which was proved in four different surface textures and found that its possible to obtain optimal performance of the proposed classification of surfaces in this experiment. It is concluded from the results that the approach used for the detection and classification of textured surfaces shows the potential of this technique which can be implemented in different autonomous robotic systems.

Chapter 5

Conclusions and Future Work

This chapter summarizes the work described in this thesis and the achieved results by stating the main contributions in the area of haptic surface texture classification. In addition, it also includes the further work that can be done in the thesis research and discuss how its limitations can be overcome.

5.1 General Conclusions

In this thesis, a novel approach for surface texture classification for haptic systems was presented. A custom low-cost haptic sensing device (Novint Falcon) was integrated with a modified EF to obtain haptic feedback that resulted from the waveform surface pattern of a texture.

A supervised learning classifier has been trained with real-world data samples of textures, which included features computed from the frequency spectrum of the waveform of the surface texture measurements. The classifier could reliably distinguish four different surfaces types of texture even with the limitations of the haptic device used as a base for the haptic surface waveform extraction and subsequent feature generation.

According to the research questions posed, and the results obtained in the development of this thesis, it can be concluded that it is possible to design a robotic haptic system for classifying surface textures by extracting the frequency spectrum from the surface waveform via the DFT. Furthermore, these results, as shown in Chapter 4, prove the efficiency of the implemented system and the way that emulates the behavior by which humans identify textures.

In addition, while the results were obtained in a simplified test setup under a controlled environment, they point the way for the application of methods to identify and estimate the properties of the surface textures in unknown environments. This will be helpful in performing tasks using robotic systems that require precise control of the action being done by identifying the haptic properties of objects and hence improve the overall performance, as in the case of the activities performed by service robots.

Furthermore, the obtained haptic information can be included and combined with data from other sensors as are the vision systems. This will allow the implementation of more complex activities that require multisensory information as the identification of objects both in form and texture.

Finally, at the highest level of description this thesis is concerned with finding ways of improving the haptic interaction in robotic systems and provides further motivation for the study of haptic information. With this in mind, the research provides a conceptual framework of how haptic data can be used to provide information to robotic systems and based on that, achieve learning and improve performance on the activities developed.

5.2 Contributions

At the highest level of description, the main contribution of this thesis to the state of art is the validation of the methodology used for surface texture classification with a robotic haptic system that emulates the kinesthetic system by which humans gather and identify the properties of the surface textures. This methodology defines a conceptual framework and characterizes haptics from the perspective of both the haptic device and the human haptic system.

An aim of this thesis was the development of a prototype system for measuring and mapping automatically a surface using the Novint Falcon as a haptic interface. A major contribution of this thesis was the implementation of the mass-spring-damper force model for the automatic motion of the end-effector as a force choice paradigm to use the Novint Falcon as a robotic system.

This thesis has shown a modified version of the Novint Falcon end-effector to allow the acquisition of the surface properties by mapping its waveform using the motion pattern performed by the system. Another contribution of this thesis was the design and implementation of the end-effector on the Novint Falcon in order to accurately achieve the waveform mapping.

An objective of this thesis was to provide an approach for texture classification using Fourier coefficients as a suitable feature. Despite previous research using Fourier coefficients as a feature for classification, this research has shown that its implementation is feasible not only for virtual textures but also for physical textures.

5.3 Future Work

The research examined in this thesis was the haptic surface texture classification using the frequency spectrum as a feature. Future work could adopt a similar approach to that used in this thesis to explore other haptic information. On this context, further investigation on human kinesthetic perception will be undoubtedly beneficial for the overall research in haptic texture classification as well as the cutaneous perception.

Given the complexity of the sample surface textures used in this research, it is also reasonable to assume that the work done could be replicate for other haptic properties of the objects. This might include features as the hardness or viscosity of an object, among others.

In addition, the limitations of this thesis research are partly consequence to assumptions of a controlled environment where the experiment was performed. In spite of this, it will be reasonable to seek the surfaces texture identification in unknown environments where other forms of haptic exploration need to be implemented.

Another area of research, that could complement the work done, is the implementation of multisensory information by combining the obtained haptic information with data from other sensors as are the vision systems, in order to perform more complex tasks.

However, based on the obtained results in this simplified research, it is believed that the application of haptic surface texture classification in more complex robotic systems and under no controlled environment is a challenge worth to tackle.

Appendix A

Novint Falcon

Technical Specifications for Novint Falcon [6]

- 3D Touch Workspace 4 in x 4 in x 4in
- Force Capabilities > 2 lbs
- Position Resolution > 400 dpi
- Quick Disconnect Handle < 1 second change time
- Communication Interface USB 2.0
- Size 9 in x 9 in x 9 in
- Weight 6 lbs
- Power 30 watts, 100V-240V,50Hz-60Hz

Recommended System Requirements [6]

- Processor: 2.4 GHz Processor
- OS: Windows XP Service Pack 2, Windows Vista
- Graphic card: 256Mb 3D hardware accelerated graphics card
- DirectX Version: DirectX 9.0c
- Hard Drive: 1.5 GB free disk space
- Memory: 1 GB RAM
- Other: Broadband Internet Connection, USB 2.0 connection

Appendix B

HDAL Layers Novint Falcon

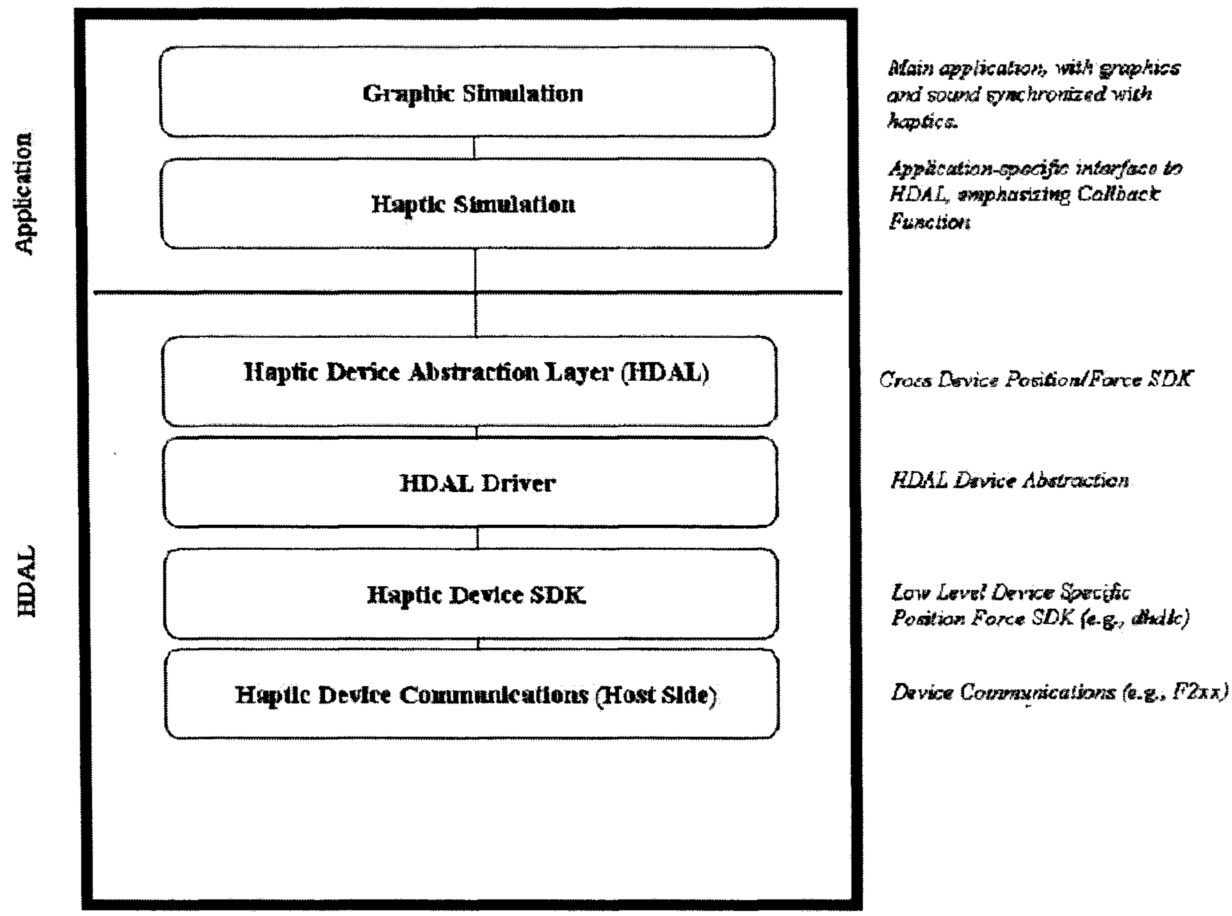


Figure B.1: HDAL Layers [6].

Appendix C

End-Effector Blueprints

C.1 Blueprint: Detail View

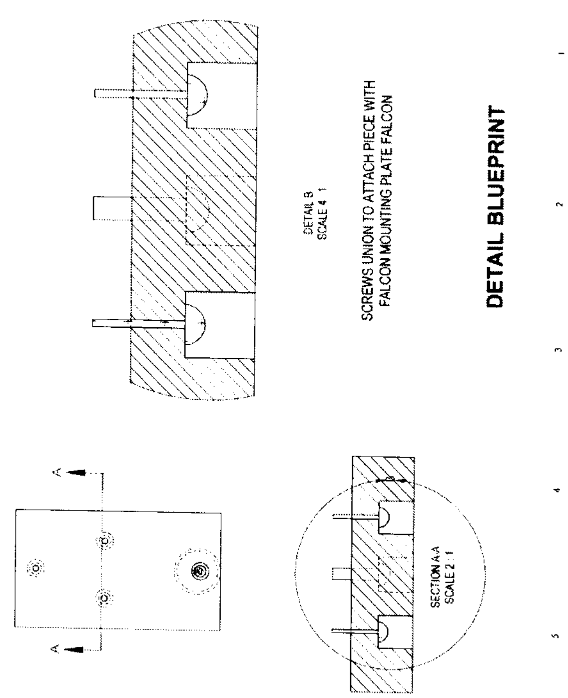


Figure C.1: Detail View

C.2 Blueprint: Section View

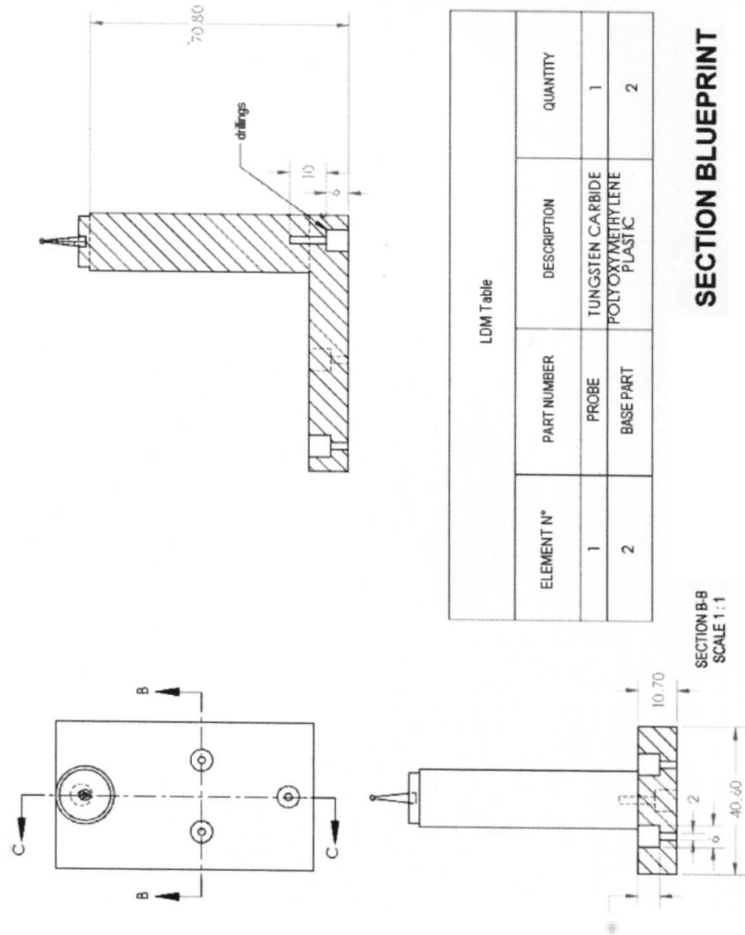
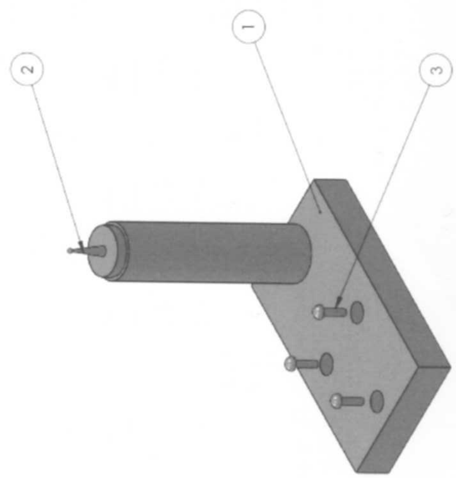


Figure C.2: Section View

C.3 Blueprint: Exploded View

Exploded View



Elements table

ELEMENT N°	PART NUMBER	DESCRIPTION	QUANTITY
1	BASE PART	POLYOXYMETHYLENE PLASTIC	1
2	PROBE	TUNGSTEN CARBIDE	1
3	SCREWS		4

Figure C.3: Exploded View

C.4 Blueprint: Bottom View

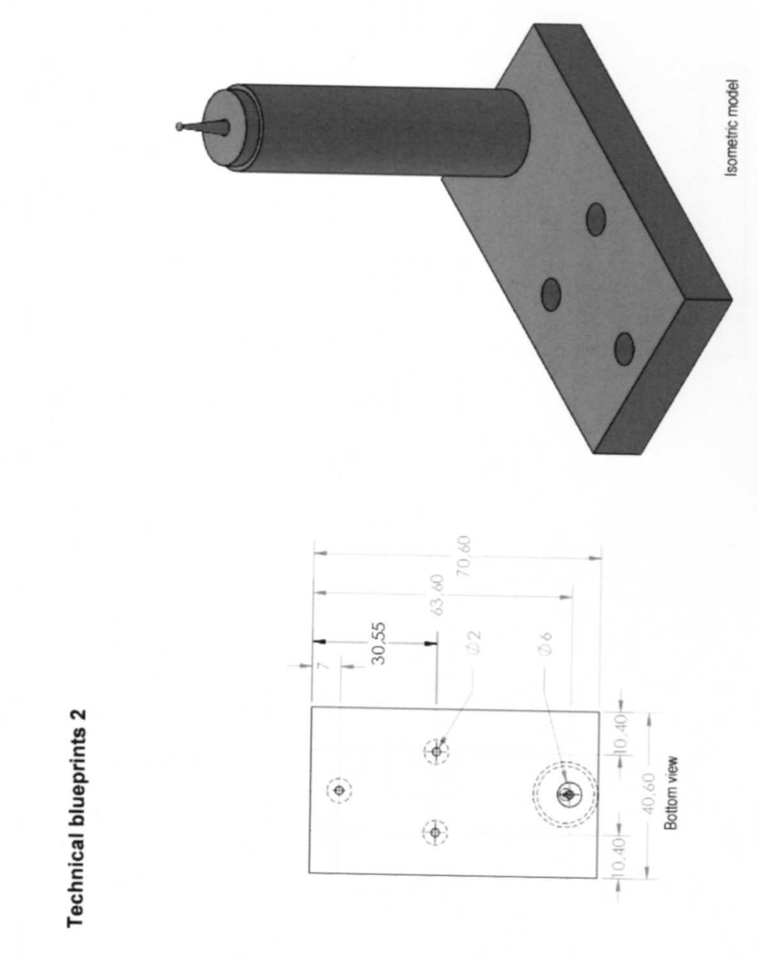


Figure C.4: Bottom View

C.5 Blueprint: Views

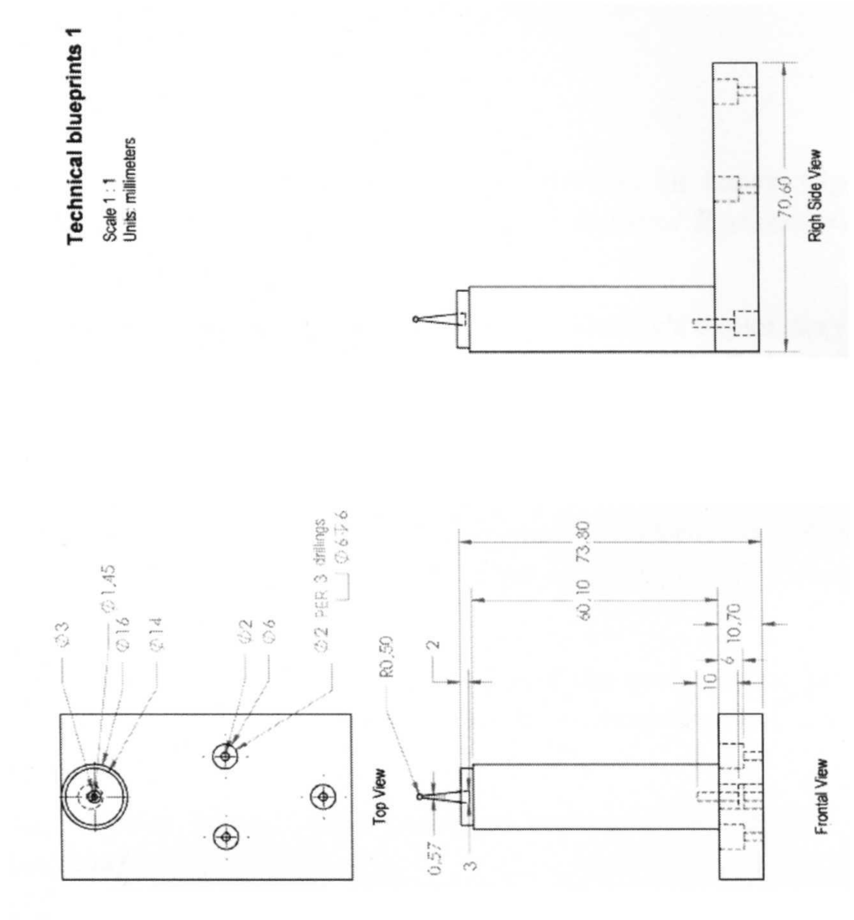


Figure C.5: Top View, Frontal View and Righ Side View

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