Tactile-based Control Strategies for Robotic Object Manipulation in Unstructured Environments

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Introduction

The ultimate goal of robotics is to bring robots into the real world, beyond controlled factories and laboratories. This is a challenge largely due to the many uncertainties present in uncontrolled environments. In the present study, we look at robotic grasping in such environments. Uncertainties in object position and orientation within the robot's workspace must be controlled if objects are to be grasped and manipulated reliably. The best way to devise control strategies is to look to nature: how do animals and humans manipulate objects in the real world? Because the mammalian motor system is so complex, it is hard to give a single answer to this question. However, we can try to develop an understanding of its basic elements. For example, it has been shown that the main reason for dextrous manipulation abilities in humans is due to high-level control structures embedded in the central nervous system [35], [36], [38]. In other studies of human physiology, it has been demonstrated that without tactile afferent signals, the motor system has much difficulty in completing basic object manipulation tasks [7], [24].

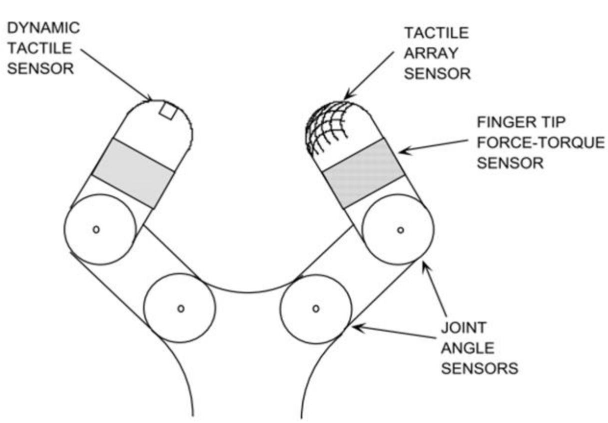


Figure 1.1: Schematic drawing of a robotic hand with several types of contact sensors. [6]

The main contribution of this work is to uncover a control strategy for a robotic manipulation system based on tactile feedback and other intrinsic measurements, combined with a high-level control structure based off of human physiological studies.

The report is structured in six sections. Following this introduction, the related work section looks to the robotics literature and presents state of the art tactile-based grasping systems. In the next section, Background and Motivation, we present important neurological and physiological findings that can be useful in devising a robotic manipulation control strategy. In the Theory of Operations section, we present our experimental setup including the robotic equipment (i.e. the BarrettHand and WAM from Barrett Technology Inc.). This is followed by an introduction to the Experiments conducted as well as the Results obtained from these experiments. We finally Conclude with what we hope to achieve in future research. The text is accompanied by two documents containing the figures for (1) the Theory of Operations & Experiments sections as well as (2) the Results section.

Related Work

In the present study, we focus on the research question: how does the hand attain a stable grasp of an object? There are two common approaches to this problem in the robotics literature. One approach is to commission the robot hand to grasp an object in two stages: planning and execution. Planning is done in simulation with geometrical object models, followed by execution via physical robot actuation. One disadvantage to this approach is that due to imperfect models and robot calibration, executed grasps can easily become unstable [1]. A more recent approach is to formulate the grasp as a control problem that utilizes force, torque, and tactile sensors to obtain a feasible grasp, while being able to adapt to unexpected changes in the environment. The key advantages of this approach are that a priori object models and excess planning are not required to obtain a feasible grasp. This results in a system that is both efficient and robust to pose uncertainties [1]. One more advantage of the latter formulation is that it is closer to how the human motor system is known to function.

There is ample physiology and neuroscience reference material from which inspiration and insight on devising successful grasping schemes can be drawn. Much success has already been attained [2–5].

This section begins with an overview of human-inspired robotic grasping; moves on to discussing how emulated tactile afferents are analytically processed; presents literature on a current hot topic, namely grasping from experience; and concludes with an outlook to important lessons that robotics still has yet to learn.

Human-inspired grasping schemes

If we have learned anything from the human motor system it's that it is highly complex. Creating a robot hand with dextrous manipulation skills that could even come close to what a human is capable of is no easy task. There are a wide variety of receptors in the skin and muscles which in turn respond to a wide variety of stimuli. Sensed parameters include skin stretch, skin curvature, vibration and muscle force and length. One baffling aspect of the human motor system however is that information bandwidths range from just a few Hz to possibly several hundred Hz. In terms of technological performance, this is horrendously slow. It is also time varying, nonlinear, and the pulse-frequency encoding scheme obscures much of inputs from the nerve endings. How this is made up for, however, is a high degree of parallelism and redundancy [6].

It is also well-known that the human motor system executes grasps as a series of discrete states that transition based on afferent signals [7]. Since this type of model is appropriate for execution on a computer, it has been quite popular to model the robotic grasping task as a Finite State Machine (FSM) dependent on tactile or other intrinsic contact input events as transition conditions [2], [5].

In [6], Howe presents a comprehensive overview of robotic hand systems in his 1993 review article. Figure 1.1 shows a simplified schematic drawing of his design, which obtains inspiration from the physiology of the human hand. Howe's design has since been left unchanged [8]. Not shown in Howe's diagram, however, is another popular fingertip sensor implementation based on calculating the deformation of a bag of fluid, as shown in Figure 1.3.

In [3], the authors present sensor-based atomic controllers for a robotic hand/arm system to empty a box containing an undefined number of unknown objects. Manipulation primitives are defined that search, grasp and transport objects from the box to predefined locations. A FSM is used to transition between motion primitives based on corresponding sensory feedback. This FSM is presented graphically in Figure 1.2. The authors also compare a vision-plus-tactile-based version of their system to a purely tactile-based version. They found that while the version which incorporated vision was more efficient at completing the empty-the-box manipulation task, the tactile version was also successful. Vision was only crucial in determining if the box was empty; in the non-vision based system, a human moderator was required to tell the robot when it had finished its task.

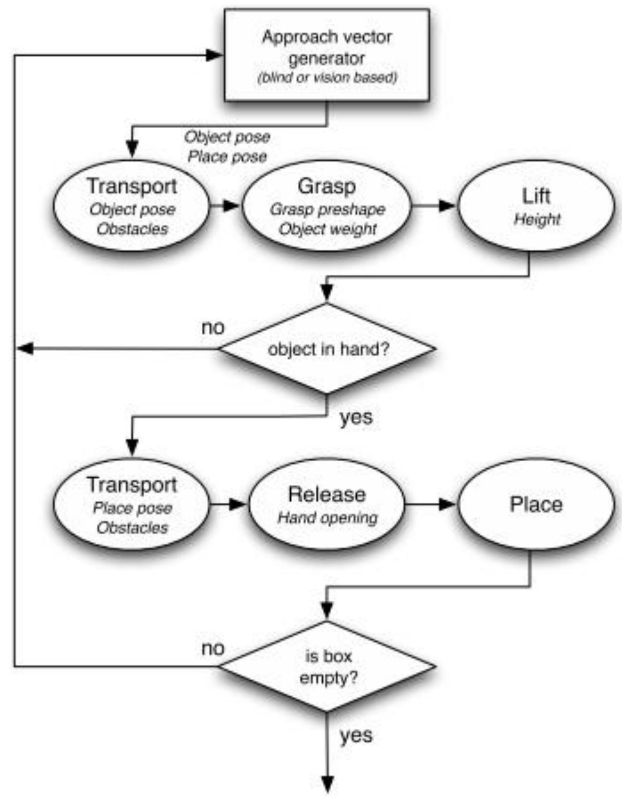


Figure 1.2: Discrete states and transition conditions in the FSM that defines the empty-the-box manipulation task [3].

The authors in [3] also present an interesting scheme that compensates for errors in translation of the robotic hand. The hand repositions itself if there is force experienced by only one finger, denoting a single hand/object contact. The controller compensates by moving the hand in direction of single contact, which effectively repositions the manipulator above the object.

The authors in [2] present a tactile-motor coordination of a robotic hand based on a neurological model of the human tactile-motor system. This model is implemented as a series of Artificial Neural Networks (ANNs) whose function and structure reflect findings of neuroscience on human sensorimotor areas specific to object grasping. For example, due to specific known properties of the motor area such as its requirement of dynamic control, a Recurrent Neural Network model was chosen for its specialization in dealing with dynamic processes by way of online adaptation to sensory inputs. For the sensor area, which must deal with a high rate of combined tactile and somatosensory input, a scheme based on the concept of Self-Organizing Maps (SOMs) was chosen. This helped control the volume of incoming inputs by making small, efficient adjustments to the model each time a new input vector becomes available. See Figure 1.4 for a graphical overview of their overall system.

The authors in [4] developed a human-inspired robotic grasp controller that gently picks up and sets down unknown objects. They employ pressure sensors and accelerometers to mimic SA-I, FA-I and FA-II tactile channels. A Finite State Machine (FSM) is programmed to transition between six discrete states: (1) Close, (2) Load, (3) Lift and Hold, (4) Replace, (5) Unload, and (6) Open. Transitions are based entirely on tactile event cues. Their controller also dynamically adapts its initial grasp force depending on tactile events such as slipping, and judges when to set down the object in light of detected contact events with the table.

In [5], a new tactile-based object manipulation strategy

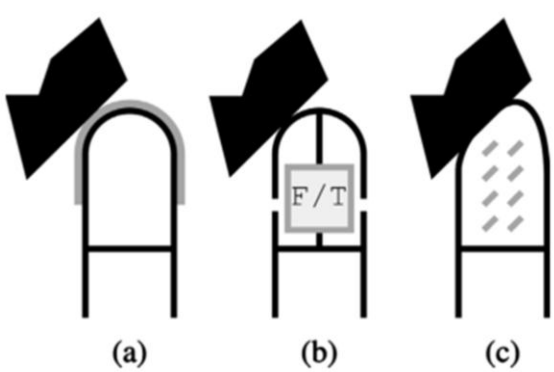


Figure 1.3: Different fingertip sensors: (a) tactile array - extrinsic; (b) force/torque sensor - intrinsic; and (c) fluid-filled. [12]

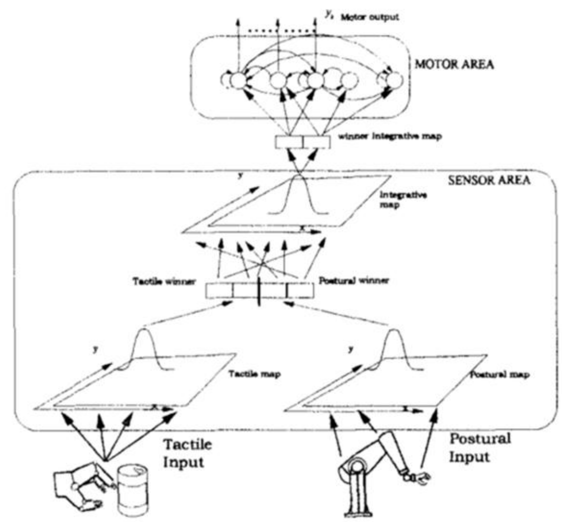


Figure 1.4: Structure of ANNs chosen by the authors to model findings of neuroscience on the topic of human grasping.

was proposed, called tactile-servo. Analogous to vision-based visual-servo, each state in the manipulation task sequence is characterized by tactile images detected via tactile sensor arrays aboard the robot hand. An example of such a tactile image can be found in Figure 1.5. The author's conclusion is that tactile sensors are useful in simple, direct and effective control of manipulation tasks. The fact that tactile data is processed by the human motor system much like visual data is processed through vision is supported by a few neurological studies such as [9], [10].

Figure 1.5: example tactile image during the rolling-pin task by planar robot finger equipped with tactile sensor array in [5]**. Darkness indicates pressure intensity.**

Tactile Information Processing

Lee and Nicholls [11] define the tactile sensor as "a device or system that can measure a given property of an object or contact event through physical contact between the sensor and the object." This definition is misleading, however. It turns out that it is not quite as trivial to detect contact events or measure properties of grasped objects as the definition makes it seem. Nevertheless, the application of tactile sensors to many robotics problems affords new solutions that have previously been intractable via traditional, often Computer Vision-based methods.

In their 2005 review article, Tegin and Wikander [12] stress that in spite of the densely populated space of Robot Vision research, the application of contact information to robotic problems has been sparse. While vision is argued as the dominant sense in larger primates, including humans, there are certain scenarios where vision fails. Examples are during object occlusion or when sensory resolution is too low for a given task. In such cases, more detailed and versatile contact information may compensate for these deficiencies.

The authors define tactile information as useful in detecting (1) object contact/no contact; (2) contact configuration (surface, edge, point, etc.) based on pressure-patterns (3) object slip via vibrations in the grasped object, (4) properties of an object (whether it is stiff/compliant, what its texture and friction coefficient is, etc.) via haptic exploration; and finally (5) feedback for control. Using the above information, force and moments at contact locations with an object can be controlled to accomplish the desired manipulation task.

In order to understand how this high level object-hand configuration information can be acquired, we must first discuss how tactile information is interpreted from raw sensor data. In [8] the authors present a high-level view of tactile information flow: the various layers of processing that takes raw tactile input and produces high level output such as object shape and contact types. This high-level view is shown graphically in Figure 1.6.

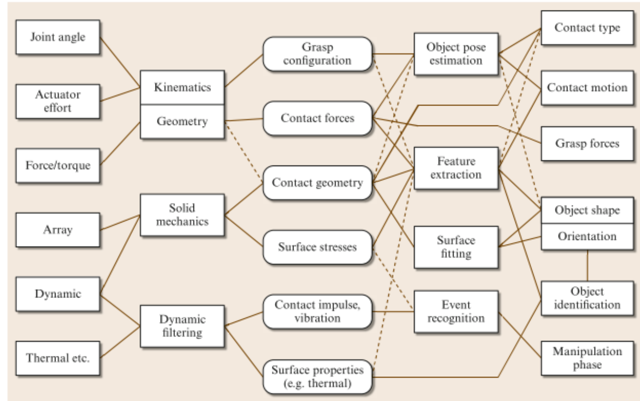


Figure 1.6: Force and tactile information flow and signal processing. [8]

As a prerequisite to manipulation, contact locations and forces must be obtained so that objects can be grasped securely and accept desired forces and motions relevant to the task. For object exploration, information such as local geometry, hardness, friction, texture, etc. must be obtained and integrated. In order to respond to events, the type and magnitude of events enacted, by for example an external agent, must be detected and properly assessed.

Here is a thought exercise: how do humans accomplish the task of turning a pen end over end between our fingers? What information are we using? Well, the position and orientation of the object must somehow match our imposed forces to maintain stability. These three measurements depend on many variables, such as the *configuration* of our grasp, the *locations and movements of contacts* with our fingers, the *magnitudes of grasp forces*, the *contact conditions* with respect to friction limits, plus a few more. How is it that, with enough practice, we can control all of these parameters effortlessly, even if our eyes are closed? Now, how might we program a robot to accomplish the same feat?

Returning to our diagram in Figure 1.6, starting at the upper-left corner, from the forward kinematic model of the hand together with joint angles, we can extract positions and orientations of the coordinate frames of the finger tips. From there, it is possible to obtain local information of object shape, surface normal orientation, etc. which may be integrated to gain an overall geometric pose of the object.

For robotic hands with tactile sensor arrays, such as the BarrettHand, curvature and shape information can be obtained by measuring the local curvature at each element of the sensor array [13]. From there, the next step is to extract features, such as corners and edges of the object by combining local shape information. This task can be greatly enhanced if at least a partial model of the grasped object is available a priori, in which case the object can be statistically matched via surface or data fitting methods [14].

The most common application of tactile information has been to classify and recognize objects from a known set based on calculated geometric information of the object from raw tactile data. Features, such as holes, edges and corners [13] and object surfaces [15] have been used and extracted via tactile array, force and/or joint sensor information. For example, Siegel [16] devised a way to extract object pose of a known object in a robot's grasp from joint angle and torque information.

Since tactile sensors provide only local information, it is prudent for the robot hand to move the sensors for the purposes of haptic exploration and object recognition. These types of strategies are categorized as *active sensing*. There exist many example applications of this, such as tracing object contours, measuring compliance and determining lateral extent of object surfaces. Edge finding has been proposed, which matches segments between successive tactile array impressions [17].

Dynamic sensing is also of interest for the purposes of detecting tactile events with respect to time, such as object slip. The challenge is detecting such events reliably in light of sensor noise. Highly sensitive tactile sensors can be easily affected by vibrations from the robot drive train or rapid robot hand acceleration. Robust dynamic detection can be solved via comparing dynamic tactile sensors at and away from contact regions, or even more robustly via statistical pattern recognition methods that attempt to extract the *signature* of true contact events [18].

Grasping from Experience

Another common approach to robotic grasping in the literature has been to analyze data compiled from a series of grasps and extract features that are indicative of success. Once these features are acquired, they can then be used to predict success in future grasps.

One example of such a learning scheme is called the Self-Organizing Map (SOM), an architecture of ANNs that spatially and uniformly organizes features automatically from input signals [19]. An example where SOMs have been used successfully is in [20]: objects are grasped based on hand posture and tactile experience of previously successful grasps. Experience is represented as a low dimensional smooth manifold in hand posture space, which is implemented as a SOM variant. Successful grasps are used to continually update the SOM experience base that is then used to guide subsequent grasps to their closest matching posture in the experience base. Figure 1.7 depicts the experience base graphically.

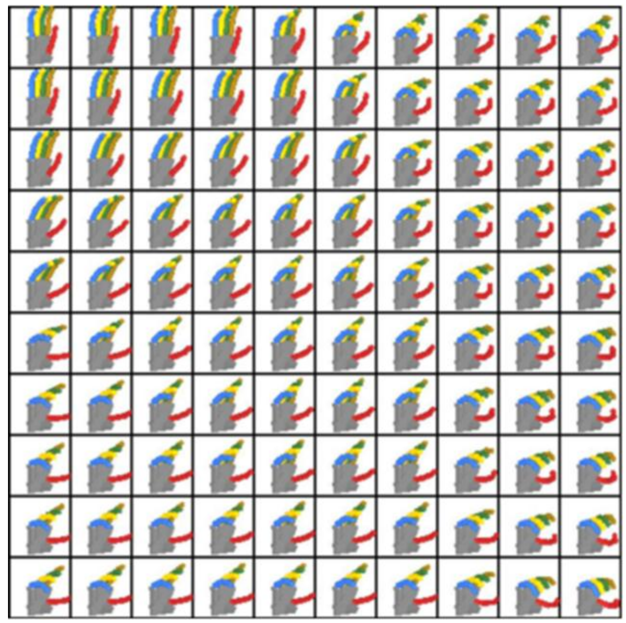


Figure 1.7: Discrete grasp manifold of successful grasps based on the SOM. Note how similar grasp postures are organized together which results in fast queries of the experience base.

A similar system was devised in [21], where a SOM was used to map finger joint angles & tactile readings to object shape and size. The system could identify previously grasped objects as well as categorize new objects as being a particular shape and size. The system recognized 89% of 25 different objects.

The authors obtained similar results with another algorithm inspired by biological spiking neurons, called a spiking neural network [22]. For this scheme, joint angle input is encoded into a series of spike trains which result in three feature outputs that are then used to recognize and classify grasped objects. In addition, similar objects tended to cluster in output feature space (see Figure 1.8). The authors' system was able to recognize objects of different shapes as well as objects with the same shape but different size.

In [23], the author's present *blind grasping*: a novel approach to object grasping that does not require visual feedback or a priori 3D object models. Their scheme works from a database of one thousand stable grasps from the Columbia Grasp Database with the model of a BarrettHand. Corresponding tactile feedback during simulated grasps of objects are also recorded. Grasps are simulated in GraspIt!. They proceed to create feature vectors composed of simulated tactile and kinematic data which they then use to train an SVM to classify grasps as being stable or unstable. In this way, the system was able to learn tactile feedback necessary for a stable robotic grasp. Once these successful tactile and kinematic features are learned, the robot hand can move its wrist & re-shape its hand to explore the object until similar tactile contacts to grasps in the database are achieved. Figure 1.9 demonstrates such a feature vector as representing a stable grasp.

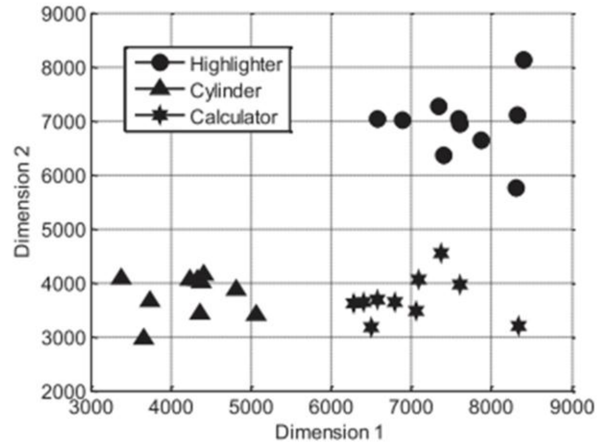


Figure 1.8: Clusters of outputs from trained spiking neural network for certain objects.

Background and Motivation

The field of robotics has much to learn on the topic of dextrous manipulation of objects. Indeed, the surface has barely been scratched. Many researchers argue that the main reason for this is due to a lack of detailed tactile processing capabilities in robots today. While vision has seen a lot of attention over the years, touch is invaluable for many tasks. Tactile sensing provides information on forces and motions at contact points, as well as compliance, friction and mass of the object being manipulated. Obtaining this information is essential to manipulating objects, especially in unstructured environments.

Humans, for example, are able to effortlessly manipulate objects of virtually any shape. This is both due to mechanical properties of the hand as well as the control capabilities of the motor system, which heavily relies on tactile afferents. Without tactile support, humans become clumsy and lose much of their object manipulation ability [7] [24].

Studying the grasping capabilities of humans and animals for the purpose of designing better robotic systems is a challenge. First, it is hard to deduce how humans perform so well. Secondly, human mechanics are complex and thus how they function may not be appropriate for the

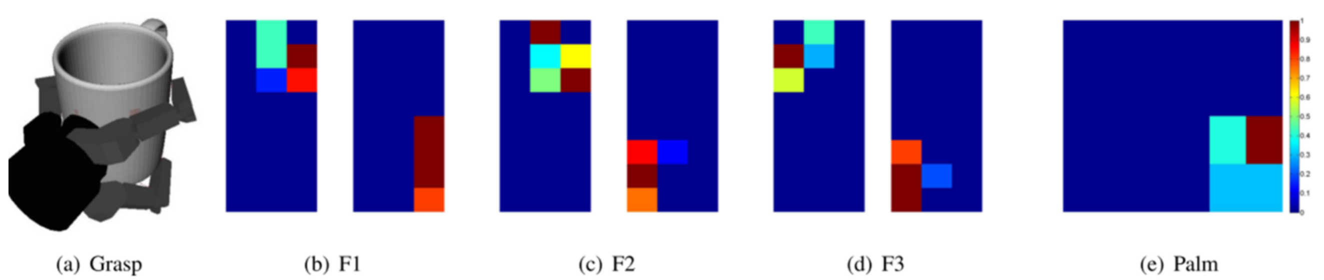


Figure 1.9: Example grasp feature vector in successful grasp database: (a) shows the kinematic state of the grasp around the object, (b) (c) (d) and (e) represent the tactile feedback experienced by the first, second, third fingers and palm of the BarrettHand respectively.

relatively simple mechanics of a robot.

Nevertheless, studying human grasping can provide useful insight in the designing of better robotic systems. Therefore In this section, we attempt to draw such insight in exploring the human motor system as investigated by neuroscience and physiology.

Object Grasping: Definitions

Let us first start with a few definitions. There are a wide variety of grasps that humans employ depending on the force/torque required to manipulate objects. When opening a jar, for example, first a power-style grip is required to loosen the jar. Once the lid is loose and required torque is lessened, a lighter grip is adopted for speed and precision. This dichotomy of prehensile movements was proposed by Napier in 1956. [25] provides an example of these two types of grasps in the manipulation task of tying a knot. There also exists a class of non-prehensile object manipulation actions wherein a complete grasp of the object is not attained; however we are not concerned with this type of hand movement in the current study.

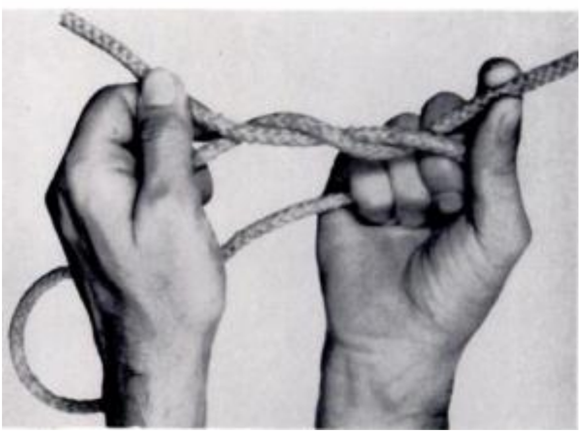


Figure 2.10: Tying a knot: manipulation task combining precision and power grips. Power is required to hold the rope in place while precision is required to tie the knot. [25]

Cutkosky and Howe propose a taxonomy of human grasps in [26], breaking down the dichotomy of power/precision even further. Depending on the weight and size of the object as well as the desired dexterity, the human hand will adopt a different style of grip. See for the breakdown of power grips and for a similar breakdown of precision grips.

For use in robotics the authors also present analytical models of grasping wherein common measures of grasp quality may be optimized or become part of the set of grasp constraints of a given manipulation task. An overview of these variables is presented in Table 2.1. The set of ideal grasps then rests within the space of grasps that satisfy all hard constraints and optimize important soft constraints of the task. For example, Nakamura et al search for a grasp that minimizes internal forces (i.e. grasping effort) subject to constraints on force closure, friction and manipulability [27]. According to physiological studies, humans tend to employ a similar scheme as proposed by Nakamura et al where a certain frictional safety margin is maintained. [24], [28]

Table 2.1: Common analytical measures that may be optimized or become a part of grasp constraints [26]**. Bracketed words indicate closest subjective counterpart in human grasping.**

Measure	Description
Compliance *(Sensitivity)*	Inverse-stiffness of the object with respect to the hand
Connectivity *(Precision)*	Number of DOFs between grasped object and the hand
Form closure *(Security)*	External forces are unable to unseat the grasped object
Force closure *(Stability)*	Object held without slipping (a.k.a. frictional form closure)
Grasp isotropy *(Precision)*	Fingers are able to accurately apply force/moment to object
Internal forces *(Dexterity)*	Kinds of internal grasp forces hand may apply to the object
Manipulability *(Dexterity)*	Fingers can impart arbitrary motions (i.e. connectivity = 6)
Slip resistance *(Security)*	Amount of force required before object starts to slip
Stability *(Stability)*	Tendency of grasped object to return to a spatial equilibrium

Human grasps have also been studied in terms of these analytical measures. For example, power grasps can be thought of as having higher compliance, stability and slip resistance than precision grasps. Power grasps also tend to have a connectivity of zero (since the fingers do not play a manipulating role). In contrast, precision grasps have high manipulability and connectivity (of at least three and often six). [26] A subtle yet important distinction must be made between force and form closure. Only rarely do humans adopt complete form closure of objects (i.e. without the use of friction); some examples requiring form closure would be handling a bar of soap or a slinky. These manipulation tasks would require something like the Sphere or Disk grasps from the taxonomy.

While adequately large grip forces must be maintained to keep the object within a force-closure grasp, exceedingly large forces are also not desirable as they cause unnecessary fatigue and may even crush fragile objects [29], [30].

Therefore there are two constraints on grip force: slipping & crushing thresholds. See for some examples of these thresholds in everyday objects. The amount of force that the subject applies over and above the slipping threshold is called the *safety margin*, the magnitude of which is dependent on the dextrous manipulation skill of each subject for the given task [7].

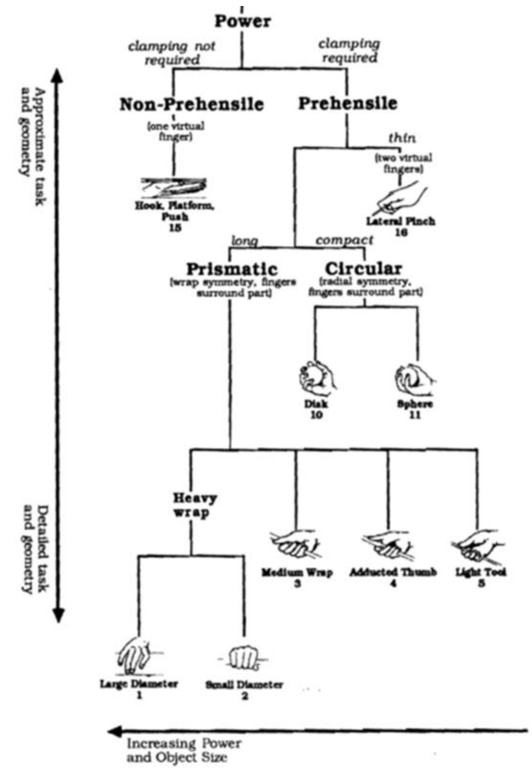


Figure 2.12: Taxonomy of power grasps. [26]

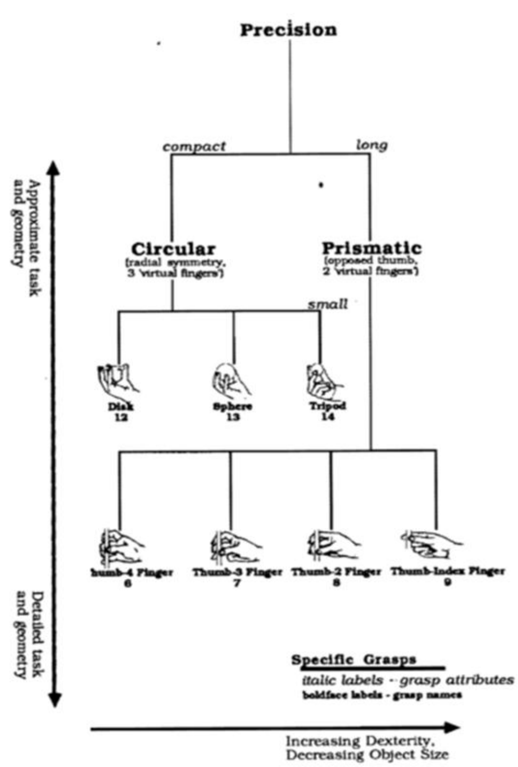
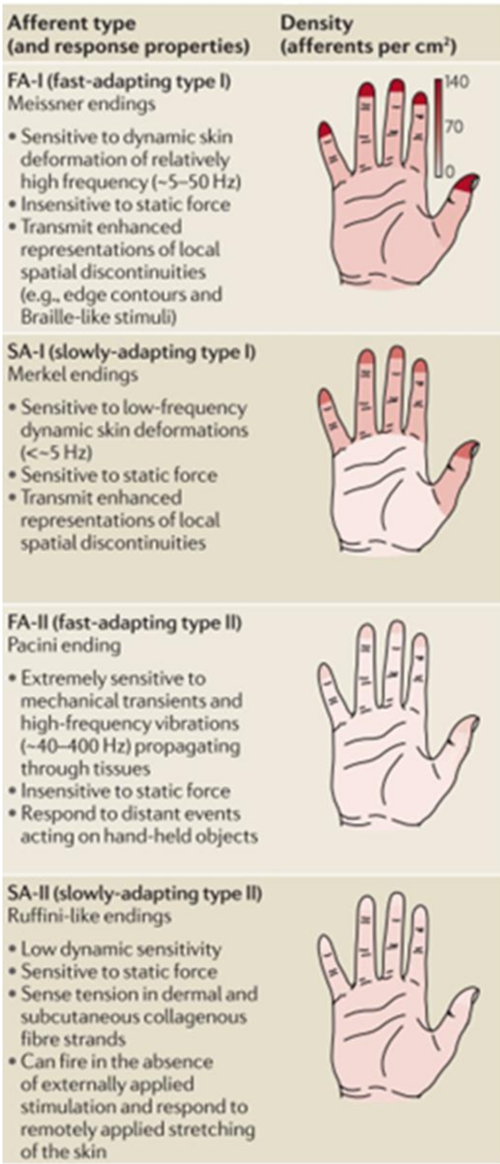


Figure 2.11: Taxonomy of precision grasps. [26]

Table 2.2: Characteristic of tactile afferents within human fingertip skin. Adapted from [10].



Afferent type (and response properties)	Density (afferents per cm²)
FA-I (fast-adapting type I) Meissner endings • Sensitive to dynamic skin deformation of relatively high frequency (~5–50 Hz) • Insensitive to static force • Transmit enhanced representations of local spatial discontinuities (e.g., edge contours and Braille-like stimuli)	140 70 0
SA-I (slowly-adapting type I) Merkel endings • Sensitive to low-frequency dynamic skin deformations (<~5 Hz) • Sensitive to static force • Transmit enhanced representations of local spatial discontinuities	
FA-II (fast-adapting type II) Pacini ending • Extremely sensitive to mechanical transients and high-frequency vibrations (~40–400 Hz) propagating through tissues • Insensitive to static force • Respond to distant events acting on hand-held objects	
SA-II (slowly-adapting type II) Ruffini-like endings • Low dynamic sensitivity • Sensitive to static force • Sense tension in dermal and subcutaneous collagenous fibre strands • Can fire in the absence of externally applied stimulation and respond to remotely applied stretching of the skin	

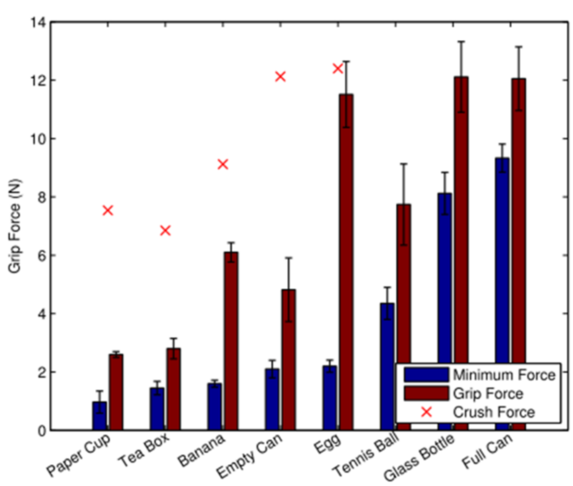


Figure 2.13: Example of imparted safety margin when grasping everyday objects [4]. Unfortunately, it appears as though the hand accidently crushed the egg in one of the experiments.

When manipulating visually fragile objects, the initial force in human subjects is lighter and their action is slower compared to when manipulating visually non-fragile objects. Once contact with the object is made, tactile feedback complements the missing information on the true fragility of the object and then allows subjects to properly carry out the planned action [31].

Information on objects involved can be predicted as well. If errors occur, real-time corrective actions can be launched. Accurate predictions are crucial however due to the relatively slow response rate of corrective actions [32].

Tactile Afferents

The elements of human touch can be broken up into two distinct categories: *proprioceptive sensing* and *tactile sensing*. Proprioceptive sensing refers to the perception of limb motion and forces with internal receptors, such as muscle spindles (responding to changes in muscle length), tendon organs (measuring muscle tension), and cutaneous afferents (reacting to skin deformations around the joints) [32]. Tactile sensing deals with the perception of contact information with receptors in the skin [33]. Receptors within the joints of the hand are also present, which report joint angles, forces and torques [6].

Actuation of the hand is imparted by muscles in the forearm through transmission of tension by tendons passing through the wrist. It has been shown that due to dynamics of transmission such as friction, backlash, compliance and inertia, accurate control of endpoint position and forces based on proprioceptive signals alone is difficult [34]. Thus, tactile afferents are essential for fine-grained mechanical measurements at contact locations.

Tactile afferents have received much attention in the physiology and neuroscience literature; a comprehensive summary of which may be found in [33] and, more recently, [32]. There are in total four specialized types of mechanoreceptive nerve endings within the skin of the human hand, each of which can be categorized as having large or small active areas (Type I and Type II respectively) and responding or not responding to static stimuli (SA for slowly adapting and FA for fast adapting, respectively). See Table 2.2 for a description of each of these types. There are in total 17,000 specialized mechanoreceptors in the grasping surfaces of the human hand. In addition, there are free nerve endings that are sensitive to thermal and pain stimuli [6].

High-level Processes

In addition to low-level tactile and proprioceptive processing, the mammalian central nervous system has at its disposal many high-level processes such as prediction, planning and memory. These processes support, guide and organize our more primitive manipulative functions to accomplish more complex manipulation tasks.

In [29], the authors preclude that the magnitude of fingertip forces are determined by at least two high-level control processes: (1) Anticipatory parameter control (APC) and (2) Post-contact control. The authors model APC as a feedforward controller that uses predictions of critical characteristics of the object (weight/friction/initial condition, etc.) based on the results of previous object manipulation experience. Following contact with the object, sensory information can be extracted to (1) modify motor commands automatically; (2) update sensorimotor memories for APC; (3) inform central nervous system of the completion of each subgoal of a task; and (4) trigger subsequent subgoals. Central nervous system monitors specific, expected events and produces control signals appropriate to each subgoal. In contrast to feedback controllers, this feedforward, sensory driven control strategy predicts appropriate control output several steps in advance. Slips are avoided and force across digits is coordinated by independent control mechanisms based on local sensory information.

Planning plays an important role in anticipating future events as well. In [10], Johansson, et al. demonstrate the importance of eye-hand coordination during manipulation tasks. Subjects' gaze was tracked during a block-stacking task. It was found that their gaze played an important role in planning each pick-and-place action. The authors then further propose and demonstrate in [35] the direct matching hypothesis, which predicts that subjects will unconsciously produce eye movements when observing a familiar action as if they were performing the task themselves. This suggests deep coupling between gaze and object manipulation.

Indeed, in a study conducted by Bicchi et al [9], it was found that the equivalent to the optical flow problem exists in the processing of tactile flow, i.e. movement detected via tactile afferents. Their results showed that the V5/MT cortex (the same areas in the brain that responds to optical flow) is activated during tactile-flow perception. This is consistent to other findings that there exists a supramodal organization of regions in the brain involved in tactile and optic flow processing [36]. In another study by Bicchi et al [37], it was found that certain experiments could fool the subjects' tactile flow processing in the brain via *haptic illusions*, much the same way as their optical counterparts fool optic flow processing.

Action-phase Controller

One of the ideas that Roland S. Johansson has been advocating over the years has been his conjecture that the human motor system, during grasping tasks, functions as a sort of state machine. Transitions of this machine depend on sensorimotor predictions combined with sensory input. States, or *action-phases*, are defined as a sequence of specific sensory events that are each linked to subgoals. The brain then selects and executes appropriate *action-phase controllers* for the task at hand [32].

Action-phase goals are evaluated via patterns in tactile afferent signals. For example, *grasp contact*, a required action-phase subgoal for many manipulation tasks, is provided by SA-I and FA-II afferents. Ensembles of afferents give variables such as contact timing, location and force intensity and direction. Contact location is defined as the spatial center of all afferents involved in the overall signal. Force intensity is characterized by the number of afferents involved as well as the firing rates of each. Finally, patterns of activity in ensembles of afferents give us the direction of the detected contact force.

Once a grasp is attained, adequate normal force must be imposed on the object to retain force closure. Dextrous manipulation is then defined as adapting the balance of grip and load forces to object surface properties. This ability of dextrous manipulation is attributed mainly to tactile afferents since a loss in this ability is experienced during digital anesthesia [7], [24].

Tactile afferents during initial contact also provide object surface property information, which is combined with visual cues and/or sensorimotor memory. Reactions of FA-I, SA-I and SA-II afferents to object surface are used to determine object surface properties. For example, FA-I afferents react more strongly to slippery surfaces [38].

Finally, the processing of tactile afferent information is attributed to the brain's innate ability to detect coincidence when its central neurons receive synchronous input spikes from many distinct tactile afferents [39].

Theory of Operation

We begin this section with an overview of the equipment (i.e. the WAM and BarrettHand) followed by a brief look at how this equipment is monitored and controlled throughout the experiments.

WAM

The WAM is a 7 degree-of-freedom (DOF) robotic arm and wrist system from Barrett. There are three input types when controlling the WAM: (1) joint position, (2) joint torque, and (3) Cartesian position. All inputs are automatically translated into joint torques and fed to puck motors in the arm [40]. The simplest control input is Cartesian (X, Y, Z) however it does not guarantee exact positioning within the robot's Cartesian workspace (approximated as a 2-meter diameter sphere), nor does this control scheme support any kind of collision avoidance. In contrast, joint-space input offers complete and accurate control over all DOFs of the arm.

The WAM is PID-controlled in realtime mode whereas all other function is non-realtime. This poses some restrictions on controller execution. For example, output to the console during realtime operation is forbidden and forces the control program to halt. The WAM comes with built-in gravity compensation mode, which, when active, adds a high level of compliance to the arm.

See Figure 3.2 for the WAM's joint angle and velocity/acceleration limits and Figure 3.3 for further specifications.

Force/Torque Sensor

The Barrett 6-Axis Force/Torque Sensor expands the force sensing capability of the WAM and BarrettHand systems. The Force/Torque sensor processes signals from all the strain gages and outputs three forces and three torques within the Cartesian workspace of the WAM. Full specifications are presented in Figure 3.5.

BarrettHand

The BarrettHand is a 4 DOF, under-actuated, three-fingered robotic hand from Barrett. The DOFs are the joint positions at the base of each finger, and the spread of the first and second fingers around the circumference of the wrist. See Figure 3.7 for details. The hand's under-actuation is possible via the TorqueSwitch technology, which is presented in Figure 3.6. The hand is controlled in four fashions: (1) joint-torques; (2) joint-velocitie; (3) joint-positions; and (4) high-level commands. Joint-position commands are executed with a trapezoidal motion profile meaning that accelerations change instantaneously at the point the command is given. High-level commands include commanding any or all fingers to open or close. As with the WAM, all commands are eventually translated to joint-torques by the associated puck motors in the hand [41]. Apart from standard joint-encoders, the BarrettHand has optional sensors, which include tactile and strain-gage sensors.

BarrettHand Tactile Sensors

Tactile sensors onboard the BarrettHand localize pressure across the palm and fingers. They are arranged as four sets of cell arrays; one set within the distal segment of each finger as well as one set in the palm. There are 96 cells in total (24 in each set). See Figure 3.11 for full tactile sensor specifications.

BarrettHand Strain-gage Sensors

Strain in the hand is measured as torques experienced about the distal joints of each of the hand's fingers over a range of +/- 1 N-m. Strain-gages measure the differential tension in the tendon-like structure running through each finger to the second joint.See Figure 3.8 for a schematic drawing of the joint-torque sensor system of the hand.

The strain-gage output parameters represents the amount of strain on the sensors. This parameter is calibrated to relate strain to joint torque. Due to imperfect calibration (balancing of associated potentiometers), the hand strain measurements have a variable no-load value that corresponds to zero torque. Strain-gage parameter to joint torque conversion was carried out in the current study based on the example curve provided in [41], and is represented as a simple ratio of 118:1. Please see Figure 3.9 for further details and Figure 3.10 for further specifications.

Libbarrett API

The API used to communicate with the robot is called Libbarrett: a C++ library from Barrett Technology Inc. This library simplifies control and operation of the WAM and BarrettHand and allows for them to be controlled in tandem. It also provides sample programs that perform simple control and sensor monitoring routines, from which our controller in the current study is based.

Libbarrett provides three high-level constructs for interfacing with the robot: (1) the WAM object (2) the Hand object and (3) the ProductManager. The WAM and Hand objects provide high-level control of the WAM and attached BarrettHand respectively. The ProductManager provides access to the WAM's optional components, such as attached tools (e.g. BarrettHand) and Force/Torque sensor.

Data types for interfacing with the WAM and BarrettHand are presented in Table 3.1.

Table 3.3: Common Libbarrett data types [1]

Type	Short Name	Units
Cartesian Position	cp_type	Meters
Joint Position	jp_type	Radians
Joint Velocity	jv_type	Radians per s
Joint Torque	jt_type	Newton-Meters

Experiments

We performed two experiments with the WAM and BarrettHand system. The first was a simple grasp and lift of three primitive shapes (cube, triangular prism and cylinder). The second experiment was formulated from a human physiology experiment conducted by Johansson and Westling in 1984 [7]. The purpose of these experiments is to track reactions by the tactile sensors and to recreate results obtained by Johansson and Westling. We then ultimately hope to develop a tactile-driven control strategy for a robust grasp-and-lift using the WAM and BarrettHand based on our findings.

Experimental Setup

Objects being grasped were mounted on a foam pedestal directly in front of the WAM (in the X direction) at a distance of one meter. Measurements are obtained through encoders and sensors onboard the WAM and BarrettHand.

Throughout each experiment, data was collected at the rate of 100Hz. All data are compiled and analyzed; results which are presented in the next section of this report.

Experiment 1: Grasp-and-lift

The purpose of our first experiment is to determine how the tactile sensors of hand react to grasping simple convex shapes. It is then our goal to extract interesting features from this tactile feedback that can be used in identifying future grasps of similar shapes.

The Objects

The three primitive shapes grasped are described in Table 3.2. The objects are shown graphically in Figure 3.14 a).

Table 3.4: Primitive shapes used in experiment

Shape	Description
Cylinder	Height: 4.4cm, Radius: 2.1cm
Triangular Prism	Base/Height: 4cm, Depth: 4.2cm
Cube	Width, Height and Depth: 3.7cm

Grasp-and-lift: The Task

The robot began the task in its home position. It was then immediately given a joint-angle goal so that its end-effector (the BarrettHand) would be placed within the vicinity of an object mounted on a foam pedestal. For all objects, the hand is oriented with all fingers parallel to the ground plane, and with its second finger in the inferior position, in line with the object to be grasped. Thus it is the second finger (F2) that is primarily engaged throughout each grasp-and-lift experiment.

Upon reaching the desired goal position, a signal is sent for all fingers to close in on the object completely. Once a stable grasp is obtained, the robot is ordered to return to its home position while still grasping the object. Finally, the robot is idled; completing the task.

Experiment 2: Action-phases

The purpose of this experiment is to match results obtained through a human physiology experiment conducted by Johansson and Westling in 1984. Their conclusion is that the human motor system grasps objects in seven distinct *action-phases*:

1. preload (first full contact with object attained),
2. loading (grip and load forces increase in parallel),
3. transitional (load force overcomes gravity, forces are peaked),
4. static (forces/position retain stable values),
5. replacement (object brought down until table contact)
6. delay (slight delay before grip is released), and
7. unloading (parallel grip and load force decrease).

By performing a similar experiment with our robot, we attempt to recreate the authors' results. It is then our hope to develop a controller that transitions autonomously between these phases based on sensory information (including tactile feedback).

The Object

The object grasped in this experiment was a 500 ml water bottle filled with 400 ml of tap water. Therefore, its approximate weight is 400 grams. The grasping surface was also lined with 320-b grit silicon carbide waterproof sandpaper for easier grasp force-closure.

Action-phases: The Task

The robot began the task in its home position. It was then immediately given a joint-angle goal so that its end-effector (the BarrettHand) would be placed within the vicinity of the object mounted on the foam pedestal. The hand was oriented to approximate a precision grip, grasping the object between its middle finger (F3) and palm.

Upon contact of the object with the palm, tactile sensors trigger the first phase of the action called the *preload* phase. The hand and arm then proceed through a series of action-phases until the experiment is complete. Refer Figure 3.13 for an outline of how each phase is programmed. The robot was then ordered to return to its home position. Finally, the robot is idled; completing the task.

Collected Data Analysis

Experiment #1: Grasp-and-lift

Shape #1: Cylinder

The first grasp-and-lift experiment was performed with the cylinder. Since the cylinder was slightly taller than the other shapes, it was the only object that engaged both F2 and F3 throughout the grasp (see Figures 4.1 & 4.2). Also of note was the fact that while F3 was engaged, its tactile sensor sensor array was not (see Figure 4.3). This demonstrates that the strain readings and tactile readings can both be used independently in identifying object shape.

Shape #2: Triangular Prism

The second grasp-and-lift experiment was with the triangular prism. One insight into the results shown in is that the way in which the object was grasped by F2 caused a form closure of the object, with the finger wrapped around it. F2's strain sensors are again necessary in extracting the fact that the grasped object was the triangular prism (Figures 4.5 & 4.6). The contact surface area of the object is largest and thus engages the most number of tactile sensor cells in the palm (see Figure 4.7).

Shape #3: Cube

When the cube was grasped, its orientation shifted such that one of its corners became embedded in the tactile sensor arrays of F2 and the palm (see Figure 4.9). In spite of this unstable seating of the object, it was still secured by way of force closure between F2 and the palm. If the object were to have been oriented with one of its sides pressed against the palm, we would no doubt have seen similar results as with the triangular prism in Figure 4.7.

Experiment #2: Action-phases

Our final experiment was to recreate results obtained by Johansson and Westling during their physiology experiment in 1984. We were able to recreate the results with only minor discrepancies. For example, the time in which the preload and loading phases executed was relatively short. This may be due to the relatively slow movements of the WAM compared to corresponding human movement. See Figure 4.11 for this comparison and Table 4.1 for tactile array output during the experiment. For further details see the experiments section of this report.

Conclusions & Future Work

We have seen that while there has been great progress in the development of dextrous manipulators in the field of robotics, there is still much work to be done. Some of the most successful schemes have looked to biology for insight. These strategies have shown that, while the human motor system is highly complex, there is still much we can learn and emulate through mechanical robotic hardware. The hardware has finally caught up to the imaginative minds of tactile-driven robotics researchers and the next step is the devise algorithms and higher-level control structures that make use of this hardware in intelligent ways. There have been studies which hint that the manipulative skill of the human hand is due largely to the way tasks are organized and controlled by the central nervous system [35], [36], [38]. This high-level function must be emulated if we are to see robots function comparably to even the most simple of animals. The next most important element to dextrous manipulation is the acquisition and interpretation of tactile afferent signals [7], [24].

One of the goals of the current study was to experiment with the WAM and BarrettHand system to see how its tactile sensors reacted to the grasping and lifting of three simple shapes. In spite of some similarities in the grasped shapes, the tactile sensor arrays' reactions to each were surprisingly unique. For example, the grasp of the triangular prism and cube, whose sides share similarities in surface-area, resulted in highly distinct tactile feedback. This is largely due to the orientation in which the objects were in at the time a stable grasp was obtained. Results of the experiments demonstrate that tactile feedback can indeed be employed to get an idea of the overall shape of an object to be grasped. Through combination of tactile sensor information as well as the strain experienced by the hand can be used in tandem to recognize unique responses to certain shapes at various orientations. This fact is supported in the literature [8], [12], [42].

Our second set of experiments was to determine the effectiveness of a controller inspired by physiological experiments conducted in 1984 by Johansson and Westling. Results show that this controller is indeed effective at the grasp-and-lift task of an object located at a predictable location within the robot's workspace.

The natural extension to this controller is to allow the object to be placed in any arbitrary location within the workspace. Grasping of this object would require some form of haptic exploration or through the addition of a vision server (as in [3]).

To obtain a better understanding of the hand's reaction to basic shapes, more experiments will need to be conducted and the variability in responses to these shapes should be statistically analyzed. In particular, I would like to try to grasp the objects from different angles (e.g. top-down) as well as place the objects in various starting locations and orientations.

It is the ultimate goal that robots transcend the controlled factory environment and enter more uncertain, human centered environments. The addition of tactile afferents into their control loops is a necessary step in this direction.

I close with a quote from Howe in 1993, the essence of which still rings true today:

> "*Ten years ago a commonly-cited impediment to progress in tactile sensing was the lack of suitable tactile sensing devices and algorithms for interpreting tactile signals. Adequate devices and low-level signal processing techniques have now been demonstrated, and we have made a good start at understanding how touch can be used to provide information about a variety of geometric and mechanical properties of the environment. The primary issues in touch sensing are now concerned with the integration of these devices and algorithms into practical manipulation systems that combine sensors, controllers, and manipulators. The next step will be the expanding use of these systems in manipulation experiments to ascertain the information requirements and appropriate role of touch sensors in dextrous robotic manipulation.*"

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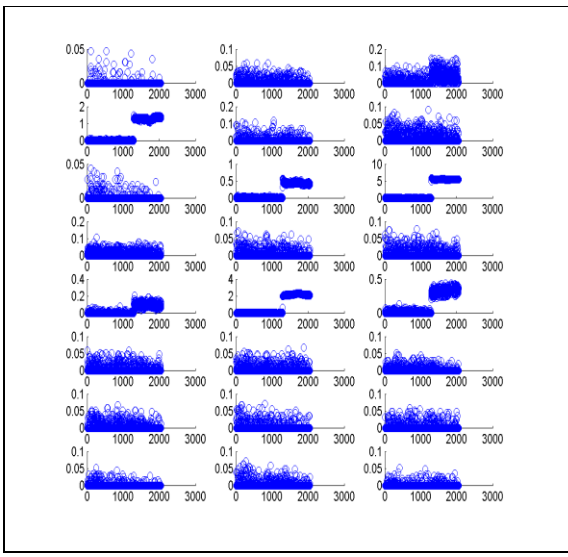
Appendix A

Interpreting the BarrettHand tactile sensor array output tables

Each table of tactile sensor information corresponds to a physical array of sensors on the BarrettHand. From left to right, tactile information for the first, second, third fingers and palm are presented respectively. For the fingers, mapping physical sensors to elements in the table is trivial: the top-most row represents the three tactile sensors located at the tip of each finger; subsequent rows correspond to tactile sensors further down toward the base. This mapping is trivial because there also exist three columns of physical tactile sensors on each finger. Mapping physical sensors to elements in the table for the palm however is non-trivial. For interpretation of the information with respect to the tactile sensor array located on the palm of the BarrettHand, please refer to Figure A.1 below.



(a)

(b)

Nil	*7,2*	*7,1*	*8,3*	*8,2*	*8,1*	*Nil*
5,3	*5,2*	*5,1*	*6,3*	*6,2*	*6,1*	*7,3*
2,1	*3,3*	*3,2*	*3,1*	*4,3*	*4,2*	*4,1*
Nil	*1,3*	*1,2*	*1,1*	*2,3*	*2,2*	*Nil*

F3

Figure A.1: Mapping output table s (a & b) to physical tactile sensors on the palm of the BarrettHand. Each tuple consists of the table's corresponding row and column number (indexed from 1). For orientation, finger F3 would be located below the diagram. Nil denotes part of the palm that does not have tactile support.

Appendix B

Comparing Libbarrett output to collected data

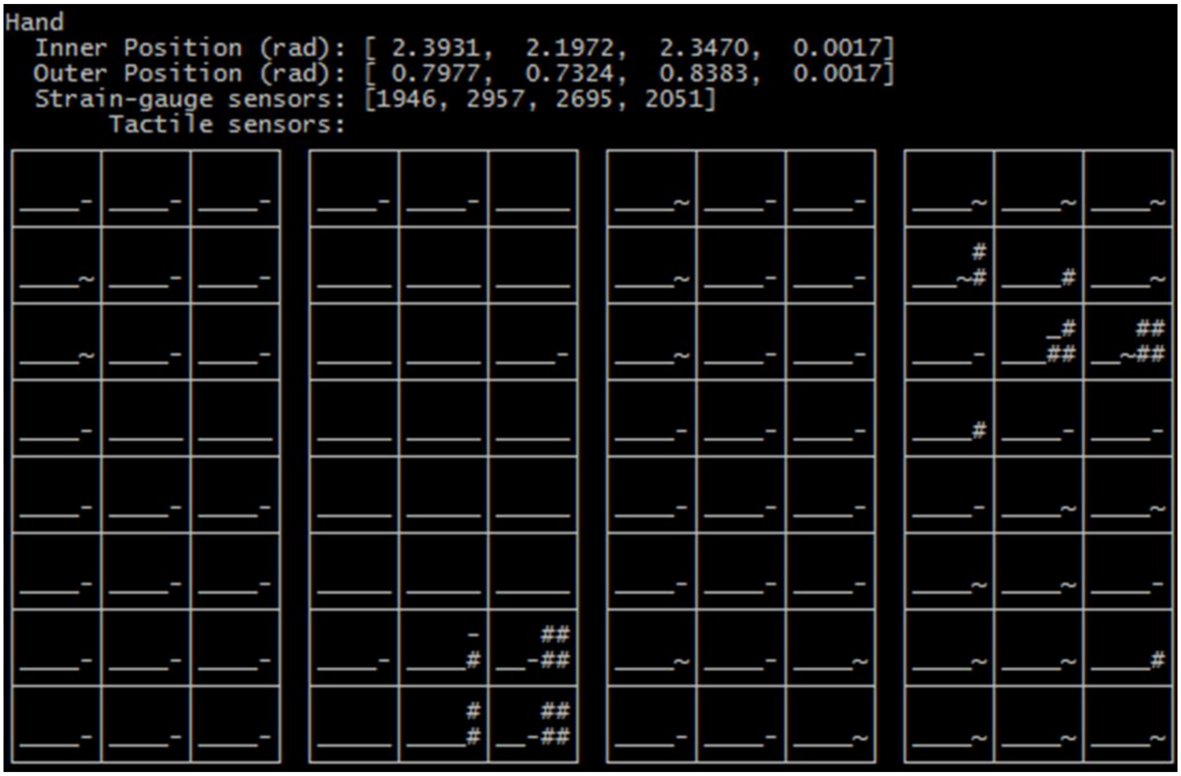
Before interpreting experimental results, it is useful to first verify that data has been collected correctly. I compare tactile sensor output from Libarrett software to collected data compiled and plotted in Matlab. In all of the below Matlab figures, the x-axis is time and the y-axis is tactile sensor output value.

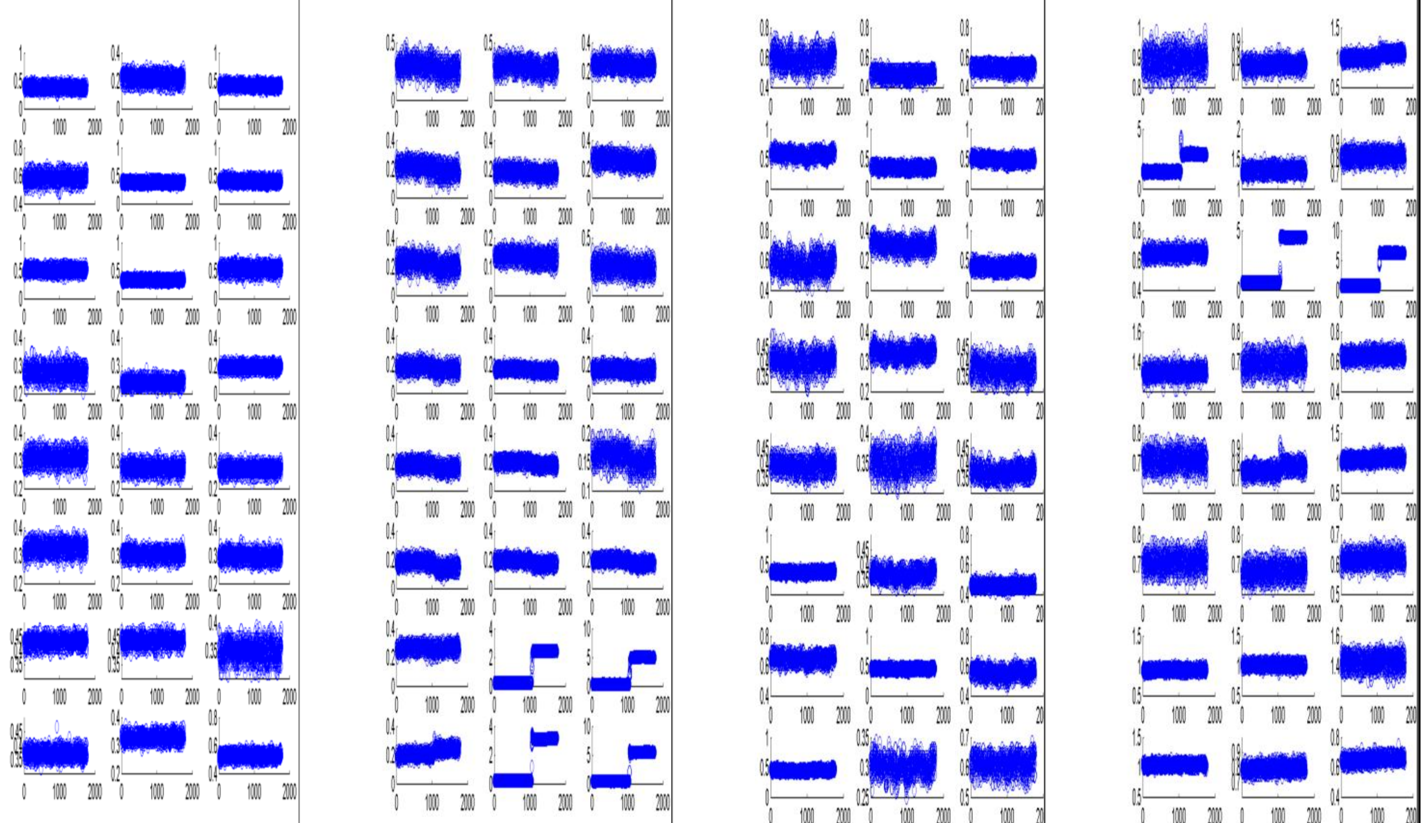
Discussion on comparison

The comparison between Libbarrett supplied output and the data collected demonstrates a high correlation. A minor discrepancy could be argued for data collected from grasped shape #2; wherein the table displays zero response in spite of a distinct change to the collected tactile sensory data.

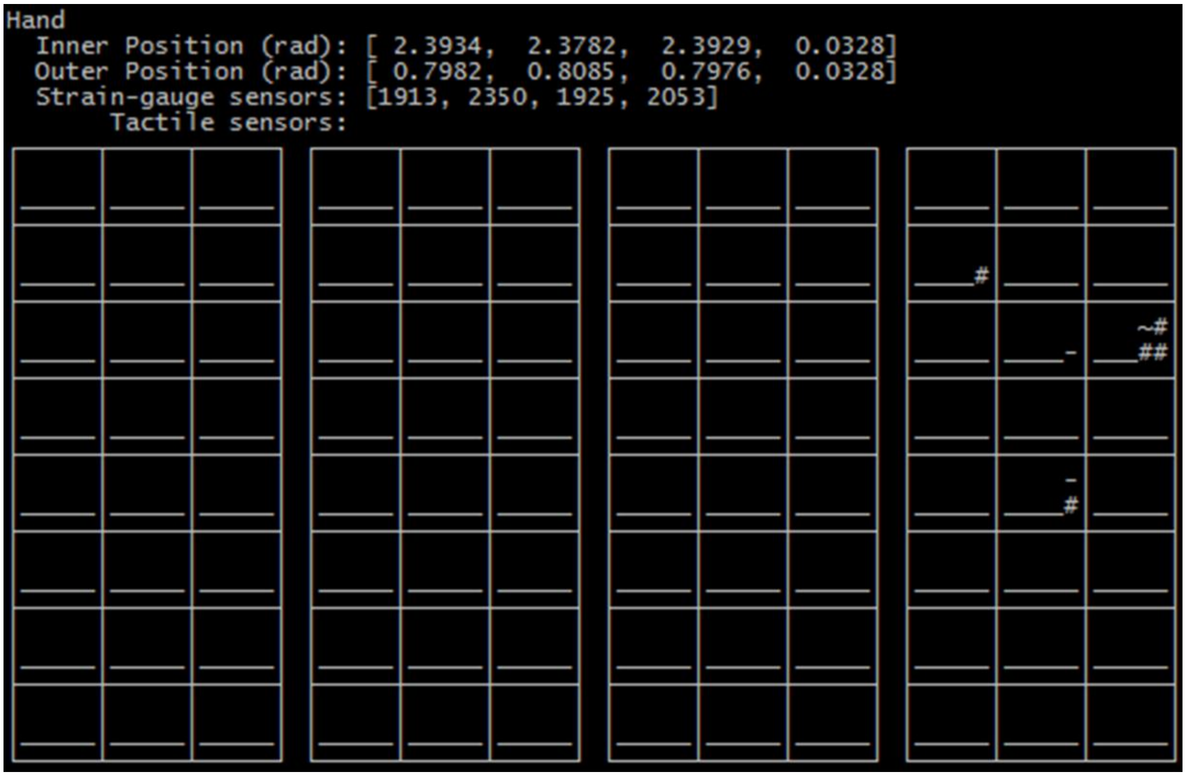
However, this minor discrepancy could simply be due to the relatively low output value registered by the corresponding block of tactile sensors. Values below a certain threshold would therefore not be displayed.

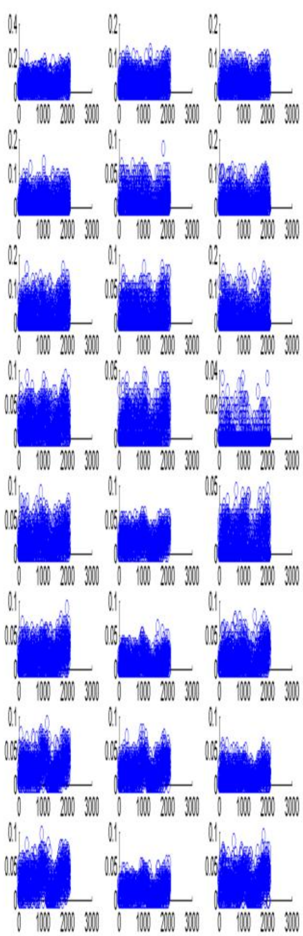
Grasped Shape #1: Cylinder

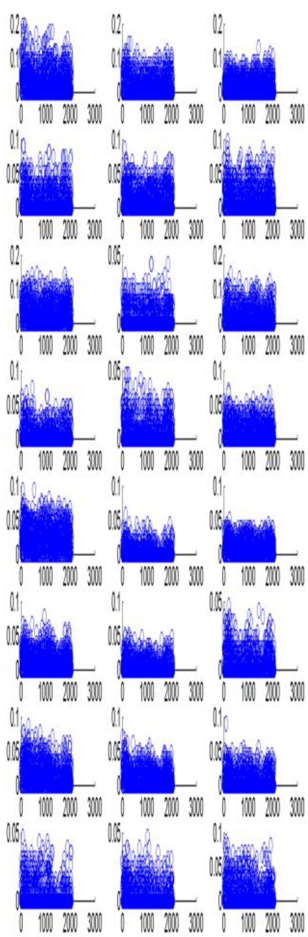


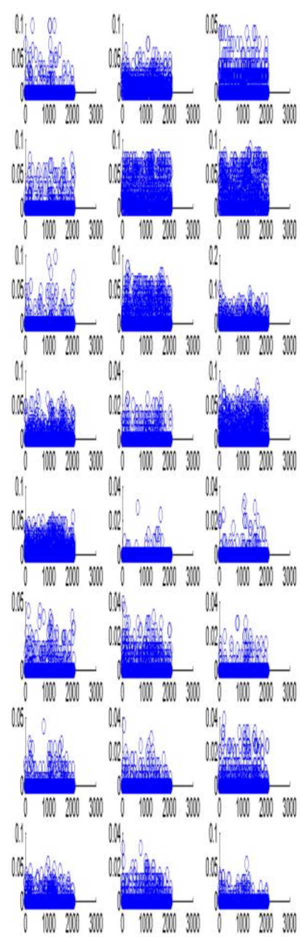


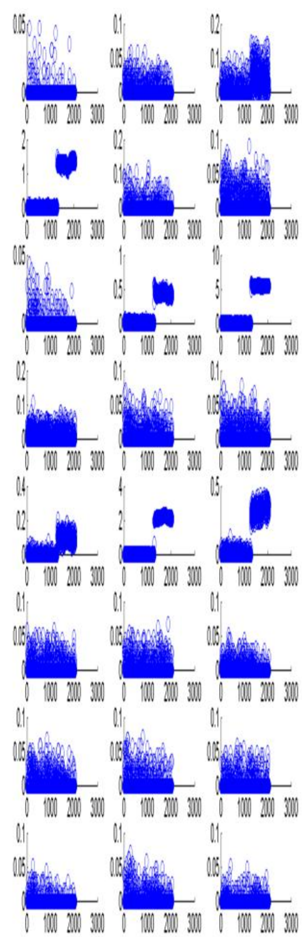
Grasped Shape #2: Triangular Prism











Grasped Shape #3: Cube