

Assistive Robotic Grasping

Jonathan D. Weisz

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ABSTRACT

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This thesis describes contributions towards the implementation of Human-in-the-Loop (HitL) grasping for assistive robotics, with a particular focus on low throughput, high noise interfaces such as electroencephalography (EEG) or electromyography (EMG) brain-computer interface(BCI) devices in natural environments. Although progress in the robotics field has been swift, it is unlikely that truly independent operation of robots in situations where they will interact closely with objects, obstacles, and perhaps even other people in their environment will evolve in the immediate future. However, with the help of a human operator, it is possible to achieve robust, safe operation in complex environments. This work describes a system that can accomplish this with minimal interfaces that are accessible even to individuals with impairments, which will enable the development of more capable assistive devices for these individuals.

Grasping an object generally requires contextual knowledge of the object and the intent of the user. We have developed a user interface for an on-line grasp planner that allows the user to effectively express their intent. Grasping in natural environments requires grasp planning algorithms that are robust to target localization errors. This work describes grasp quality measurements that generate more robust grasps by considering the local geometry of the object as well as how uncertainty will affect the proposed grasp. These new measures are integrated into an augmented reality interface that allows a user to plan a grasp online that matches their intent for using the object that is to be grasped. This interface is validated by testing with real users, both healthy and impaired, using a variety of input devices suitable for impaired subjects, such as low cost EEG and EMG devices. This work forms the foundation for a flexible, fully featured HitL system that

will allow users to grasp objects in cluttered spaces using novel, practical BCI devices that have the potential to bring HiTL assistive devices out of the research environment and into the lives of those that need them.

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Chapter 1

Introduction

1.1 The Promise of Assistive Robotics

Although progress in the robotics field has been swift, it is unlikely that truly independent operation of robots in situations where they will interact closely with objects, obstacles, and perhaps even other people in their environment will evolve in the immediate future. However, with the help of a human operator, it is possible to achieve robust and safe operation in complex environments. This work describes a system that can accomplish this with minimal interfaces that are accessible even to individuals with impairments, which will enable the development of more capable assistive devices for these individuals.

Grasping is important for many activities of daily living (ADL) that physically impaired individuals need assistance performing, such as fetching food or communication devices. There is a large and growing population with upper limb mobility issues in the United States. There are currently 400,000 individuals with spinal cord injuries, 50% of whom suffer upper limb mobility issues, 5 million individuals that have suffered from strokes, and a generally ageing worldwide population. This presents an urgent need for better assistive technologies. The individuals with the greatest need for assistive technologies are those with severe impairments. By the nature of their health challenges, they are often limited in their ability to provide input to an assistive device. To address

this concern, there has been a great deal of interest in Brain Computer Interface (BCI) devices over the last few years. In general, these devices are restricted to low bandwidth, noisy signals. Therefore, using these devices to control an assistive device poses many challenges.

1.2 The Challenge of Robotic Grasping

Irrespective of the problems of BCI interfaces, robotic grasping is challenging for a number of reasons. First, complex robotic hands have many degrees of freedom, which makes the space of possible grasps extremely difficult to explore. Standard approaches to planning in high dimensional state spaces are likely to fail with many fingered hands, especially as the grasp itself involves purposeful collision with the object, but most of the "near grasp" states will be overlapping the object in some way. Second, evaluating grasps involves several properties that are difficult to model, such as friction and closed chain kinematics. Many state-of-the-art analysis tools are only effective if the contact points can be perfectly predicted and the grasp acquisition can be perfectly controlled so that the object is not moved. Finally, robotic hands are extremely heterogeneous in terms of their physical size, the arrangement of their sensors, and their actuators, which makes finding generic strategies difficult.

In addition to all of these issues, in natural environments any set of grasps that is preplanned may overlap with obstacles in the environment or fail to grasp the object in a way that is well suited to the desired use of the object. Thus grasp planning algorithms must be fast enough to run online and be able to reflect the intent of the use of the grasp beyond simple stability. Until these challenges are overcome, robots will remain of limited utility as helpers for improving the lives of people outside of the lab.

1.3 The Eigengrasp Planner

Previous work in our lab presented in Ciocarlie et al. [2008] has attempted to address the main challenges of grasp planning by producing the Eigengrasp Planner. The planner addresses these issues by following a dimensionality reduction strategy that reduces the

state space of the hand so that a sampling based stochastic optimization strategy can be used with a relatively simple grasp quality metric. The quality metric that is used by the planner evaluates a projection of the desired contact points on the hand on to the target object, which makes the state space easier to evaluate because the quality function is valid in configurations where the hand is not in contact with the object. The nature of the optimization approach, which gradually moves towards lower values of the quality function, should produce solutions where nearby finger contacts will also provide similar quality grasps because grasps where nearby points are poor will have narrow basins of attraction that are less likely to be found. This implies a certain amount of robustness to small displacements of the object during grasp acquisition. The planner is easy to generalize because the only robot specific parameters are the state space reduction strategy and a set of desirable contact locations, which can be easily specified for any given robot.

The planner is fast enough to run in near real time, and can be made responsive to user intent by biasing the search of the stochastic optimization towards a pose that is demonstrated by a human operator. In this model, the desired intent of the user is indicated by demonstrating a desired direction and approximate location to grasp from, possibly by moving a virtual hand in a simulated environment.

The efficacy of Eigengrasp Planner's approach was demonstrated by having an operator hold a robotic hand's base and move it around a target object while running the planner. When the planner found a grasp that appeared reasonable, the operator would grasp the object by simply clicking a single key. The approach of the hand to the object and the application of force to the hand as it contacted the object were controlled manually by the operator. This demonstration was extremely compelling, and the problem appeared to be largely solved. However, some limitations of this approach were exposed in attempting to translate this work from the initial demonstration to a platform that could be used by a disabled person, given the limitations of the input devices available.

1.4 An Integrated Assistive Robotic Grasping Platform

To begin addressing even the most basic needs of an impaired individual with assistive robotics technologies, we need an underlying platform for robust grasping. Such a system would need to integrate path planning, object localization and identification, and grasp planning with a user interface suitable for whatever signals the user is able to supply. Although fully automated approaches for each of these components have been the subject of extensive and ongoing research, integrating user input to create a shared-control environment that uses as much input as the user is able to supply is still a relatively unexplored field. There are many possible paradigms for integrating BCIs with a shared-control assistive robotic device. Traditional electromyography (EMG) and electroencephalography (EEG) setups are expensive and difficult to deploy. Recently, cheap and portable EEG headsets have become available, and new devices such as portable near-infrared-spectroscopy (NIRS) devices and single electrode EMG devices are also reaching the market.

These devices expand the potential for a practical, multimodal BCI system that can be taken out of the laboratory to create an assistive robotic grasping system for less structured environments. However, grasp planning remains a difficult, unsolved problem. Online planning and grasp planning under sensor uncertainty are each independently unsolved problems that need further exploration. Putting the human in the loop when planning and executing the grasp in real time fundamentally changes the nature of the problem as compared to a fully automated system. The key part of the problem becomes conveying information to the user effectively about the state of the system and then using the low bandwidth information gained from the user efficiently. This requires us to think carefully about the interfaces provided to the user and how we infer intent from the users input. Additionally, in order to present the user with reasonable grasping options, we need to extend the existing grasp stability analyzes to deal with the most common problem that arises in unstructured environments, object localization errors due to sensor noise.

1.5 The Contribution of This Thesis

This thesis extends and refines the initial work on the Eigengrasp Planner to a flexible integrated assistive robotics grasping platform, and demonstrates its application to a number of different input devices designed for severely impaired individuals. In Chapter 1.5, I will discuss relevant work in assistive robotics and pose robust grasping. In the main body of this thesis, two main issues are addressed. Without the benefits of complete control over the grasping process and the assumption of perfect localization of the target object, significantly more care has to be given to selecting robust grasps. Additionally, the user cannot be assumed to have fine control over the demonstration pose because their input device may not provide the bandwidth that such control requires. This means we need to devise a user interface that can accommodate a more limited input.

To address the first issue, I present the first large scale analysis of how the seminal grasp quality measures proposed by Ferrari and Canny are expected to vary under realistic models of object location uncertainty in Chapter 3. This analysis shows that the grasps produced by the Eigengrasp Planner are not sufficiently robust under even modest location uncertainties. From this analysis, I derive an extension of the grasp quality measure that produces significantly more robust grasps.

I present the novel platform that we have developed to apply this planner using several different brain computer interfaces. We have followed an iterative approach in refining the capabilities of this platform. The rest of this thesis presents the feedback driven development of the platform through a series of experiments with both impaired and unimpaired users on a series of potential input devices. We began this research with input devices that read electrophysiological signals arising from activation of facial muscles. These interfaces take advantage of the fact that many severely impaired individuals who lose function in their limbs still maintain control over their facial muscles, from which we can extract a few control signals reliably. These devices are relatively low cost and noninvasive compared with most other modalities of getting signals from impaired individuals. In Chapter 4, I describe the implementation of an augmented reality interface for facial EMG based grasping using the Emotiv EPOC, a commercial EEG/EMG device, and a combination of facial gestures and EEG control, and the re-

sults achieved by a healthy cohort of subjects. In Chapter 5, I describe an interface which uses a much more minimal and practical surface EMG device that is much more easily deployable than the Epoc and other similar cap devices, because it requires only a single recording site and a few wires. I present a pilot study with an impaired individual using an this device and show that he is able to grasp objects using this minimalistic device after only a short introduction to the grasping platform. I present how the findings of this pilot integrated into a second revision of this interface that is validated on a cohort of healthy individuals. Finally, I will discuss how we extended this system to a completely different EEG based input paradigm in Chapter 6.

Chapter 2

Related Work

2.1 Brain Computer Interfaces For Robotics

2.1.1 Overview

There is a long history of engineering assistive systems using electrophysiological signals to drive robotic devices [Schmidl, 1965], with a commercial version being introduced by [Sherman and Lippay, 1965] as early as 1965. In the time since, there have been myriad approaches and refinements of proposed interfaces for disabled individuals with robotic assistive systems, and this work will not review even a small fraction of them. There are two ways of categorizing these systems. One way is to categorize a system by its input modality; That is, whether it uses physical buttons or pointing devices, some external sensor of motion such as eye or hand trackers, or some specific electrophysiological signal such as EMG, electrooculography (EOG) and EEG. Within this category, modalities can be further divided by where the signals are recorded from. EMG can be recorded from distal muscle sites, which may be larger, easier to record from, and produce larger signals. However, more impaired individuals tend to maintain control over muscle functions closer to the head.

Another way to categorize the systems is by the type of control they engender - whether the control is at a task level, allowing the user to designate what is to be done, or at a state level, allowing the user to specify joint angles, or end effector positions.

This work presents a system at an intermediate control level, in which the user has some state level control that is task oriented. This requires an online planning system that generates robust grasps in realtime. Below I describe the different control paradigms used in related systems using BCI devices.

2.1.2 Direct Demonstration

The most intuitive, low level of control of a robotic arm involves having the robot arm directly mimic the motions of the user. It is possible to reconstruct a user's movements using surface distal limb surface EMG signals, as in [Artemiadis and Kyriakopoulos, 2011; Castellini and van der Smagt, 2009]. This type of control allows the user to express their desires explicitly, allowing the user to specify how the arm is to avoid objects. A mapping from the subject's joints to the robotic arm can be found that ensures that the robot stays approximately the same distance from its joint limits as the subject does, which ensures that the robot's workspace will be compatible with the intent of the user in manipulating objects.

This paradigm is not suitable for assistive robotic interfaces because many seriously impaired individuals have lost exactly the capability used as the control input to this type of interface.

2.1.3 Joint Level Control

Rather than implicitly controlling the arm, some paradigms allow the user explicit control of joints of the robot. This generally imposes a much higher cognitive load on the user, as they have to attend closely to each joint. The movement of the joints are not directly related to user's goal of manipulating some object. Control of a manipulator through such an interface is generally not possible because they have many joints. The manipulator is generally controlled by simple open and close commands. For example, in [Horki *et al.*, 2011] hand opening/closing and elbow flexion/extension are controlled by EEG signals.

For a prosthetic arm with essentially two degrees of freedom, this sort of control may be appropriate, but more degrees of freedom will strain the bit rate of these types of

devices and their unreliability will make the coordination necessary to perform complex tasks in natural environments difficult or impossible. For example, to grasp an object using a six degree manipulator with a gripper, the user must move in a straight line towards an object, or the gripper will not move straight and the finger may knock over the object while moving the palm into place. This requires that the user simultaneously send coordinated signals to all six degrees in exactly the right ratios, or it may not move in anything close to a straight line.

2.1.4 End Effector Cartesian Control

The main goal of a robotic manipulator is to interact with the world with some end effector. Giving the user direct control over the end effector location can be more intuitive, because the end effector location is the variable that the user most directly observes. These works range in invasiveness and signal quality from using a high fidelity implanted electrode array to reconstruct the desired end effector movement, as shown by [Vogel *et al.*, 2010], to using much lower bandwidth surface electrode based systems for tracking eye movement, as in [Postelnicu *et al.*, 2011]. Several authors have proposed using various facial EMG reading systems to achieve cartesian end effector control [Sagawa and Kimura, 2005; Gomez-Gil *et al.*, 2011; Ranky and Adamovich, 2010; Shenoy *et al.*, 2008].

Although this approach is similar to joint level control in requiring continuous attention to a relatively large number of degrees of freedom simultaneously, the user's control is directly in the task space. Control that is directly in the task space allows the user to more easily decouple the different controlled degrees of freedom. This makes it more practical to use facial muscles for control for a number of reasons. First, because facial muscles are close together, it is more complicated to separate the source of the input signals picked up by an electrode at a particular muscle site if several muscles are activated at the same time. Additionally, control over these muscles is generally less fine grained, as individuals generally don't use their facial muscles for fine manipulation. Being able to decouple the controlled degrees of freedom can allow the user to make reasonable progress towards their goal while closely attending to only one degree of freedom at a

time, which makes predictable, fine grained control less important.

2.1.5 Discrete Mode Control

In discrete mode control, the user is able to switch between a set of predetermined configurations. The aforementioned control methods involve control over some continuous state space. These modes require continuous user attention, high data rates, and require a great deal of understanding of the robot itself from the individual. Additionally, because manipulators have a large number of degrees of freedom, these continuous methods do not attempt to control them at all. Rather, they switch the manipulator between two simple discrete states, open and closed. In some paradigms, the user is able to switch between a number of different discrete modes that control the configuration of the hand [Yang *et al.*, 2009; Woczowski and Kurzyski, 2010; Ho *et al.*, 2011; Cipriani *et al.*, 2008; Matrone *et al.*, 2011].

These control schemes represent a tradeoff between flexibility and simplicity of use. This tradeoff is especially important for complex, multijointed robotic hands. Direct control over the fingers of a manipulator is not feasible for more complex hands for a number of reasons. There are generally many degrees of freedom, and the configuration of each finger is important to whether the hand will unintentionally interact with the environment as the end effector is used. Additionally, the fingers may have overlapping workspaces, so without extremely accurate control, it is likely that they will hit each other. By allowing the user to switch between discrete states, they are able to get utility out of hands that are more complex than the simple grippers that are generally used in the simple open/close schemes. More complex hands can more accurately approximate the surface of the object that the user wants to interact with, which increases the number of possible interactions and makes them more stable.

However, these schemes limit the user's flexibility to the preset configurations. Additionally, the user has to remember how to get to the configuration that they want to use at a given time, which may require multiple steps through a branching decision tree. In continuous control schemes, the user can make small changes and observe the outcome to get the robot to do what they want, but in discrete control schemes the result of the

next input may not be related to the previous one. Because there is not necessarily an easy way of associating the path that they need to take in that decision tree with the goal they want to reach, these control schemes have a steep learning curve.

2.1.6 Task Level Control

The key challenge of using noninvasive brain computer interfaces is that the bit rate is low and that the input is somewhat unreliable. In addition, the user experiences limited feedback, which makes direct control difficult. Under these conditions, it would seem intuitive that users would find task level control, where the user directs the robot on what to do but has little input as to how to, would be more effective. Indeed, it has been shown that users find BCI control easier using even higher level, goal oriented paradigms [Royer *et al.*, 2011], and we have begun to see work that attempts to exploit higher level abstractions to allow users to perform more complex tasks with robotic arms.

In [Bell *et al.*, 2008], EEG signals were used to select targets for pick and place operations for a small humanoid robot. [Waytowich *et al.*,] used EEG signals to control pick and place operations of a 4-DOF Stäubli robot. [M. Bryan, V. Thomas, G. Nicoll, L. Chang and Rao, 2011] presented preliminary work extending this approach to a grasping pipeline on the PR2 robot. In that work, a 3D perception pipeline is used to find and identify target objects for grasping and EEG signals are used to choose between them. In [Müller-Putz *et al.*, 2005], grasping is decomposed to a four-stage pipeline where EEG signals are used to control transitions between stages. And in [Scherer *et al.*, 2011], the authors demonstrate an interface to navigate in two dimensions and select goals in a complex virtual environment and propose a hierarchical control scheme for learning high-level tasks dynamically.

2.2 Robust Grasping

In this work, we will present users with appropriate grasps for the object. The system will present the user with options, and they will select the option that best reflects their intent. Because the user does not exercise direct control over grasp acquisition, we need

to be able to present the user with grasps that the manipulator can acquire reliably in the face of sensor noise. Analyzing the robustness of a grasp in the presence of object localization errors and external force perturbations is an important and difficult problem, which has thus been studied by a large number of researchers following many different strategies.

2.2.1 Wrench Space Metrics

A key criterion that has been used to define a stable grasp is that the contact points of the grasp are able to generate a wrench in an arbitrary direction, termed force closure. This property is considered fundamental in grasp analysis because it provides a simple, necessary condition for grasp stability, as shown by [Salisbury and Roth, 1983]. This property is determined by the set of wrenches that can be produced from the contact points of the grasp, termed the grasp wrench space (GWS). Force closure provides a binary analysis of grasp robustness. In order to analyze the strength of the force closure, we commonly use the the epsilon quality (ϵ_{GWS}), first described in [Ferrari and Canny, 1992]. ϵ_{GWS} is defined as the radius of the largest ball around the origin that fits in the convex hull of the grasps contact wrench space. This radius is the magnitude of the minimum norm wrench that will break the object free of the grasp.

2.2.2 Wrench Space Metrics Robust to Contact Location Uncertainty

In previous work, measures have been proposed to quantify the robustness of contact location based quality metrics, with particular focus on the ϵ_{GWS} . One well developed approach considers the effect of contact model or contact location uncertainty with respect to the object. The independent contact region approach (ICR) introduced in [Nguyen, Van-Duc, 1988] considers the effect of contact location uncertainty on the ϵ_{GWS} of a grasp. This approach grows a convex set of acceptable contact locations for each planned finger contact on the object. Any set of contact locations chosen from this set produces a grasp whose quality metric is above a preselected quality threshold. Faverjon et. al. developed analytical approaches to finding ICRs for complex 2D and simple 3D models[Ponce and Faverjon, 1991; Ponce *et al.*, 1996;

Faverjon and Ponce, 1991]. In Roa and Suarez [Roa and Suarez, 2009], this approach is extended to complex three dimensional shapes and minimal thresholds on the ϵ_{GWS} . [Pollard , 2004] followed a similar approach with a focus on larger numbers of original contacts and with extensions to task wrench space quality metrics, and also presented a method for generalizing sets of ICRs between objects. Zheng and Qian proposed a quality metric based on a similar region growing approach by measuring the radius of the smallest ball in the configuration space of the regions produced for the grasp parametrized by contact location, contact normal, or frictional coefficients[Zheng and Qian, 2005]. All of these approaches consider the effects of contact location uncertainty independently, but do not directly address the effect of calibration error and object pose uncertainty on the ϵ_{GWS} . These approaches assume that uncertainty causes the contacts to land near the planned contact points on the object. However, simulating the entire grasping procedure often produces very different sets of contacts in the presence of uncertainty. In fact, none of the ICR approaches described are able to fully account for the effects of these resulting deviations from the planned contact locations.

2.2.3 Simplified Analytical models of Robustness

Rather than analyzing the wrench space of the applied grasp, another approach to grasp synthesis is to model each finger as a point or hemisphere where the contacts are represented as a set of spring-like elements connecting the finger to the object. With this simplification, it is possible to analytically calculate the wrench applied to the object by the fingers. By using some optimization approach, it is then possible to find the joint torques that apply zero total wrench to the object while maintaining some minimum internal force which stabilizes the object through friction. By combining this approach with assumptions about the geometry of the fingertip and the smoothness of the contact location on the object, it is possible to use an analytical approach or an optimization approach to find regions with large stability boundaries using the same joint torques. Such models have been pursued by authors under some simplified conditions in 2D [Sugar and Kumar, 2000] or simple 3D models with simple contact formulations [Yamada *et al.*, 2001]. However, it is not clear how to generalize these results to arbitrary hands and

objects. Additionally, these models require many parameters of the analytical model to be chosen ad hoc.

This methodology shows promise, but hasn't been demonstrated outside of these highly simplified situations.

2.2.4 Sampling Based Heuristics

Some work has addressed the effect of object pose uncertainty in grasping tasks for measures of grasp stability other than the ϵ_{GWS} . In Balasubramanian et al. the authors derive a novel grasp measure for robust grasping from observations of human guided grasping [Balasubramanian *et al.*, 2010]. Bekiroglu et al. proposed a method to learn haptic features of grasp stability to assess grasps during their execution[Bekiroglu *et al.*, 2011]. The general problem of motion and manipulation planning robust to pose error was addressed by Lozano-Perez et. al [Lozano-Prez *et al.*, 1984] using preimage-backchaining. In [Berenson *et al.*, 2009b], this method was extended to hand target pose regions for grasping objects on a table top. In [Brost and Christiansen, 1997], Brost and Christiansen investigated the issue of pose error robustness for a 2D gripper using a sampling based approach on a fixed trajectory plan in physical experiments. More recently, [Hsiao *et al.*, 2011] investigated Bayesian approaches to grasp planning under object pose and identity uncertainty for a simple gripper using a sampling approach to select robust grasps as measured by a grasp quality metric in simulation .

This sampling based approach is the most generic, simplest to understand, and the easiest to implement. We have followed a similar approach in analyzing the grasps produced by our grasp planner. This analysis focuses on a quality function that is widely used in the grasp planning research but has never been analyzed with respect to object localization errors on a large scale.

Part I

Robust Grasping

Chapter 3

Robust Grasping

To build a Human-in-the-Loop grasp planning system, we need an underlying grasp planner that is responsive to human input and runs in near real time. Because we have a human in the loop, it is acceptable for the planner to generate grasps that are either not suitable for the object or that are not reflective of the users intent some of the time, as the user can reject them. However, because this platform is meant to be used through a low bandwidth, somewhat noisy input, it is important that there not be a large number of grasps for the user to reject.

In this chapter, we describe the online grasp planner used in our system and the modifications which we have made to improve to its performance under the conditions of our system. This work was initially presented in [Weisz and Allen, 2012]. In particular, it is difficult for the user to reject grasps which appear stable but which are likely to fail when there are errors in object localization that might interfere with realizing the grasp which is displayed to them. Here, we present a detailed description of the basis of our online grasp planning system, an analysis of the grasps that are produced by the online planner without considering the problems posed by object localization errors, and the method we use to ameliorate this difficulty.

3.1 Grasp Planning With Contact Points

Analytical models analyzing the probability of grasp success have not been found, and so far the most generic methods involve sampling. The configuration space of the “grasping” problem has several formulations, but the two most common are potential contact points or hand configurations. In analyzing potential contact points, one can either analyze points on the hand or on the object. There are numerous considerations that one can take into account that make intuitive heuristic sense, including geometric concerns such as local flatness.

Historically, it has been common to analyze the forces that can be applied at each contact point. There are no perfect models for this analysis. Models are generally classified by the physical systems that they roughly approximate. A point contact model assumes that the contact point can only apply forces in the direction opposite the normal of the surface on which it contacts. This is a conservative model. In order to generate a stable grasp from point contacts, it is necessary that any small (i.e., differential) motion cause the object to overlap the proposed contact points. This is called *form closure*. When this is the case, it is also the case that the positive span of the set of wrenches produced by transforming the contact normals to some common references frame covers all of \mathbb{R}^6 . This is an example of *force closure*. For point contacts, these constraints are *duals*, and one strictly implies the other. For the rest of the contact models, which take friction into account, this is not the case - one can have *force close* without *form closure*.

This model is simple and conservative, but unfortunately it is too conservative to be useful for arbitrary objects. If rotations are considered, cylindrical objects cannot be grasped through *form closure*, because there is no contact normal that can oppose rotations along the length of the cylinder. More generic models include frictional forces in addition to pure normal forces. Point-contact-with-friction models allow friction to be employed at each of the contact points in the plane orthogonal to the normal. In this case, the forces that can be produced at the contact point through friction are related to the normal force through the friction coefficient of the surface. This creates a cone of potential forces that can be created as the normal forces are scaled up.

Further, if the contacting surface is assumed to be ‘soft’ so that one surface conforms

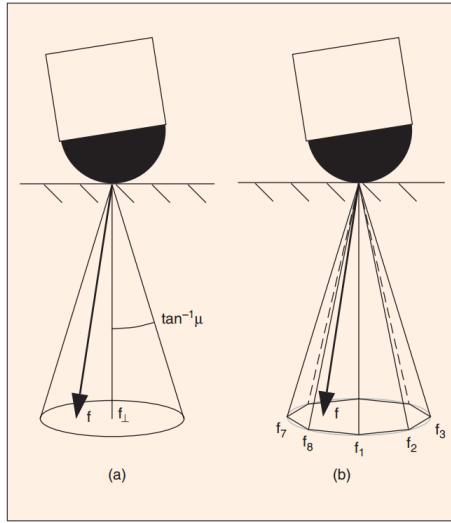


Figure 3.1: The cone of forces that can be produced by a contact point can be represented by a simple linearization, making the base of the shape a regular polygon rather than a circle. This illustration is taken from [Miller and Allen, 2004]

to another forming a contact patch, rather than a point, the contact can also apply torque around the normal direction. If the surface is significantly softer, the patch can be modeled as a set of points on the perimeter of the patch. These points will be able to apply torques around all three dimensions with respect to the original contact point, and forces along any direction in the positive halfspace of the surface normal.

In order to analyze how the contact forces affect the object, the forces and torques need to be summed up in the same reference frame. Most often, they are transformed to the centroid of the surface mesh or to the center of mass, if known. Transforming the cone of forces that can be produced by the point with friction model is difficult because it cannot be represented by a linear model, and so the linear transform to the new reference frame leads to a complex representation. In order to avoid this, the cone is represented by a simple linearization, making the base of the shape a regular polygon rather than a circle. Then the potential forces can be represented by the edges from the contact point to the points on the perimeter, normalized by the number of edges. This is illustrated in Fig. 3.1.

3.2 Grasp Wrench Spaces

To characterize the contribution of the contact wrenches to constructing stable grasps, we need a way to analyze the entire set of wrenches holistically. Irrespective of the contact model used, so long as it is linearized, the contacts can be summed up in the same reference frame, and all potential forces that could possibly be generated by these contact points can be represented. This set of forces is called the “Grasp Wrench Space.” In plain terms, the Grasp Wrench Space represents the set of wrenches that can be applied by this grasp. A key criterion that is often used to define a successful grasp is the ability to generate a wrench in an arbitrary direction, which is the generic definition of *force closure*. This property is considered fundamental in grasp analysis because it provides a simple, necessary condition for grasp stability[Salisbury and Roth, 1983].

3.3 The ϵ_{GWS} Quality Metric

The ϵ_{GWS} metric of grasping extends force closure from a binary property which is or is not satisfied to a measure of how stable a grasp is with respect to grasp forces. The ϵ_{GWS} measure is one of the most widely cited benchmark metrics in the grasp planning field[Ferrari and Canny, 1992]. Formally, for a set of contact wrenches $C \subset R^6$, one can define the neighborhood ball $B(\epsilon)$ and wrench space metric ϵ_{GWS} as follows:

$$B(\epsilon) = \{x \in R^6 \mid \|x\|_{L2} < \epsilon\}$$

$$\epsilon_{GWS}(C) = \max_{\epsilon}[B(\epsilon) \subseteq \text{convexhull}(C)]$$

Any grasp that does meet the minimum requirement of an $\epsilon_{GWS} > 0$ cannot apply force in some direction, which means that some infinitely small force in that direction will cause the object to begin to move. This quality metric is popular largely because it analytically addresses an intuitively necessary condition for grasp stability, the ability to resist force perturbations. One shortcoming of this measure is that it is sensitive to the choice of center of mass of the object. A variant of this measure is to consider the volume of $\text{convexhull}(C)$, denoted V_{GWS} in this work. This variant functions as an

approximation of the average case ϵ_{GWS} over many estimations of the center of mass of the object.

3.4 Optimization Based Grasp Planning

Given a quality measure that is computationally tractable, it is feasible to create a stochastic optimization based grasp planner. Sampling potential contact points directly on the object leaves the problem of finding a hand configuration that matches that contact configuration unsolved. For the generic case of arbitrary hands, this problem is difficult and unsolved. Similarly, sampling candidate contact points on the hand is equally intractable, because most hand configurations produce no contacts at all. To make the problem tractable, the state space needs to be relatively low dimensional and the quality metric must generate valid, informative values on most of that state space.

3.4.1 Potential Contact Quality Function

This lab produced such an optimization based planner using simulated annealing to optimize cost functions that derive from the ϵ_{GWS} in [Ciocarlie *et al.*, 2008]. To make the quality metric accessible to this method and more computationally tractable, the potential contact points on the hand are projected to the object and the resulting contact wrenches are weighted by their distance and the agreement of their normal directions. This “potential contact” quality function creates a smoother optimization function.

3.4.2 Implications For Pose Error Robustness

A stochastic optimization based approach is capable of escaping local minima in complex, nonconvex optimization functions like the projected distance and alignment between nonconvex shapes. However, the net affect of the optimization procedure is still to approximately follow a gradient. We should thus expect that the most optimal grasps that are found should usually be found in areas where the quality function is fairly smooth and the basin of attraction is wide. Given the quality function, especially the component which takes into account the relative alignment of the potential contact location and the

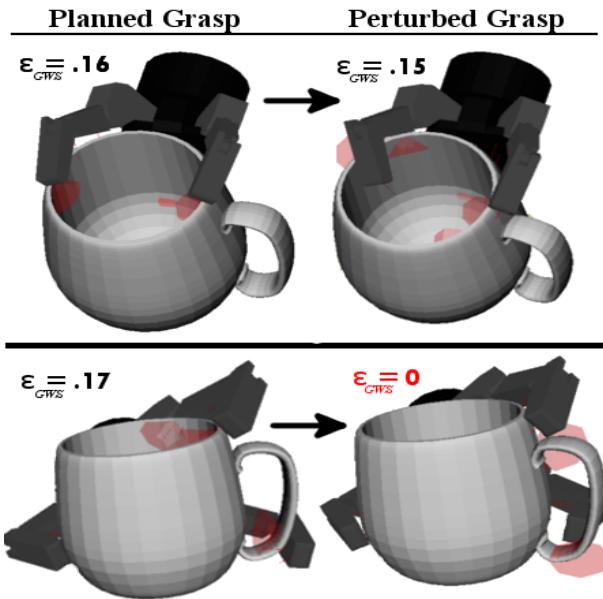


Figure 3.2: An example of a grasp where the ϵ_{GWS} is consistent with respect to the common localization errors, and one where it is not.

hand, it follows that the local geometry should be expected to be relatively smooth, and that the quality function, when evaluated, should be robust to small errors in contact location.

However, in real robotic applications, if the object is known, then the largest sources of contact location uncertainty are errors in perception of the location of the object itself with respect to the robot, miscalibration of the robot, and intrinsic uncertainty in control of the end effector's location. This implies that the errors in contact location are not randomly distributed, but are structured, in that they are offset in the same direction because the entire object is offset. In fact, the actual contact location is a product of the entire grasping procedure, in which a different part of the finger may make contact than is planned, and this contact location may not be near the planned location. The normals may face a different enough orientation that the smoothness of the projected contact point's quality function may not be sufficient to guarantee that the actually achieved contact points produce a stable grasp. Some planned grasps may have nearly the same quality measure if the object's pose is slightly perturbed, while

others may not. Fig. 3.2 shows an example of each.

3.5 Analyzing the Effects of Pose Error in Simulation

3.5.1 The Columbia Grasp Database

In order to test how robust the grasps that are produced by the Eigengrasp Planner are to localization errors, we need a large database of grasps. The Columbia Grasp Database (CGDB), produced by [Goldfeder *et al.*, 2009], contains a large number of grasps produced by the Eigengrasp Planner. The database is based on objects from the Princeton Shape Benchmark, a set of 1814 models with class labels. Starting from this set of grasps, we developed a simulation model to estimate the effects of localization error across many objects.

3.5.2 Grasping Pipeline

The CGDB parametrizes grasps as pre-grasp and final-grasp pairs. The pre-grasp is a collision free pose and joint angle set found by the simulated annealing planner. The final-grasp is the set of corresponding parameters found by applying a grasping heuristic to the pre-grasp that simulates closing the hand around the object until contact is made or joint limits are reached. The grasps in the CGDB are intended to be used by preshaping the hand to the pre-grasp under the assumption this is a collision free pose, but in the presence of uncertainty this may not be the case for all grasps. In this case, it is necessary to generate an initial pose which is certain to be collision free.

The general problem of optimal hand trajectory planning for grasping is complex. In this work we consider a basic three-phase grasping heuristic.

- 1a.** Move hand and fingers to an initial pose and posture far from the object along a pre-specified approach direction.
- 1b.** Move to the planned pre-grasp hand pose from the initial pose along the approach direction, stopping if contact is made.

- 2a.** Move fingers to their pre-grasp postures by linearly interpolating from initial posture, stopping each finger if contact is made.
- 2b.** (optional) For grasps with any contact points that are not on a distal most link of a finger, approach object to contact if none has occurred so far.
- 3.** Close fingers until each joint is constrained by contact or joint limits.

We use the normal to the center of the palm as the approach direction for all of the grasps considered. To determine the finger positions for the initial posture, we open the fingers so that the hand in the initial pose can wrap around itself in the pre-grasp position. We illustrate this strategy in Fig. 3.3. We open the hand at a constant rate for all joints until the tips of each finger are outside of the projection of the second most distal link along the approach direction of the hand in the planned pre-grasp pose.

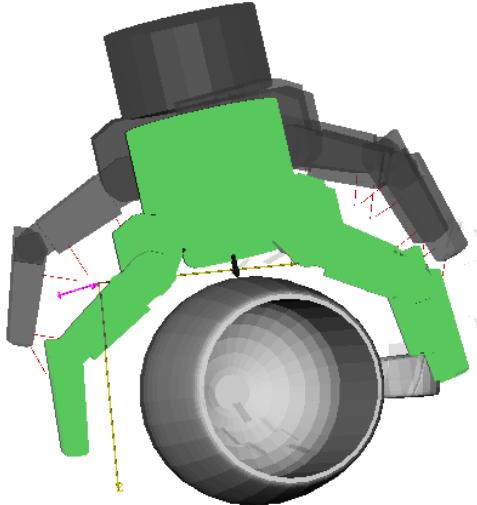


Figure 3.3: *Illustration of the initial pose and posture.* The hand begins in the green position and is withdrawn along its approach direction and all of the fingers opened at the same constant velocity until each of the fingertips are outside of the knuckles of the hand in its pre-grasp configuration. The hand is then opened an additional ten percent of the remaining joint range. This starting position is shown in black.

3.5.3 Model of Pose Uncertainty

Because it is computationally intractable to densely sample the full six dimensional space of poses near the planned pregrasp pose, we consider a three dimensional error model representing an object on a support surface. We assume that each object is restricted to a set of stable poses on the surface. This error model is parametrized by $[x, y, \theta]$ as illustrated by Fig. 3.4. We use the centroid of the planned contact locations as the origin of the object because parameterizing the rotation around the center of mass of the object will have a disproportionate effect on grasps planned further from the center of mass. We chose bounds for the error model that were motivated by our anecdotal experience in aligning a known object to a point cloud using common methodologies. A reasonable

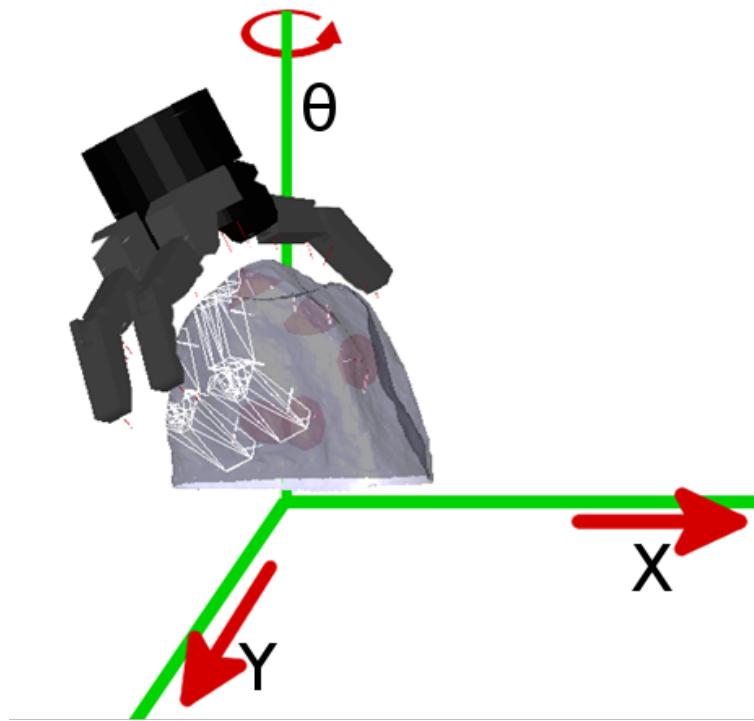


Figure 3.4: Illustration of the tabletop error model used in this paper. The object is can be translated $[-10, 10]$ mm in both X and Y and rotated $[-20, 20]^\circ$ around θ . The red cones mark the planned contact points. The white wire frame indicates the planned end configuration of the fingers.

range to explore using this parametrization should allow each parameter to move the relative position of the planned grasp's contact point by at least 10 mm. If we make the rough approximation that the projection of the contact points perpendicular to the axis of rotation lie on a circle with a 5 cm radius, a reasonable range for these parameters is $\theta \in [-20^\circ, 20^\circ]$ and $x, y \in [-10\text{mm}, 10\text{mm}]$. Exploring this parameter space uniformly in increments of 1[mm,°] in simulation requires 18,081 simulations per grasp. Using the GraspIt! grasping simulator [Miller and Allen, 2004] on a Xeon 2.67GHZ processor we can perform this many kinematic simulations of the grasping pipeline in under two hours for the worst case. The time required for each simulation is object and grasp dependent. With cluster computing this approach can be used to analyze large numbers of grasps from a database off-line.

3.5.4 Simulation Results

These simulations resulted in a large dataset of grasps, perturbations from planned positions, and associated quality functions. From this data, we sought to answer two questions. First, how well do the quality measures of the planned grasp predict expected grasp qualities after perturbation. Second, how do grasp qualities affect the probability of attaining a *force closed* grasp in the presence of pose uncertainty.

3.5.4.1 Expected Grasp Quality

The grasps we analyzed were produced by the optimization procedure described in section 3.4.2. As we argued previously, it is reasonable to expect that the grasps produced by that planner should be locally near optimal with respect to the hand position. The resulting planned grasps are thus locally optimal with respect to the pose of the hand. To quantify how much the imposed pose perturbation affects a particular grasp, we can look at the expected value and standard deviation of its ϵ_{GWS} and V_{GWS} . However, to understand these effects on average across many grasps and objects, we normalize the expected value and standard deviation of these qualities by the quality values of the planned grasp with no error. We call the simulated quality measures of the planned grasp with no error the 'planned' quality values. Because the planned quality values

are locally optimal, the expected value of the quality normalized to the planned value should have a maximum value of 1 for very robust grasps and a minimum value of 0 for extremely fragile grasps. We then consider the average of these quantities across all of the analyzed grasps.

3.5.4.2 Probability of Achieving Force Closure

Another important measure that contributes to grasp success is how likely the perturbed grasp is to fail to be *force-closed*(*fc*), which is defined as having an $\epsilon_{GWS} = 0$. These grasps are expected to be fundamentally unstable, and so a grasp with a higher average quality but a larger variance, leading to more non-*fc* positions may succeed less often than a grasp with a lower average quality that has lower variance. To measure this effect directly, we counted the number of *fc* grasps of the perturbed samples and divided that by the total number of samples, giving us a measure we have called $P(fc)$, as it represents the probability of achieving an *fc* grasp given that our sampled perturbations are uniformly likely.

Calculations involving convex hulls, such as the ϵ_{GWS} are known to be sensitive to numerical inaccuracies, and the cluster we used to generate this dataset was heterogeneous in both hardware and software environments. This initially lead to grasps that appeared *fc* with a small ϵ_{GWS} values to appear non-*fc* when evaluated on a different machine in the cluster. To achieve consistent results, we had to choose an arbitrary small positive δ that is larger than the cross-machine variability that we observed, and redefine *fc* to require that $\epsilon_{GWS} > \delta$. In this work, we arbitrarily chose $\delta > 0.001$, as this was several orders of magnitude above the largest discrepancy we ever observed between two machines analyzing the same grasp, and several orders of magnitude lower than the quality of the average unperturbed grasp that we evaluated.

We calculated these statistics across all of our grasps. These results are summarized in Table 3.1. We see that the expected ϵ_{GWS} and V_{GWS} are 50% and 67% of their planned values, respectively. This shows that pose uncertainty has a large effect on the expected value of these measures. Additionally, we see that there is relatively high variance of these measures across all of the sampled perturbations for a single grasp.

Measure across sampled perturbations	Average across 'Tool' grasp dataset
normalized expected ϵ_{GWS}	0.5091
normalized std(ϵ_{GWS})	0.2915
normalized expected V_{GWS}	0.679
normalized std(V_{GWS})	0.3588
$P(fc)$	0.7957

Table 3.1: Summary of Simulation Results: These results quantify how robust each quality measure is to pose uncertainty. For each grasp, the expected value and standard deviation of the respective quality measures are calculated across the poses sampled. These measures are normalized by dividing them by the planned quality of the unperturbed grasp to allow comparison of the effects of uncertainty across grasps. $P(fc)$ denotes the measured probability of achieving an fc grasp, which we have calculated as $P(\epsilon_{GWS} > .001)$

The average standard deviation of the measures across the perturbed samples of a single grasp is 29% of the ϵ_{GWS} and 35% of the V_{GWS} .

The observation that the within grasp variability is high is what led us to consider whether the number of non- fc perturbed samples varied significantly across grasps with similar ϵ_{GWS} qualities. We found that the average $P(fc)$ is around 80%. This implies that even the best five grasps for the object should be expected to fail 20% of the time, if we only filter grasps by their ϵ_{GWS} quality.

3.5.5 Choosing Optimal Grasps: ϵ_{GWS} vs $P(fc)$

In the case of choosing a single grasp out of a set of many, we are faced with the problem of ranking grasps. The fundamental question we seek to answer with this research can be rephrased simply as whether performing that ranking relying solely on the ϵ_{GWS} is sufficient to chose the grasp most likely to achieve stable *force closure* in the presence of location uncertainty.

In Fig. 3.5, we have plotted the planned ϵ_{GWS} against the estimate of the probability

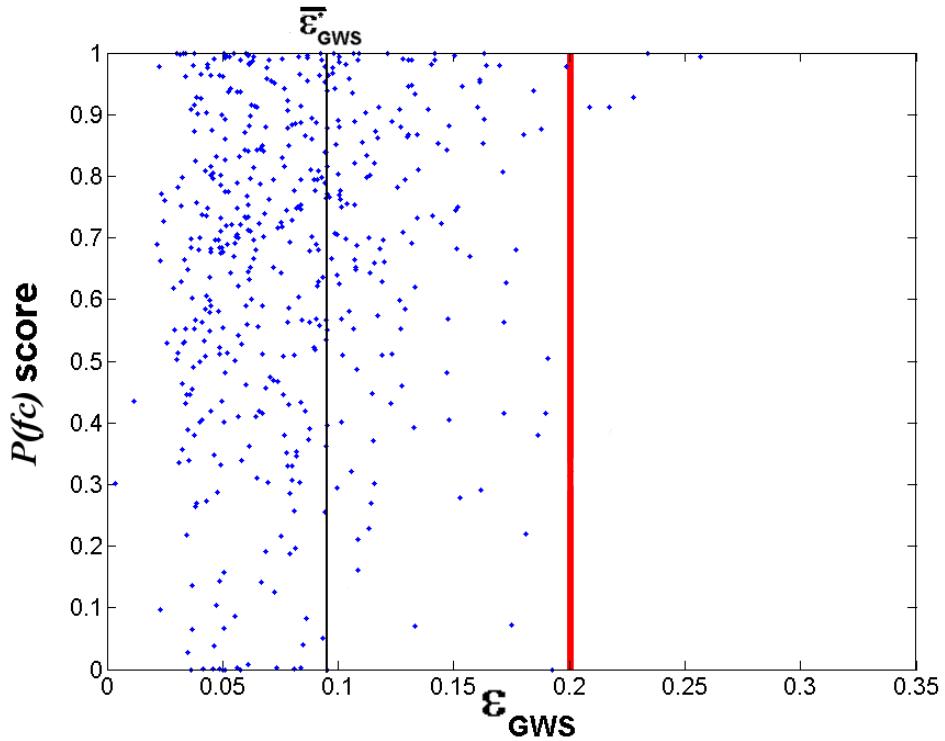


Figure 3.5: ϵ_{GWS} plotted against $P(fc)$, which is equivalent to the probability of attaining an fc grasp under our error model from a planned starting grasp configuration. 480 grasps over 96 objects are presented in this figure. This figure demonstrates that the ϵ_{GWS} is generally a poor predictor of pose error robustness as measured by the $P(fc)$. The mean ϵ_{GWS} , denoted by the black line, is 0.095. There appears to be a cutoff, denoted by a red vertical line on the graph, around $\epsilon_{GWS} > 0.2$, after which all available grasps have a high $P(fc)$, but note how few grasps there are in the database with quality values that high. Only five objects have a grasp with a quality that high, which implies that for most objects, ϵ_{GWS} cannot be used to predict $P(fc)$.

of achieving force closure, for each grasp. $\overline{\epsilon^*}_{GWS}$ indicates the average ϵ_{GWS} for the best grasp available for each object, which is 0.095. For most objects, the best grasp by ϵ_{GWS} lies in the range where $\epsilon_{GWS} \in (0, 0.2)$, bordered by the red line on the right of the figure. This figure shows that there is no correlation between ϵ_{GWS} and $P(fc)$ in that range.

This implies that the ϵ_{GWS} cannot be used to chose grasps that are expected to be robust. On average the best grasp by $P(fc)$ for each object has a $P(fc)$ that is 0.21 greater than the $P(fc)$ of the highest ϵ_{GWS} grasp. Under the error model described, choosing the highest $P(fc)$ grasp will result in an fc grasp 21% percent more often than choosing the best grasp by ϵ_{GWS} . This analysis yields approximately the same results for the V_{GWS} in comparison to the $P(fc)$.

3.6 Physical Experiments

These simulation results show that using $P(fc)$ as a quality metric for ranking grasps from a database may select grasps that are more reliable in the face of object pose estimation error. To test whether these simulation results can be verified against physical experiments, we attempted to grasp ten objects for which we had high quality mesh models readily available courtesy of the the DARPA ARM-S project and the Willow Garage object database [23]. We added these models to our database, and calculated the $P(fc)$ for the top five grasps by ϵ_{GWS} value.

To test these grasps on a real robotic grasping system we used a Barrett 280 model hand attached to a Staubli TX60L 6 degree of freedom arm to implement the grasping pipeline described in 3.5.2. To emulate the friction coefficient used in our simulations, we wrapped the contacting surfaces of the hand in rubberized shelf liner. One object attempted was a blue detergent bottle made of very smooth plastic. We added a rubberized tape to the contact locations on this object to increase its friction coefficient. For each object, we selected the best grasp ranked by ϵ_{GWS} and the best grasp ranked by $P(fc)$. The objects were calibrated to the robot using a printed template of the bottom outline of the objects. We align the edge of each template to a known coordinate system

in our robots workspace. We selected a perturbed position by sampling our error model and then applying the grasp pipeline as though the objects origin was at the perturbed location.

We tested up to ten randomly selected perturbed positions for each grasp. The same perturbations were applied to both of the tested grasps for each object. We moved the arm and hand at very slow speeds to simulate quasi-static conditions. In the first two stages of the pipeline, we moved the arm at 1% of its maximum speed, and the fingers of the Barrett hand at 10% of their maximum speed. In the final closing step, initial contact had been achieved or joint limits had been reached for each finger. We then raised the finger speed to 50% to drive the underactuated fingers to their final positions. After the fingers stopped moving, we lifted the object 3 cm perpendicular to the tables surface. If any part of the object was still touching the table when the arm came to a stop, we graded the trial as a failure, otherwise we graded the trial as a success.

We find that the grasps ranked best by the $P(fc)$ are successful more often. The results of this experiment along with the grasps and objects analyzed are in Fig. 3.6 and Fig. 3.7. Overall, for these ten objects the $P(fc)$ ranking selected successful grasps on 85 out of 93 trials (91%), whereas the grasps selected by the ϵ_{GWS} ranking succeeded on 63 of 93 trials (67%). For some objects, nearly all of the grasp attempts were successful irrespective of the $P(fc)$ score. We separated the objects in our experiment into two groups. One group is composed of larger, more complex objects shown in Fig. 3.6 and the other group is composed of light, roughly cylindrical objects shown in Fig. 3.7. We see that all of the objects in the roughly cylindrical category were grasped very robustly irrespective of $P(fc)$ score. For these objects, the Eigengrasp planner finds grasps that more or less encompass the object. In contrast, for the five objects that could not be enveloped by the hand, we see that the $P(fc)$ ranked grasp is successful in 35 out of 43 trials (81%), as compared to 16 out of 43 trials (37%) using the ϵ_{GWS} grasp. These results show that the $P(fc)$ ranking chooses more successful grasps; especially on the larger, more complex objects where the success rate is doubled.

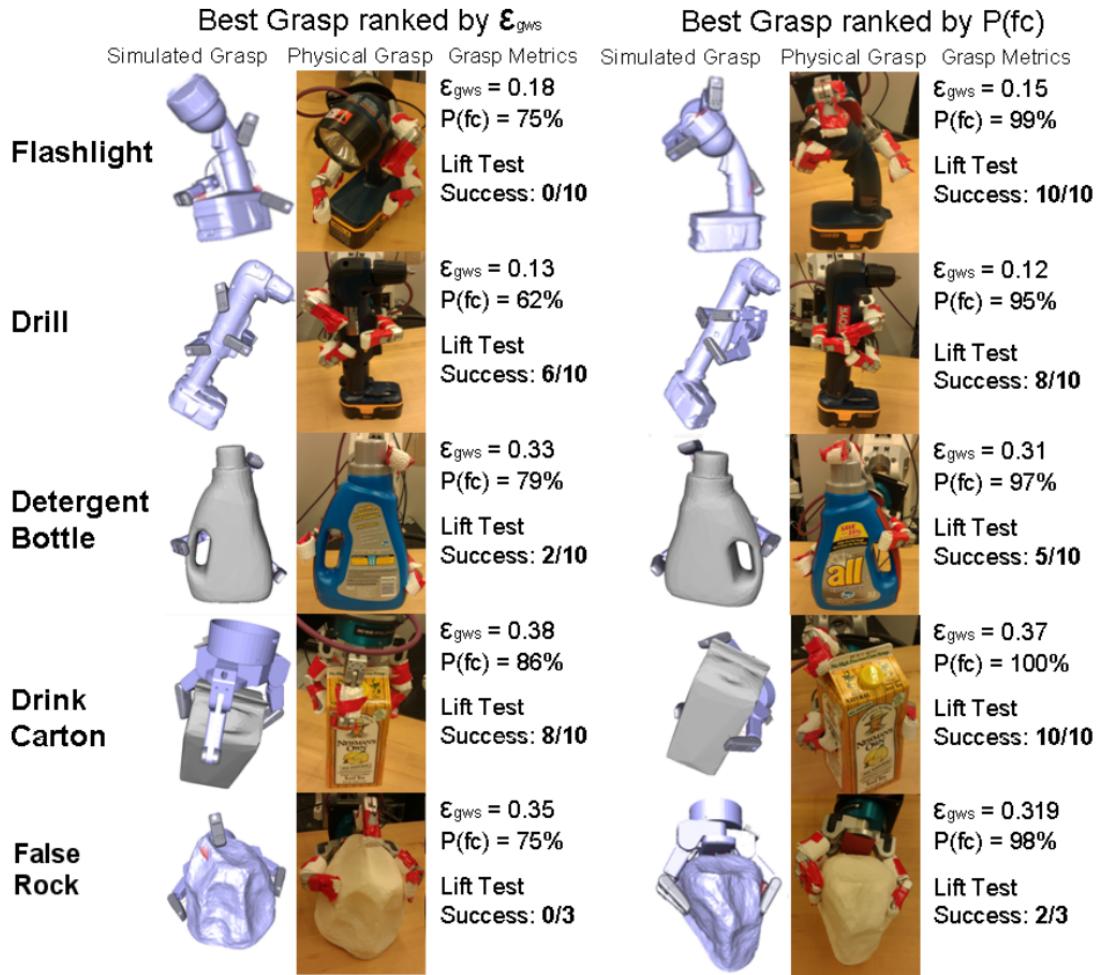


Figure 3.6: *Results A*: The results of physical experiments on five large, complex objects. In the left column are the best grasps for each object ranked by ϵ_{GWS} . An example of the simulated and physically realized grasp is illustrated for each grasp attempted. Additionally, the figure gives the $P(fc)$ and ϵ_{GWS} for each grasp attempted, as well as the fraction of attempts which succeeded in lifting the object by 3 cm in physical experiments. The higher $P(fc)$ grasp is successful on many more trials than the higher ϵ_{GWS} grasp for these objects.



Figure 3.7: *Results B*: The results of physical experiments on five smaller, simpler objects. In the left column are the best grasps for each object ranked by ϵ_{GWS} . In the right column are the best grasps by $P(fc)$. An example of the simulated and physically realized grasp is illustrated for each grasp attempted. Additionally, the figure gives the $P(fc)$ and ϵ_{GWS} for each grasp attempted, as well as the fraction of attempts which succeeded in lifting the object by 3 cm in physical experiments.

3.7 Discussion

In this work, we have shown that the planned ϵ_{GWS} of a planned grasp is not predictive of the probability of achieving a force closed grasp in the presence of uncertainty, neither in simulation nor physical experiments. To analyze this in simulation we generated the measure $P(fc)$ as an approximation of this probability. We then showed that the $P(fc)$ can itself be used to rank grasps from a preplanned grasp database and that this reranking predicts grasping success in physical experiments better than the ϵ_{GWS} .

The analysis presented here is less effective at discriminating fragile grasps on smaller objects than it is on larger objects. For small objects, the object is fully encompassed by the hand, and the highest ϵ_{GWS} grasp is always an enveloping power grasp, and is always spherical, as described in [Cutkosky and Howe, 1990]. As seen in Fig. 3.7, in such grasps the palm is behind the object, one finger pressing downwards, with fingers roughly evenly spaced apart. For a hand capable of achieving this configuration, it is always a high ϵ_{GWS} grasp, because the normals of the contact points are evenly spaced around the center of the grasp, which maximizes their ability to directly oppose perturbation forces. It is also a configuration that is relatively invariant to perturbations that do not move the object outside of the working envelope of the hand.

Under more constrained conditions, such grasps are not always attainable. The object may not be in the center of the workspace, there may be objects in the way, or the desired purpose to which the object will be put requires a different grasp. These cases are better represented by the results on the large objects, which couldn't be fully encompassed by the hand. Under these conditions, the higher ϵ_{GWS} grasp often fails, and we see better results ranking by $P(fc)$.

3.7.1 Online Extensions

Although the full sampling rate is too computationally expensive, in Table 3.2 we examine the possibility of approximating $P(fc)$ at lower sampling rates. By using a sampling step size of (10mm, 10mm, 10°), we see an average difference of 6% with respect to the denser sampling. In none of our samples did this change the order of our rankings.

Sampling Step Size (X, Y, θ) (mm, mm, $^\circ$)	Mean Difference	Standard Deviation	Max Difference
2-2-4	0.0128	0.0122	0.0667
2-2-4(random)	0.0097	0.0086	0.0493
10-10-10	0.0653	0.0551	0.3205
10-10-20	0.0840	0.0713	0.4782

Table 3.2: This table quantifies the effect of sampling parameters on the estimate of quality measure. The first column describes the sampling density along each dimension of the error model. The other columns describe the average change in the subsampled $P(fc)$ as compared to the densest sampling rate. These results demonstrate that lower sampling rates may feasibly be used to approximate the $P(fc)$ at the densest sampling rate without unacceptable loss of accuracy.

At this sampling rate, we can generate an estimate in under a second, which make it suitable as a filter for an online grasp planning system. At lower sampling rates, the rankings do become reordered, which may lead us to select less robust grasps. In our shared control online planner, we use the lower resolution $P(fc)$ to weight the grasp quality measure that controls the order in which grasps are tested for reachability, and the order in which they are presented to the user. Without this filter, many grasps that are presented to the user are fragile to object pose estimation errors.

In Chapters 4-6, we will demonstrate an online planner that uses a human-in-the-loop with an extremely limited interface to act as a second filter selecting the appropriate grasp. When the grasps that are presented include many fragile grasps, more of the responsibility is placed on the user, which requires both more insight and more interaction. Since the bitrate and accuracy of the interfaces we will use is limited, reducing the number of inappropriate grasps can help reduce training time, and improve the speed and accuracy of the system. By filtering out non-robust grasps, we are able to present the user with a more suitable set of grasps that they can manage even with a limited interface.

Part II

Bioelectric Potential Driven User Interfaces for Grasping

Chapter 4

A Grasp Planning UI for Facial Gestures

4.1 A BCI Input Device Prototype

In order to develop a full prototype for a grasping system usable by a disabled individual, we developed an initial test bed with a number of test objects using an industrial Stäubli robotic arm, a BarrettHand gripper, and an object localization system based pointclouds captured by a Kinect depth camera. We sought an input device that might be representative of what could be achieved by a low cost BCI device in order to evaluate a user interface under realistic conditions of error and throughput. A number of low cost wireless EEG devices began entering the consumer market in 2009. Two EEG headsets we evaluated as potential EEG devices were the Neurosky Mindwave and the Emotiv Epoc.

4.1.1 Mindwave

The Mindwave is an approximately \$100 headset that has a single dry electrode which is reported to measure a one-dimensional axis of voluntary control that the developers map to “focus” and “relaxation.” The main advantages of this device are its low cost and ease of application. Unfortunately, we were not able to extract useful signals from

the Mindwave device and abandoned attempts after several hours of training using the vendor-provided software failed to produce results among three researchers in our lab.

4.1.2 The Emotiv Epoch

The Emotiv Epoch is an approximately \$400 headset with 14 wet electrodes. Of the 16 electrodes, 14 are positioned at the International 10-20 locations corresponding to AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2. The remaining 2 channels are references and are positioned at P3 and P4. Each electrode has a sampling rate of roughly 128 hz and a resolution of 16 bits (14 bits effective). While substantially more invasive than the Mindwave, this device produces more signals with higher fidelity. The software interface provided does not allow access to the raw signals produced by the Emotiv, but there are a number of classifiers that are made available, separated into three suites representing modalities. These classifiers are essentially black boxes, but we can describe their stated purpose.

4.1.2.1 Classifier Suites

Affectiv Suite The first modality is similar to that of the Mindwave, but claimed to be measuring five different channels related to emotional state - engagement, frustration, meditation, instantaneous excitement, and long term excitement. These channels vary rather slowly and are not well suited to use as an input method. It is also not clear that they can be made subject to voluntary control. We did not investigate this modality, since it did not seem like its timescale was appropriate.

Expressiv Suite The second modality interprets the input signal as facial movements, reporting events such as “wink”, “jaw clench”, and “smile.” This interface doesn’t allow any training of the classifier, but does allow a threshold to be set for the action to be reported. Multiple actions may be reported at the same time, and there is some amount of crosstalk between each modality. We were able to verify that this classifier can be made somewhat effective through careful selection of thresholds, but its output is inconsistent. In our experience, the jaw clench classifier was

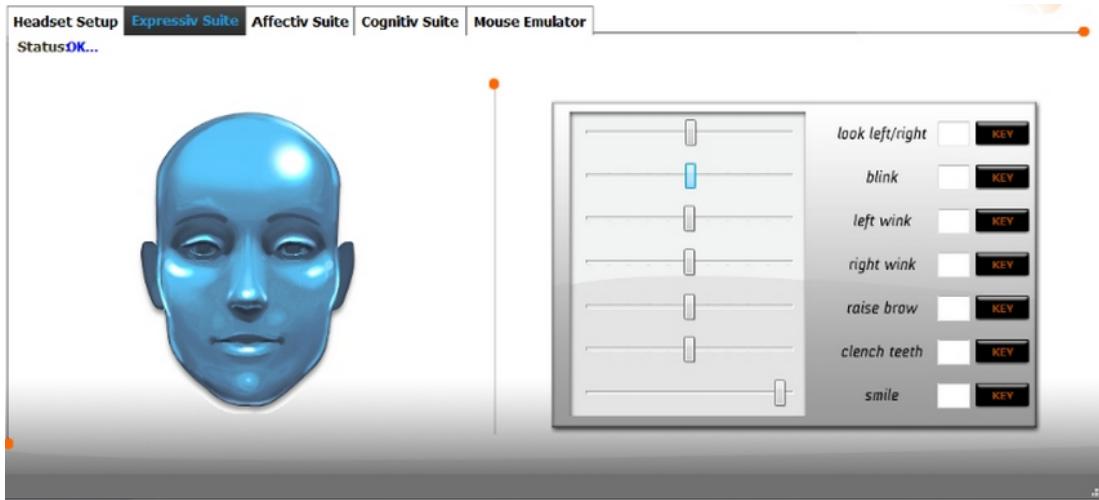


Figure 4.1: The Expressiv Suite control panel for interprets the input signal as facial movements, reporting events such as “wink”, “jaw clench”, and “smile.” This classifier requires only a simple threshold setting and is fairly robust, however multiple actions may be reported at the same time, and there is some amount of crosstalk between each modality.

the most robust. Attempting to classify more than one expression resulted in significant cross talk.

Cognitiv Suite The third modality claims to measure some mental action command.

Unlike the other two modalities, this modality has a training interface that the subject can use to train the classifier on up to four independent commands. The training interface for the classifier for this modality allows the user to affect the position of a block in space using verbs such as ‘lift’, ‘push’, and ‘pull’, and is thus presumably analogous to the imagined motion paradigm presented in other literature. As the number of trained commands increases, the difficulty of training additional commands also increases. We were not able to achieve classification of EEG based signals, but made use of the classifier in other ways.

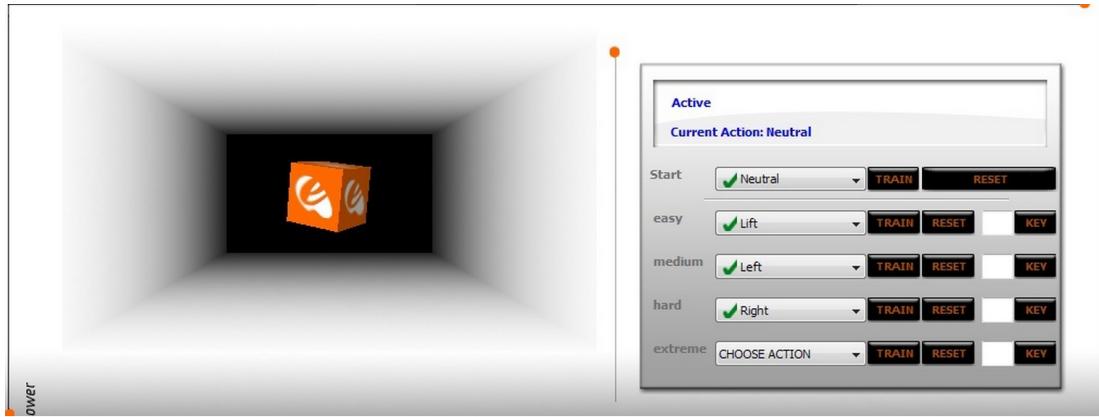


Figure 4.2: The Cognitiv Suite control panel is intended to measure some mental action command. The command is associated with some motion of the cube shown in this figure, for example “lift” will make the box float higher. As the number of trained commands increases, the difficulty of training additional commands also increases.

4.1.3 UI Design

The Cognitiv Suite appeared ideal, as it allows up to four user elicited output options with analog output levels. Of the three researchers developing the UI, none of us were able to achieve reasonable classification rates using mental imagery even with a single option. We abandoned the EEG modality in favor of using facial gestures. The Expressiv Suite could provide reliable detection of jaw clenching, but other facial gestures could not be reliably detected without interfering with casual breathing, blinking, and speaking. However, we could train the Cognitiv Suite classifier on up to three facial gestures relatively quickly, with the fourth gesture classified by the Expressiv Suite. While these outputs are only discrete values, we could train some gestures to be easier to maintain, so that they can be used as continuous control signals.

In this work, GraspIt! is used both to plan grasps and to present the user with feedback. We augmented the Eigengrasp Planner GUI with a visualization of the grasp planning scene that includes a number of guides and fiducials that allow the user to guide the planner fully inside the simulator. The augmented grasp planning scene is illustrated in Fig. 4.3.

Phase Gesture	Run Planner	Review Grasps	Execution
1	start/stop planner	cycle through grasps	restart
2	n/a	select grasp	confirm grasp
3	rotate around x axis	n/a	n/a
4	rotate around z axis	n/a	n/a

Table 4.1: This table shows the initial control flow of the grasping pipeline using facial gestures detected by the Emotiv Epoc

4.1.3.1 Grasping Pipeline

With these constraints in mind, we broke down the process of grasping an object into four stages that could be controlled using four inputs - two continuous control signals and two discrete signals. These stages are outlined in Fig. 4.4.

The grasping pipeline is divided up into four stages: object identification and alignment, grasp planning, grasp review, and grasp execution, which are described below. This pipeline is controlled using only four facial gestures. The use of these gestures in each stage of the pipeline is explained in Tab. 4.1. In general, gesture 1 serves as a trigger and moves the user through the pipeline. The exception to this is at points of decision for the user. In these cases, gesture 2 serves as the YES option and gesture 1 becomes NO and returns the user to an earlier point in the pipeline. Because false positive readings of gesture 1 and 2 have strong consequences, we found that both are best associated with a concise and strong gesture such as closing one eye or clenching the jaw. Gestures 3 and 4 control the approach direction of the hand relative to the object during the grasp planning stage of the pipeline. These gestures can be maintained to generate continuous motion of the hand over two degrees of freedom and therefore are best associated with gestures that can be contracted for several seconds without too much twitching or fatigue.

Object Localization: The Eigengrasp planner requires a complete description of the geometry and location of the target object. The object localization system we have

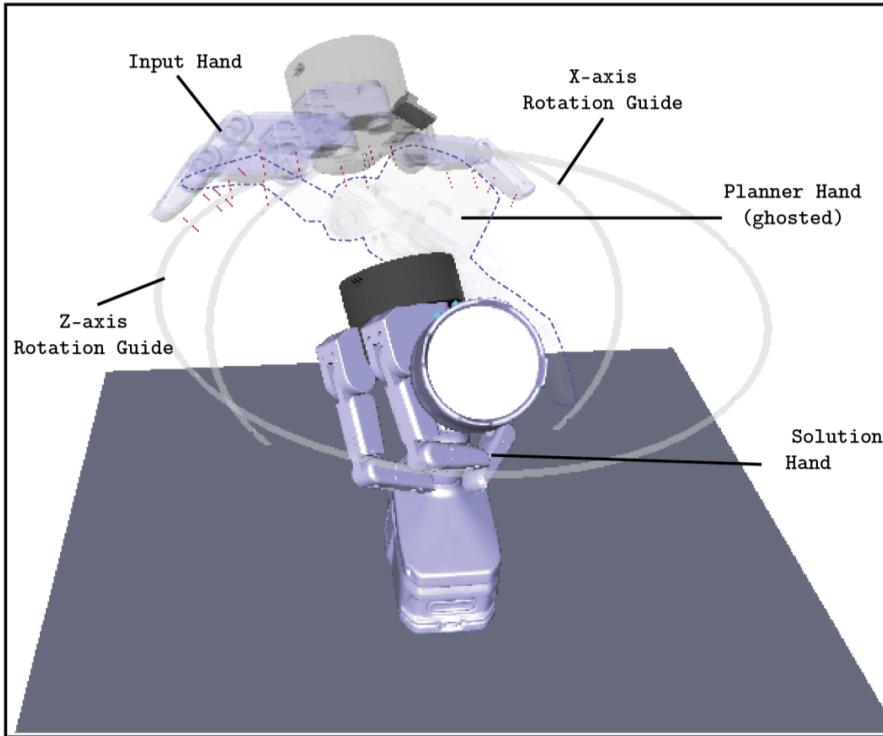


Figure 4.3: An annotated screenshot of the grasp planning user interface in GraspIt!. Here we demonstrate the three hands of the system. The Planner Hand, which is the most transparent hand, demonstrates the current state of the planner. The Input Hand, which is of intermediate transparency, is the hand through which the user directs the planning system. Here you can see the rotational guides which allow the user to visualize their available control directions. The Solution Hand, which is fully opaque, demonstrates the best grasp currently available. This is the grasp which is closest to the approach direction that the Input Hand is demonstrating and which also has the minimal grasp energy.

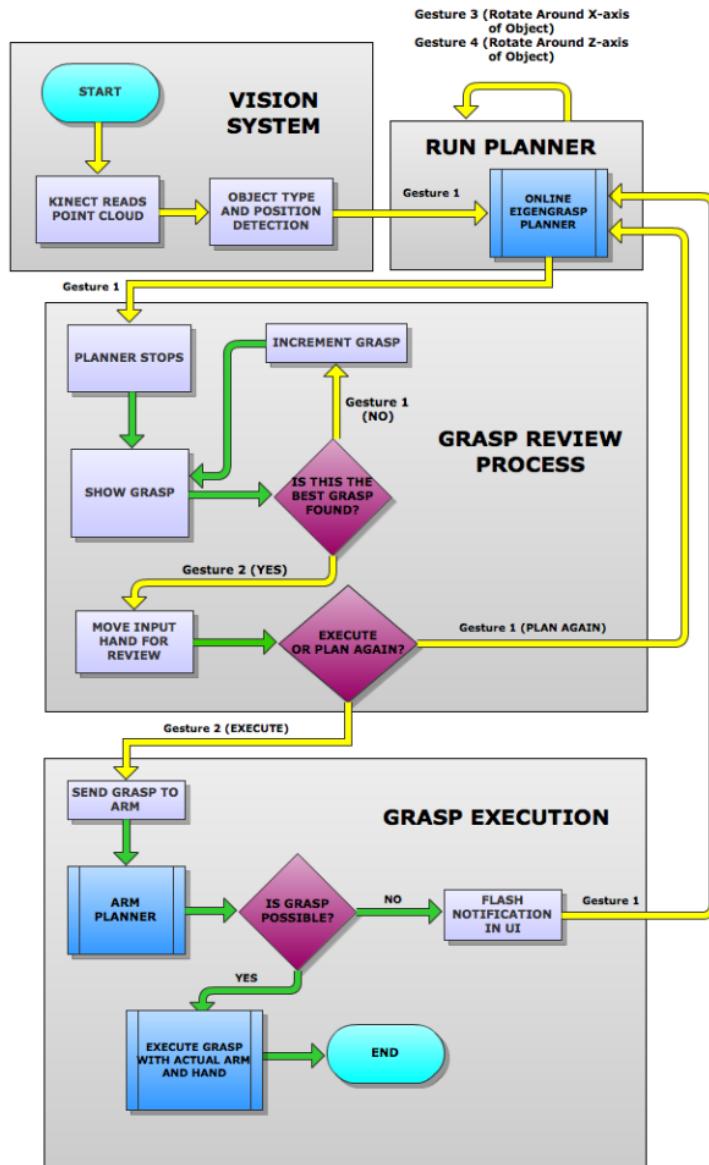


Figure 4.4: This diagram shows the initial Emotiv Epoc based grasping pipeline. The purple diamonds reflect decision points in the pipeline that require input from the user. In the first phase, the system uses the Kinect to identify and localize the object in the scene. In the second phase, the user guides the planner to an appropriate approach direction. In the third phase, the user stops the planner and reviews the available grasps. In the fourth phase, the user sends the grasp to the robot for execution.

incorporated uses a depth camera as input and is described in greater detail in Section 4.1.4.3. In the initial work, we used a single unoccluded object, and assumed that the recognition system works perfectly, so no user interaction is required.

Grasp Planning Phase: Once the object is localized, we center the hand around the object and initialize the Eigengrasp planner. In this phase the user can move the hand around the object using gestures 3 and 4, which allow “continuous” input. Each gesture moves an “input hand” around a corresponding axis guide, which allows the user to visualize how the hand will move. Gesture 3 rotates around the X axis of the object, while gesture 4 rotates around the object’s Z axis. When the planner is run, the demonstrated pose is used as a part of the objective function for the simulated annealing planner. Gesture 1 starts the planning thread. The demonstrated pose can still be adjusted while the planner is running, however it can take some time to adjust to the demonstrated approach direction, so it is beneficial to start from a reasonable pose. While the planner is running, the “input hand” is made 30% transparent. A second, fully opaque “solution hand” is rendered showing the highest quality grasp from nearby the current approach direction. To give the user feedback about the progress of the planner, a third “planner hand” is rendered with 80% transparency showing the last tested state. The user interface presented while the subject is running the system is presented in Fig. 4.3 and Fig. 4.5. While the planner is running, the top ten grasps are stored. When the user sees the “solution hand” in a position they believe will produce a stable grasp, they can stop the planner with a second instance of Gesture 1.

Review Phase: Once the planner is stopped the user has an opportunity to review the list of best grasps and choose one for execution. As in the previous stage, the solution hand is used to display the grasps to the user. At any point, the user can select a grasp which removes the “solution hand” from the world and closes the “input hand” into the chosen grasp. Now the user can evaluate the grasp more closely and examine the quality metrics for the grasp. If the user is satisfied, they can confirm selection of the grasp and send it to the next stage of the pipeline. If the user does not want to execute any of the found grasps, they can select the grasp that is closest to what they have in mind and restart the planning process.

Execution Phase: Once the robotic control software receives the selected grasp which is planned relative to the objects coordinate system, the arm planner decides if that grasp is achievable given the kinematic constraints of the arm and the vision systems estimate of the object’s position in the world. If the planner cannot find a solution to execute the grasp, it will send a message back to GraspIt! which then notifies the user. If this occurs, the user can restart the planning phase to find a new grasp. If the planner can find a solution, then the grasp is executed with the actual arm and hand.

4.1.4 Grasping Platform

4.1.4.1 Hardware

In this initial work, our grasping platform is comprised of a 280 model BarrettHand mounted on a Stäubli TX60L 6-DOF robotic arm. The Stäubli arm is an industrial arm that we have found to be accurate to within 3 mm in our setup. This is more accurate than a lower cost, portable arm is likely to be, so the only uncertainty in this experiment comes from the vision system. A Microsoft Kinect sensor is used to generate point clouds of the object.

4.1.4.2 Planning and Kinematics

Planning for the motion of the arm is done in OpenRAVE using a bidirectional random tree planner in [Berenson *et al.*, 2009a], and small linear motions near the object are planned using the built-in inverse kinematics planner.

4.1.4.3 Recognition System

The raw point cloud data is gathered by a Microsoft Kinect. In this work, we assume the target is a member of a known set of ten objects. We use the method described in [Papazov and Burschka, 2011] to identify and localize the target object in the scene. Briefly, this method generates features from pairs of oriented points on the surface of the object. Prospective models are processed offline and put into a hash table. Features are sampled from the sensor data and tested for collision in the hash table. If a sufficient number of collisions occurs with points on the same model, a variant of RANSAC is used

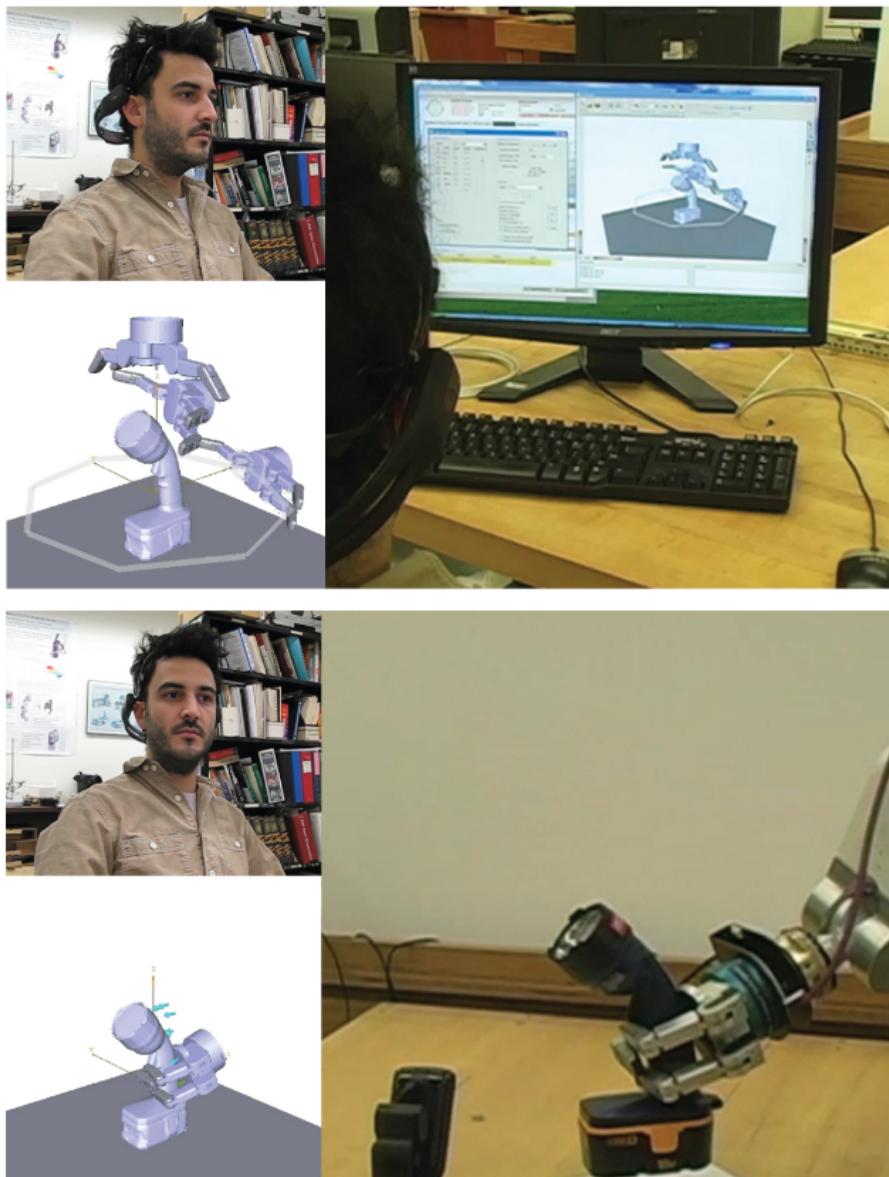


Figure 4.5: Two images captured as a user grasps an object with this system. Top: Clockwise from the top-left are an image of the user wearing the Emotiv headset and operating the system, the computer monitor with user interface, and a screen capture of the simulation. Bottom: User watching the robotic arm implementing the selecting grasp as shown in the simulator window on the lower left.

to test the hypothesis that a set of points in the sensor data corresponds to a particular model at a particular location. This method has demonstrated a high robustness and is extensible to multi-object scenes.

4.1.5 Validation

In order to test this prototype system, we had one of the researchers train to use the system and attempt to pick up a number of objects. The results of these experiments were first published in [Weisz *et al.*, 2012]. A video describing these experiments can be found at <http://robotics.cs.columbia.edu/jweisz/bciGraspingISER2012.mov>.

4.1.5.1 Training

The subject trained the Emotiv Cognitiv suite on three facial gestures for 10 successive training periods each. Each training period lasts eight seconds. During some sessions, the subject either was not able to maintain the facial gestures due involuntary motions such as coughing, and these training sessions were discarded and repeated. During training, the subject is given visual feedback via the motion of a cube and a power meter both of which represent the strength of current classification, as shown in Fig. 4.2. After the Cognitiv Suite gestures are trained, we set the threshold for detection of jaw clenching in the Expressiv Suite to a level that does not trigger for the other facial gestures.

4.1.5.2 Grasping Experiments

The subject used the system to grasp and pick up five common objects: a flashlight, a flask, a bottle of laundry detergent, a bottle of shampoo, and a canister of shaving cream. For each setup, the Stäubli arm starts such that it is completely vertical with the BarrettHand at the top. A simulation world consisting of the hand, the object, and a surface is presented to the subject who can move the input hand and start the planner at any time. For each object, the subject executed grasps from two different approach directions. The subject was able to grasp all of the objects successfully from either of the two directions.

The resulting grasps are shown in Fig. 4.6. In each case, we demonstrate the grasp planned in simulation and the final grasp achieved by the physical robot. We found that using this grasp planning environment, we were easily and reliably able to grasp objects. In each case, the physical grasp was successful on the first attempt. Planning the grasp took on the order of 10-30 seconds. The review process took an additional 10-15 seconds. Finally, the arm motion trajectory planning took 30 seconds.

4.1.6 Conclusions

These results showed significant promise in extending the Online Eigengrasp Planner to assistive devices. However, this initial work showed only that an expert user with experience in robotics and GraspIt! was able to use the system. Additionally, the grasping scenario was rather simplistic, involving only a single object in free space. This interface is also only suitable for grasping known objects. From this initial work, we wanted to extend to more realistic grasping scenarios incorporating multiple, possibly unknown objects and validate the UI on a more general population.

4.2 Handling Novel Objects

The parameters of the object recognition system described in [Papazov and Burschka, 2011] can be tuned to recognize objects with similar parts. To allow the user to grasp objects which are not in the database, we rely on the user to act as a filter to reject grasps that the planning system cannot know are inappropriate because it does not have the exact object model. An example of this alignment can be seen in Fig. 4.7a. In order to allow the user to discern how well the detected object aligns to the true geometry of the novel object in the scene, the UI has been modified to include a down-sampled point cloud from the depth camera. Additionally, since the user will need to exercise more judgement as to which grasps are reasonable, we added a display that shows all of the grasps available. This augmented UI can be seen in Fig. 4.8

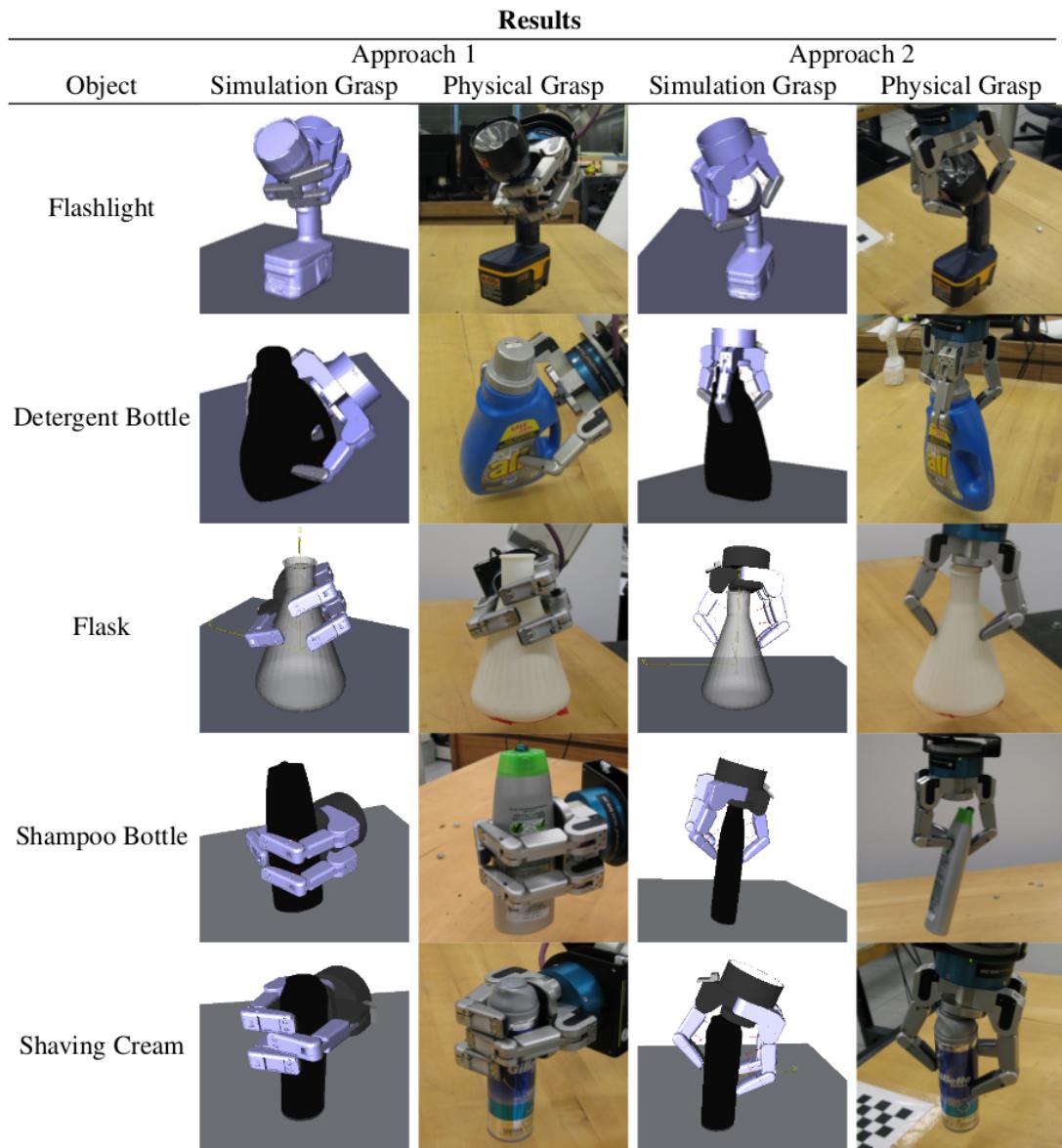


Figure 4.6: The results of ten different attempts to grasp five objects using two different user-selected approach directions per object. In each case, the user was able to generate an appropriate grasp using the simulator, which was then transferred to the robot.



(a) Point clouds with RGB texture from the vision system. On the left is a flashlight along with its aligned point cloud in white. On the right is the point cloud of a juice bottle along with the best model from the vision systems object database, a shampoo bottle, in white.



(b) The two objects which are aligned on the right of the figure above. The shampoo bottle is in the object database. The juice bottle is not. The two are roughly the same width, and this the shampoo bottle can be an appropriate proxy for the juice bottle in the planner.

Figure 4.7: Results of the object recognition system with known and unknown objects.

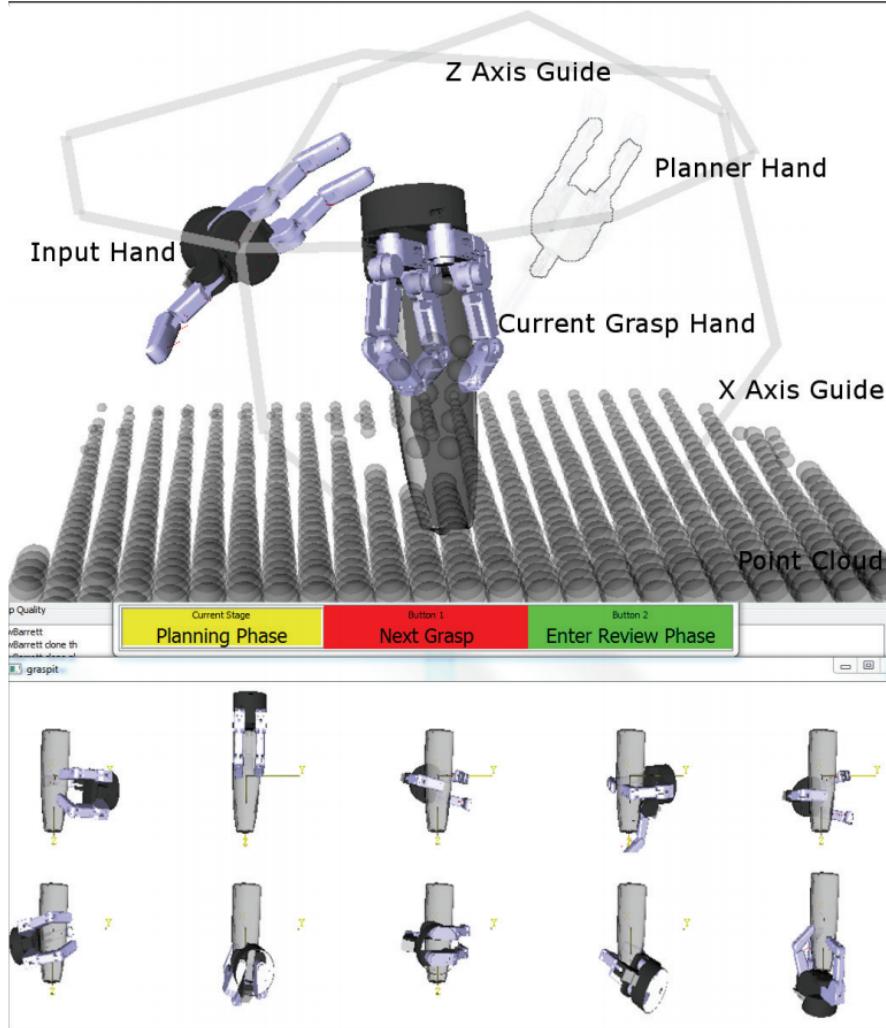


Figure 4.8: The user interface for the semi-autonomous grasp planning in the Online Planner phase. The user interface is comprised of three windows: The main window containing three labeled robot hands and the target object with the aligned point cloud, the pipeline guide window containing hints for the user to guide their interaction with each phase of the planner, and the grasp view window containing rendering of the ten best grasps found by the planner thus far. The object shown in this figure is a novel object that the planner does not have a model of (see Fig. 4.7a). The point cloud allows the user to visualize the fit of the model and act accordingly.

4.2.1 Incorporating a Grasp Database

One useful aspect of mapping the object in the scene to a limited set of objects from a database is that we can also pre-plan a set of grasps for each object. This provides a method for the user to skip the slower online planning phase, since we will already rely more on the user and less on the automated grasp quality analysis. Additionally, it is more important to start the grasp planner from a particular conformation, since this allows the user to restrict the planner to the region of the object from the database acting as a proxy for the target object that best conforms to the true object in the scene.

Using a grasp database also allows us to manually design good grasps for particular affordances. Such affordances are not generally grasped proficiently by generic grasp planners. Fig. 4.9 demonstrates such a grasp. In experiments, this grasp was successful 100% of the time, but only because the object deforms to allow the finger to pass through the hole in the handle region of the bottle. A simulation that can incorporate this behavior in any kind of real-time online planning system is beyond the state of the art. Where such grasps are available and match up with the object geometry, they are very useful.

To seed the grasp database, we ran the Online Eigengrasp planner six times for twenty minutes each with the approach direction of the palm aligned to the major axes in the positive and negative directions, using the best grasp from each direction in the database. If there were fewer than ten grasps in the database, including manually inserted grasps, then the highest quality grasps were selected from among all of the available grasps until a full ten are available.

4.2.1.1 Pipeline Version 2

These modifications require additional user interaction. Whereas our initial experiments assumed the vision system would succeed, when the true object may not be present the output of the vision system is much more variable. Because the vision system is stochastic, running the system again may present the user with different options. The second version of the pipeline allows the user to keep rerunning the vision system until a reasonable match is acquired. As seen in Figure 4.8 where the object is detected

upside-down, the alignment found does not need to reflect the semantic or geometric reality perfectly, as the user is presented with many options and can exercise their own judgement. Incorporating the database also allows us to short circuit the online planning phase when possible, which requires an extra decision point which must have its own phase. Finally, to guard against false positives in the grasp confirmation stage sending inappropriate grasps, we added a separate review and confirmation stage which returns to the beginning of the online planner stage. This new six-stage pipeline is illustrated in Fig 4.10, with the user input controls in each stage mapped in Tab. 4.2. You can see that this table is less sparse than the first version as the pipeline is more complex. Because of this added complexity, we have added a new pipeline guide window, seen between the grasp views and the grasp planning scene in Figure 4.8. In this window the left side of the window shows the current phase in yellow, the center of the window shows the result of Gesture 1 in red, and the right side of the window shows the result of Gesture 2 in green.

The second version of the pipeline differs from the version one in several of the states:

Object Localization: This stage now accepts user input, allowing the user to send Gesture 1 to run the object recognition system again and attempt to find a better fit. All data from the previous iteration is discarded. Gesture 2 accepts the current fit and moves on to the next phase.

Database Planning: This phase is inserted before the planner initialization phase. Once the object is identified, the planner loads a set of pre-planned grasps from a database. These grasps are presented to the user in the grasp view window. Gesture 1 allows the user to browse through the list of grasps and visualize them in the larger main window. The user is able to chose the grasp that best reflects their intent, and then signal acceptance of this grasp with Gesture 2.

Planner Initialization: Having selected a grasp from the initial set of pre-planned grasps, the user can chose to either execute this grasp using Gesture 1, shortcircuiting the grasp planning phase and proceeding to the grasp Confirm Grasp phase, or they can run an automated grasp planner using the selected grasp as a guide using Gesture 2. By choosing one of the grasps from the database and skipping straight to the confirmation

Phase	Gesture 1	Gesture 2
Object Recognition	Rerun Recognition	Database Planning
Database Planning	Next Grasp	Planner Initialization
Planner Initialization	Confirm Grasp	Online Planning
Online Planning	Next Grasp	Review Grasps
Review Grasps	Next Grasp	Confirm Grasp
Confirm Grasp	Restart Planner	Execute Grasp
Execute Grasp	Review Grasps	N/A

Table 4.2: This table shows the initial control flow of the grasping pipeline using facial gestures detected by the Emotiv Epoc

phase, the user can significantly reduce the amount of effort required to grasp an object. To choose grasp n, only n+4 inputs are required.

Online Planning: This phase remains the same as in version 1, except that Gesture 1 iterates through the grasp list and shows that grasp in the grasp planning scene using the “Current Grasp Hand”. Whichever grasp is currently being shown is the one that is selected when the review phase is entered.

Grasp Review: This phase is the same as version 1.

Confirmation: This phase is new in version 2. In this phase, Gesture 1 will restart the planner in the online planning phase, while Gesture 2 executes the grasp. This additional phase adds robustness to false positives in the grasp review stage.

Execution: This phase is the same as in version 1.

4.2.2 Experiments

In order to test the efficacy of our system, we recruited five subjects to participate in an experiment to use the system to lift three objects from a table. All testing was approved by the Institutional Review Board of Columbia University under Protocol AAAJ6951. The results of these experiments were published in [Weisz *et al.*, 2013], and a video illustrating the experiments can be found at <http://robotics.cs.columbia.edu/~weisz/grasp/>.

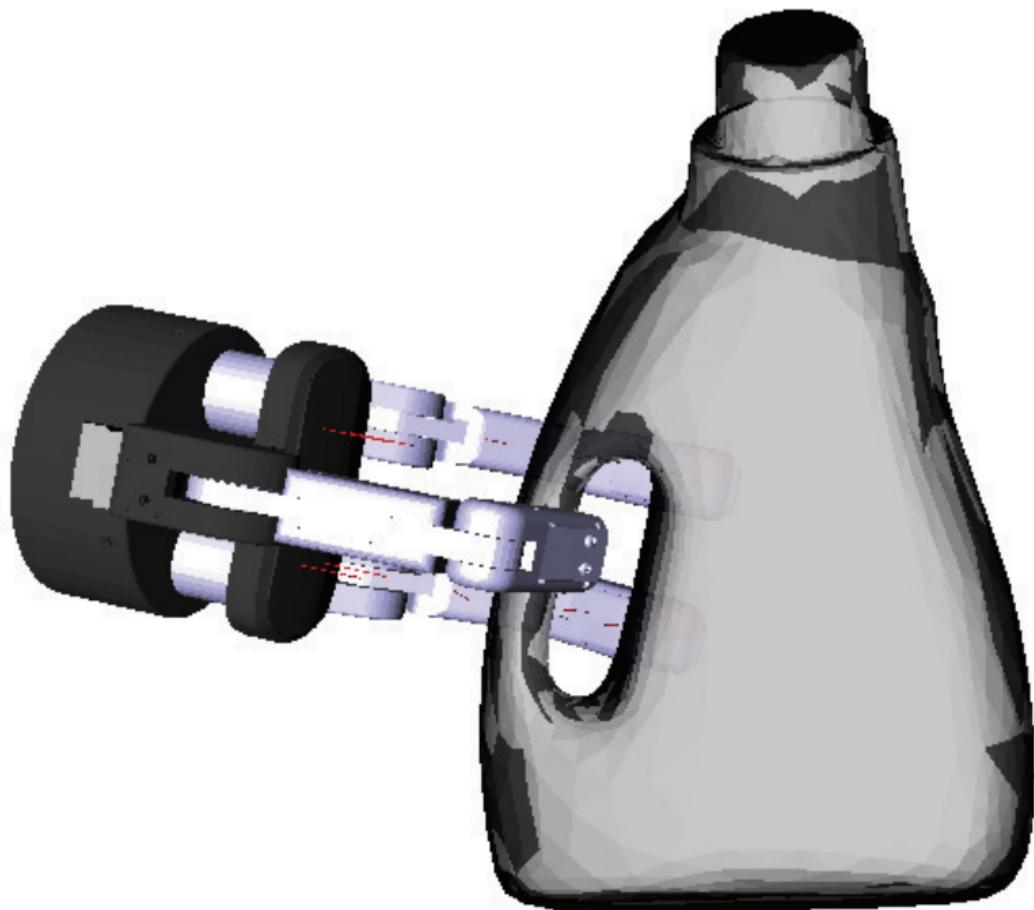


Figure 4.9: This handle grasp for the detergent bottle is not a force closure grasp, but when chosen by the subjects in our experiments it succeeded 100% of the time. Adding a grasp database allows such semantically relevant grasps to be used in our system.

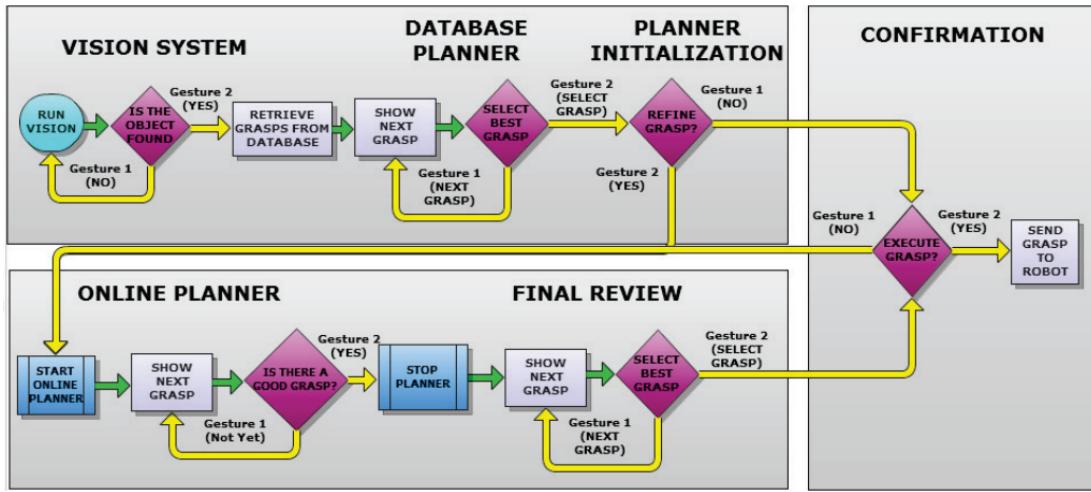


Figure 4.10: The phases of the modified grasping pipeline incorporating more control over the vision system and the grasp database. If the user chooses grasp n from the database, n+4 user inputs are required. If none of the grasps are suitable, the online planner can be invoked with a few simple inputs to refine one of the grasps further.

edu/jweisz/bciGraspingIR0S2013.mov.

4.2.2.1 Task

Each subject was asked to grasp and lift three objects using an Emotiv Epoc as input. Two of the objects, a flashlight and a detergent bottle, were in the database and used for the vision system and one object, a small juice bottle, was novel. Each subject was asked to perform two grasps, one from the top of the object and one from the side of the object. Each grasp was repeated three times. For the novel object, subjects were simply asked to grasp the object five times, irrespective of direction.

4.2.2.2 Training

In this work, we use the same training as in 4.1.5.1 to train the classifiers for the Emotiv. To train the subject to perform the task, the subject was asked to perform the task twice in the virtual environment without executing the final grasp on the arm.

4.2.2.3 Results

The results of the experiments are reported in Tab. 4.3. For each subject, we report the mean time to completion and fraction of successful attempts for each grasp. Time to completion is measured from the end of the object identification phase to the beginning of the execution phase, as this represents the time taken to plan the grasp. Overall, the average planning time was 104 seconds on the known objects and 86 seconds on the unknown object. The average success rate was 80%, demonstrating that this system is efficacious in allowing the user to plan and execute a reasonable grasp for these objects. It is notable that grasps from the side demonstrated significantly more robustness and lower planning times than grasps from above. The grasp database contained only one grasp from above for each of these objects, and this grasp was a fingertip grasp which may be sensitive to pose estimation error, which resulted in longer planning times while the subjects searched for a better grasp. In general, grasping roughly cylindrical objects such as the top of the detergent bottle from above is somewhat problematic for the BarrettHand due to its configuration and the low friction of its fingertips. In contrast, subjects were able to find a reasonable grasp from the side of the object among the grasps pulled directly from the database. The difference in planning times reflects the benefit of integrating the off-line planning phase.

4.2.3 Discussion

During the experiment, we found that it was necessary to re-wet the electrodes of the Epoch many times during the experiment. Additionally, for three of our subjects it took more than an hour to find the right thresholds and position for the headset. After the experiment, subjects were asked to describe their discomfort during the experiment and their level of control. Subjects reported little discomfort, but were frustrated with the difficulty of getting the Epoch to recognize their intended actions, especially with false negatives making it difficult to continue to the next stage of the pipeline at will. In spite of this frustration, subjects were able to complete the task.

However, these difficulties pose a major problem in testing this system on a disabled subject. Since they are dependent on caretakers, an indeterminately long setup time

Grasp	Subject	Successes	Mean Time
Flashlight Side	1	3/3	125
	2	3/3	53
	3	2/3	103
	4	3/3	95
	5	3/3	82
Flashlight Top	1	3/3	132
	2	2/3	75
	3	2/3	96
	4	3/3	93
	5	2/3	125
Detergent Bottle Side	1	3/3	75
	2	3/3	57
	3	3/3	106
	4	2/3	82
	5	3/3	75
Detergent Bottle Top	1	1/3	151
	2	2/3	114
	3	2/3	142
	4	2/3	161
	5	3/3	145
Novel Bottle	1	3/5	132
	2	4/5	63
	3	4/5	95
	4	4/5	91
	5	4/5	50

Table 4.3: Results from Experiment 2

poses a major problem in performing studies with that population. Another major source of issues is the lack of online reachability testing in the grasp planner. In these experiments, we placed the object carefully to avoid having the planner find unreachable grasps. When we extend this system to handle more cluttered scenes, this will become a much more pressing issue. Finally, users reported that the pipeline guide window was too small.

In the next chapter, we explored a different interface device that is designed specifically to measure facial EMG signals, along with some of the changes we made to the user interface to address the concerns subjects expressed during this experiment.

Chapter 5

Using a Minimal Interface Device

5.1 Integrating a Novel sEMG Device

5.1.1 Surface EMG Recording

Although the Epoch made a reasonable early testbed, there are a number of ways in which it is not optimal. For one thing, the device has a fairly large profile around the whole head, which is inconvenient for individuals with severe impairments that require head support. Additionally, the device was quite finicky to train and tended to need repeated re-seatings and maintenance. To address some of these issues, we formed a collaboration with a group at UC Davis that had developed a novel input device designed to be used by severely impaired individuals. This device has an extremely noninvasive and low profile, requiring only a single surface electromyography (sEMG) recording site behind the ear. The muscles around the ear are shown in Fig. 5.1. These muscles are innervated by nerves that come directly from the brain stem, without ever entering the spine. Thus, even individuals with the most severe spinal cord paralysis can still access these muscles. Additionally, neurodegenerative disorders tend to affect more distal muscles first, and more proximal muscles near the face and hands retain their function in more impaired individuals. The Superior Auricular(SA) muscle is a large muscle near the temple which is often activated by chewing motions or jaw clenches. The Posterior Auricular(PA) is a smaller muscle behind the ear. Although some individuals are able to independently

move their ears, we have found that even individuals that cannot move their ears can learn to activate the muscles in that region without achieving overt motion when they are given visual feedback. This activation is produces signals that can be detected by electrodes mounted on the surface of the skin.

In a series of works [Joshi *et al.*, 2011; Perez-Maldonado *et al.*, 2010; Skavhaug *et al.*, 2012], our collaborators have shown that they can record two simultaneous channels from a single recording site. This is achieved by training the subject to modulate the activation frequency of the muscles near the recording site so that they can voluntarily control the ratio of power in two separate frequency bands. These two independent degrees of control are used to drive a cursor which selects options by hitting targets on a screen. In those works, the authors produced different user interfaces such as a UI for allowing a disabled individual to control a television.

The general methodology is outlined in Fig. 5.2. The single sEMG signal is first processed through a 60 Hz noise filter to remove noise from the AC power supply. It is then run through two different band pass Butterworth filters to extract two separate signals. The bands are then linearly combined to compute the x and y cursor positions. This linear combination is necessary to generate independent control channels since there are no perfect band pass filters, and the subject may not be able to completely independently activate the frequency bands.

The total powers of two different frequency bands of the single sEMG signal were computed using two band pass filters for 80-100 Hz (Band 1) and 130-150 Hz (Band 2). These bands were selected ad-hoc, based on previous experience. The output of the two filters produced comparable powers. The filter outputs were combined linearly as described in Equation 5.1. Without this transformation the cursor could not reach points along the x or y axis as there can never be zero power in either of the frequency bands. The gains for each band are set for each subject after a short calibration procedure, as described in [Perez-Maldonado *et al.*, 2010] to establish the subjects comfort level maintaining a large enough voluntary muscle contraction to move the cursor to any part of the screen.

The sEMG signals are collected from the PA muscle with two surface Ag-AgCl cup

electrodes connected to a model Y03 preamplifier (www.motion-labs.com) with input impedance higher than 108, 15-2000 Hz signal bandwidth and a gain of 300. The electrodes were placed behind the subjects left ear along the axis of the muscle with approximately 1.5 cm inter-electrode distance (see Fig. 1). A third electrode was placed on the elbow as a reference. The cup electrodes were the type EL254S from Biopac Systems Inc. held in place with Ten20 conductive paste.

$$x_{pos} = 1.75 \frac{ChannelPower_1}{gain_1} - 0.75 \frac{ChannelPower_2}{gain_2} \quad (5.1a)$$

$$y_{pos} = 1.75 \frac{ChannelPower_2}{gain_2} - 0.75 \frac{ChannelPower_1}{gain_1} \quad (5.1b)$$

To adapt this system to our use, we have added some additional smoothing steps. The cursor position is further filtered through a low-pass filter with a cutoff frequency of .5 Hz. This produces a new position at 4 Hz. To smooth the visualization of the cursor motion, we linearly interpolate 7 intermediate positions between each successive update, increasing the refresh rate of the visualization from 4 Hz to 32 Hz. This makes the system feel significantly more interactive, at the cost of a .25 second delay between the calculated position and the visualization.

5.1.2 sEMG GUI

To send signals to the grasping system, the user controls a cursor to hit one of four targets presented, as seen in Fig. 5.3. The user begins in a rest area and moves the cursor to one of the targets, each representing a different input option. When the target is hit, the cursor changes colors to reflect the user's selection. The user returns the cursor to the rest area, at which point the input option selected is activated. After a selection, the other targets are disabled for four seconds. If an unintended target is selected, the user can avoid returning to rest for these four seconds, canceling the selection.

We map these inputs to the inputs introduced in our previous sections. For the red and green inputs, denoted input 1 and input 2, the input is activated a single time when the user returns to rest. For inputs 3 and 4, the magenta and black targets respectively,

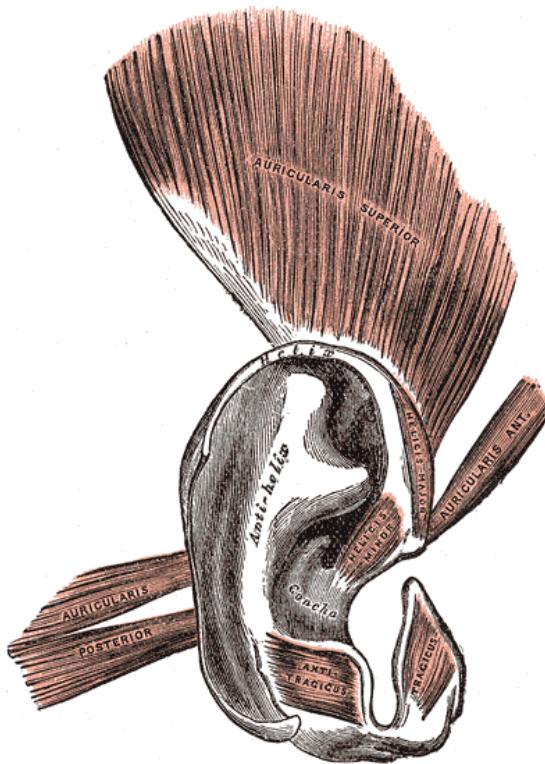


Figure 5.1: A diagram of the muscles around the ear from [Gray and Lewis, 1858]. The sEMG device has been used on both the Posterior and Superior Auricular muscles. In order to record from the Superior Auricular (SA), it is necessary to remove the hair in the area above the ear. The Posterior Auricular (PA) is generally easier to access; however it is a smaller muscle that is more difficult to voluntarily control.

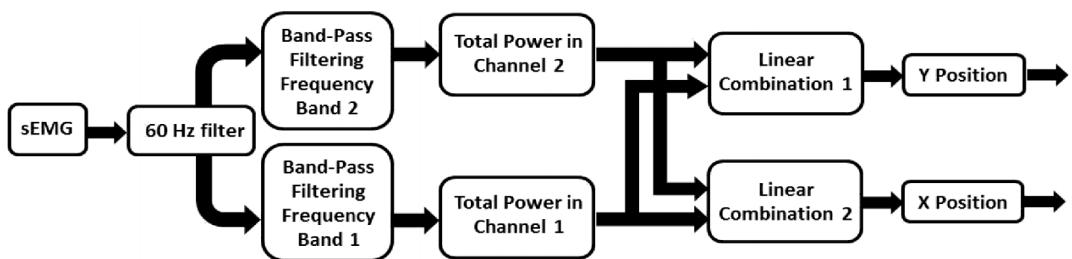


Figure 5.2: The single sEMG signal is first processed through a 60 Hz noise filter. It is then run through two different band pass Butterworth filters to extract two separate signals. The bands are then linearly combined to compute the x and y cursor positions.

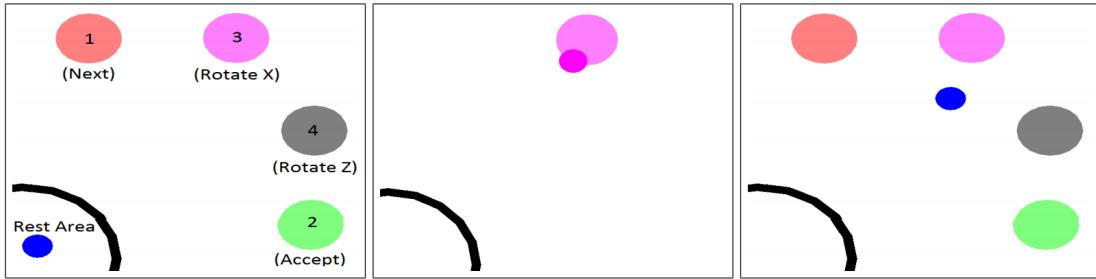


Figure 5.3: The sEMG Interface: (a) The user interface is composed of 4 targets overlaid on the grasping scene. Target 1 usually signals acceptance of the current option. Target 2 toggles the next option. Targets 3 and 4 provide input to the planner.(b) Hitting one particular target changes the color of the cursor to reflect the selection and makes the other targets unavailable. (c) If the user does not return to the rest area after a few seconds, the selection times out and is deselected and all targets become available again for selection.

the activation is sent continuously until the user exits the rest area again. This allows the user to exert near continuous control over the approach direction.

5.2 Handling Cluttered Scenes

In addition to an improved input device, we also wanted to extend our grasping system to handle more realistic scenes, including some amount of clutter. In this work, we will define “clutter” as objects being in close enough proximity that many of the grasps for the objects may collide with other nearby objects, but that they are not actually in contact with one another. We did not handle the problem of singulation, which is a specialized manipulation designed to separate objects which are too close together for the fingers to surround the object without colliding with other objects. As such, we tested grasp planning scenes where there was at least 2 inches of empty space between each objects.

Handling cluttered scenes brings up a number of challenges. First, it slows down the online planning phase. There are many fewer possible grasps and the state space has more discontinuities in the value of the quality function, which slows down convergence.

Additionally, when there are more possible collisions, grasp planning is significantly slower. Second, many of the grasps produced by the planner, while valid in their final poses, may not have a reachable path to grasp. Third, with more objects in the scene, there is more visual clutter and it is more difficult to produce a useful visualization.

In order to address this problem, we added reachability tests to the online grasp planning system and user interface. Previous iterations of this planner used a simpler, built in inverse kinematics solver to reject unreachable states. In contrast, this version checks that an entire valid trajectory can be generated. Unreachable grasps are placed at the end of the list of grasps and colored red in the grasp preview window (see Fig. 5.5).

We maintain the list of unreachable grasps so that we can reject nearby grasps without running more computationally expensive analyses. The valid grasps are ranked by their distance to the demonstration hand and alignment to its approach direction. This makes the planner more responsive in cluttered scenes. The list is re-sorted as the demonstration hand is moved.

The results of the reachability test are also used to train a nearest neighbors classifier. When the user moves the demonstration hand, we find the five grasps for which the normal of the palm of the hand is closest to the normal of the demonstrated pose. If at least 50% of these grasps are unreachable, we designate the current demonstration pose as being in an unreachable region, which is indicated to the user by highlighting the demonstration hand in the planner interface in red. These measures are crucial for a naive user that is not familiar with the kinematics of the robot arm and may not understand that the region they are trying to grasp from is not within the robots workspace.

5.2.1 GUI Modifications For Clutter and sEMG Interface

One eventual goal of this research is to allow our non-roboticist collaborators at the Columbia University Medical Center (CUMC) to test this system on impaired subjects from their clinical practice. A number of changes have been made to the user interface to accomodate both the added visual complexity of overlaying the sEMG control interface

on the planning scene and the added difficulty of interpreting the multiobject scene. In discussions with our collaborators at CUMC, Dr. Ethan Rand and Dr. Joel Stein, we have come to realize that for many potential users of an assistive device, the approachability in terms of look and feel of the interface is extremely important to making them comfortable and avoiding unnecessary confusion. With our collaborators feedback, we have redesigned the UI with a cleaner look and feel that implements a number of new features.

The new layout is demonstrated in Fig. 5.4, which illustrates the UI presented during the object selection phase. First, the point cloud displayed in the scene has been upgraded to a higher resolution, color point cloud. This change allows the user to discern the target object more effectively in the cluttered scene. It also allows the user to exercise more judgement in interpreting the scene, since they may not be physically present to observe it first hand. Second, we display only three grasp options instead of 10 to reduce the visual clutter. This also allows us to enlarge the presentation of the grasp so that the user can more easily discern how the hand may interact with the rest of the objects in the seen. Third, we moved the grasp preview window to the side of the screen and modified the way that the UI generates the view to share the aspect ratio and alignment of the depth camera so that all detected objects are visible and that the user's intuition is unimpeded by deformations due to the aspect ratio. Third, we removed all of the window decorations and grasp metric displays, as the subject is not expected to be able to interpret them correctly. Overall, this provides a much cleaner, streamlined view more suitable for non-expert users.

Unfortunately, additional visual clutter is introduced by the addition of the sEMG user interface. This interface is presented with relatively high transparency, allowing the subject to see the grasp planning scene behind the UI with relative ease. The scene is chosen so that the relevant objects are relatively centered in the scene. While the user is not actively making a suggestion, the cursor remains in the lower left of the screen and the main grasp planning scene remains unoccluded.

We placed targets 1 and 2 in opposite corners of the screen because these inputs control the progress of the user through the grasping pipeline, and we wish to minimize

confusion between and accidental selection of these two options. The middle two options modify the demonstrated approach direction, and accidental selections have minimal impact.

5.2.2 Pipeline Version 3

A number of changes have been made to the pipeline to accommodate the presence of other objects in the scene and the different input device. *Initialization:* This phase is the same as version 2, except that the view is aligned to the true view of the Kinect, rather than being centered on the target object. The user sends input 1 to activate the object recognition system. If the recognized objects align well with the point cloud sent, they can accept the results with input 1. If not, they can rerun the recognition system with input 2.

Object Selection: This phase is new in this version of the pipeline. The first object is highlighted in green as the target object. To select an object as a target, the user sends input 2. To cycle to the next object in the recognized object list the user sends input 1. The nontarget objects are all highlighted in red. The nontarget objects are replaced with lower resolution models when a target is selected, which makes the planning phases faster.

Initial Review: As in the pipeline version 2, the user is presented with a list of preplanned grasps from a precomputed database. As they iterate through the grasp list, the grasp in the middle and bottom rows shift up and the next grasp in the list moves in to the bottom position. The grasps are evaluated for reachability in order. An unreachable grasp may take up to 15 seconds to return failure using the CBiRRT planner. The user is also able to move the planner hand to demonstrate a desired approach direction, which will cause the grasp list to re-sort to bring the closest grasps to the new approach direction to the top of the list and reset the grasp visualizations to the beginning of the cycle. *y*. The user sends input 1 to increment through the grasp list. When the user finds a reasonable looking grasp, they send input 2 to select the grasp.

Planner Initialization: This phase is the same as version 2. The user is presented

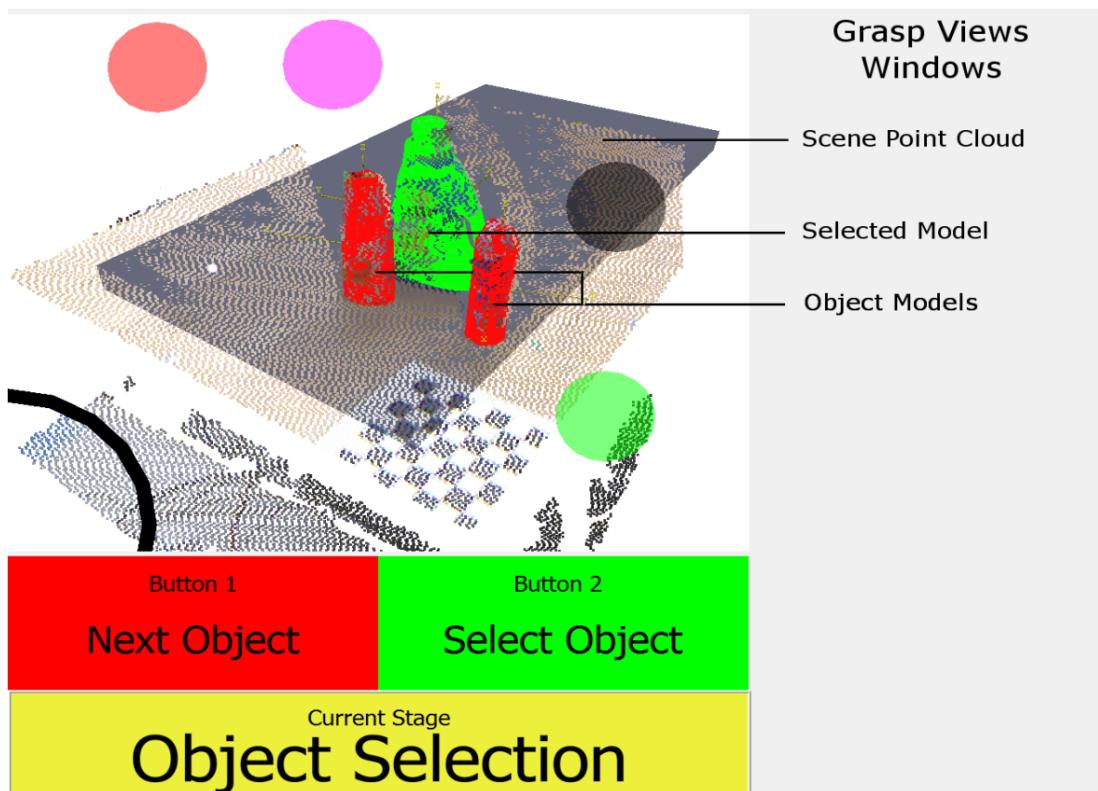


Figure 5.4: The Grasp Planning Interface - Object Selection Phase: The subject is able to see the planning scene in the main UI window. The window on the bottom tells the user the current phase and what the green and red inputs will do in this phase. In this phase, the subject sees the the pointcloud and hits the red target until the object they wish to grasp is highlighted in green. Then they hit the green target to proceed to the next phase.

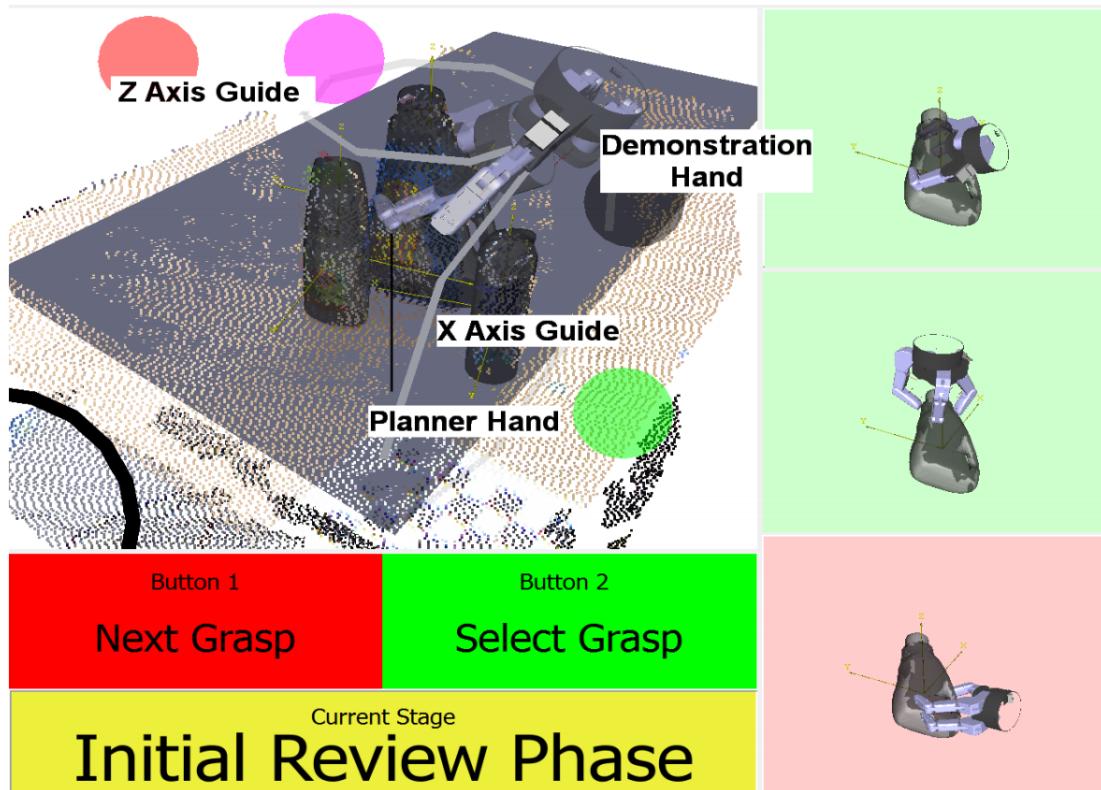


Figure 5.5: The Grasp Planning Interface - Initial Review Phase: After the subject selects the object, the Grasp View pane on the right is populated with a set of grasps from a database. Grasps that are reachable appear on a green background, while unreachable grasps are red. A robot hand appears that the user moves to demonstrate a desired starting pose. This demonstration hand is constrained to follow the two circular guides around the z and x axes of the object shown above. The topmost grasp in the grasp view window is the currently selected grasp, which is rendered in the planning scene with the planner hand.

with the choice to either accept the grasp from the third stage with input 1, proceeding straight to the Grasp Choice Confirmation stage or they can send input 2 to refine their chosen grasp further.

Grasp Refinement: This phase is slightly modified from the pipeline version 2. As grasps are generated, they are displayed with a white background in the grasp preview pane on the right side of the screen while they are being analyzed for reachability. If the analysis finds the grasp to be reachable, the background is highlighted in green and the list is re-sorted to bring the closest reachable grasps to the top. Unreachable grasps are given a red background. The successful grasps are stored in a KD-tree by approach direction and eigengrasp value. If the nearest reachable grasp is not within 20° of the approach direction of the demonstrated grasp or its eigengrasp values differ by more than 20%, the demonstration hand is highlighted in red to indicate that this approach direction may be a bad choice. Sending input 2 stops the planner and proceeds to the Final Grasp Review stage.

Final Grasp Review: This phase is similar to version 2, but adapted to provide more feedback with fewer grasp previews. The user sends input 1 to select the next grasp on the grasp list. They send input 2 to select that grasp. The user is able to move the demonstration hand as in the previous stages, which will still cause a re-sorting of the grasp list. This allows the user to more easily go through the grasp list, since the commands which control motion are continuous and need much less effort to send repeatedly than having to manually hit the next grasp option repeatedly.

Grasp Choice Confirmation: The user sends input 1 to go back to the Grasp Refinement stage and input 2 to send the grasp for execution on the robot.

5.2.3 Validation

To validate this system, we recruited a male 25-30 year old impaired subject with limited upper limb mobility due to a C3-C4 spinal injury. All testing was approved by the Institutional Review Board of the University of California, Davis under Protocol 251192-10. This subject had previous experience with the sEMG device, but had not been trained on this interface. For this work, we measured the activity in the subject's

PA muscle, as this muscle is more accessible because the hair over it is thinner. The subject was recruited and trained at the UC Davis site, and operated the robot without ever having any interaction with it or the experiment site in the real world at in the Columbia University Robotics Group lab. The setup is shown in Fig. 5.6. The top of the figure shows the subject with the device attached and using the grasp planning system. The bottom left image is a closeup of the device, which demonstrates how low profile and minimalistic this device is. The bottom right shows the target scene in the robot workspace, with three container objects. The results of this experiment were published in [Weisz *et al.*, 2014], and a video illustrating the experiment can be found at <http://robotics.cs.columbia.edu/~jweisz/sEMGGraspingIROS2014.mp4>.

5.2.3.1 Task

Due to limitations on the impaired subject's time, we were only able to complete three trials using the system. In these three trials, the subject was asked to pick up an object from a cluttered, multi-object scene. In the first two attempts, he was asked to use the online planner to refine one of the pre-planned grasps. In the first attempt, he grasped the laundry detergent bottle. In the second attempt, he grasped the shaving gel bottle. In the third attempt, he was asked to grasp the detergent bottle using one of the pre-planned grasps directly from the grasp database. Other than the image in the planner interface, the subject was not given any information about the objects he was to grasp. However, they are all well known, household objects, so the subject can be expected to have some implicit idea of the weight and friction properties of the object.

During the task, the subject reported which target he was trying to reach and we tracked the number of mistaken target activations, which would lead the user to loop back rough part of the pipeline. After the grasp is selected, the target object is lifted off of the table automatically so that the user can see whether the grasp is stable. If no part of the target object remains on the table, we consider the trial a success.

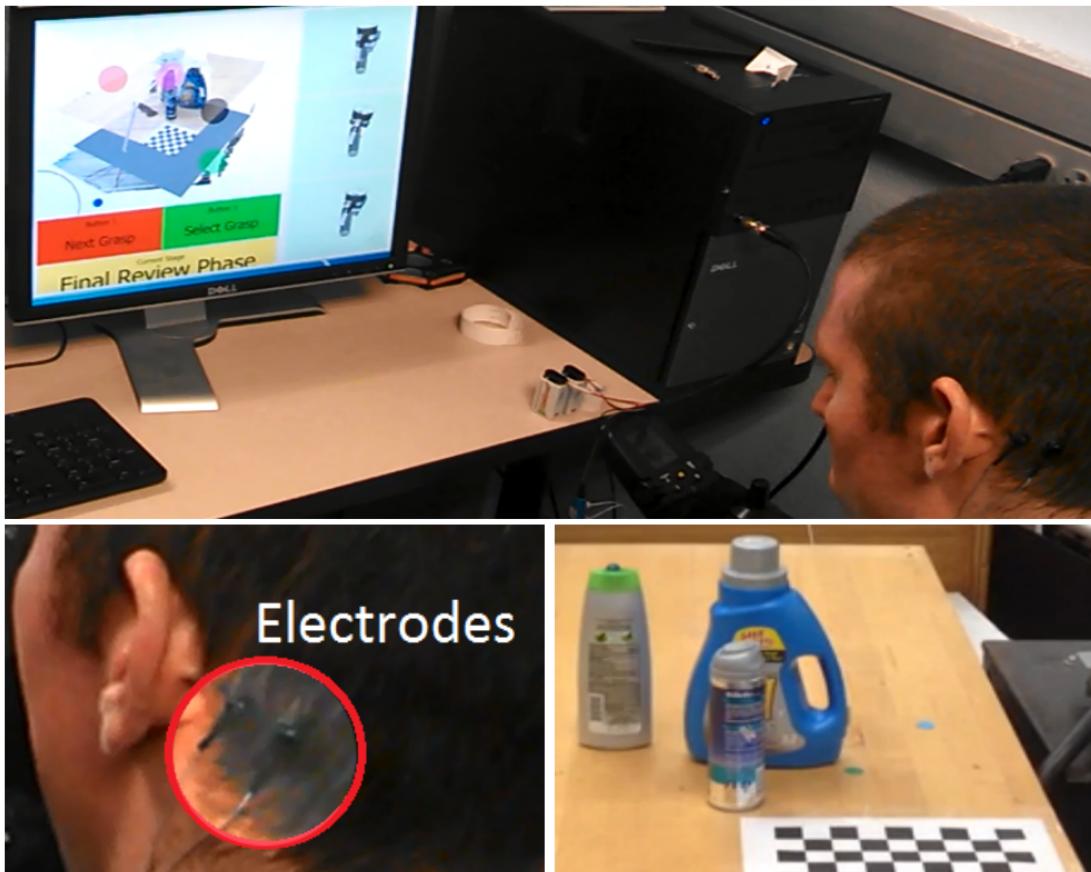


Figure 5.6: An impaired subject in the UC Davis RASCAL lab (top) operating our SEMG-Assistive Grasping interface to grasp a shaving gel bottle in the Columbia Robotics Group Laboratory (bottom right). The two small black clips behind the subjects ear (bottom left) are surface EMG electrodes (used in differential mode) to detect activation of the Posterior Auricular (PA) muscle to direct the system to pick up the object in this multi-object scene.

Grasp	Time (s)	#Inputs	#Timeouts	Mistaken Selections
Detergent 1	564	14	14	2
Detergent 2	609	9	50	0
Shaving Gel	910	12	11	1

Table 5.1: sEMG Experiment 1 Results

5.2.3.2 Training

To familiarize the subject with the interface, we demonstrated the pipeline two times with the subject just watching and asking questions along the way. We then went through the pipeline with the subject two more times while verbally instructing him on which target to hit while the experimenter controlled the cursor with a computer mouse. This allowed the subject to familiarize himself with the pipeline and navigate their way through it without having to also focus on the task of hitting targets with the sEMG interface. Once he appeared to be conversant with the system, we turned over control to the subjects sEMG interface.

5.2.3.3 Results

The results of the experiment are shown in Tab. 5.1. The subject was able to grasp the objects successfully on all three attempts. On average, it took the subject 694 seconds to grasp each object, including about 60 seconds for the vision system to detect the objects in the scene. There were 75 timeouts, and 3 mistakenly selected targets. Timeouts are an expected part of this interface, which allows the user to re-select their intended target if the initially selected target is incorrect. Occasional mistaken selections are also expected, and the pipeline is designed to be robust to these errors, allowing the user to go back to the previous step where necessary to correct mistakes. Several mistakes in a row are necessary to actually realize mistaken actions on the robot.

5.2.3.4 Discussion

These results, while promising from the perspective that a single experiment participant was able to understand and utilize the system fairly quickly, demonstrated a number of shortcomings with our system. First, the user's control over the sEMG device was not very accurate, yielding many false initial selections that had to be timed out. This may be because the user was using a new muscle. However in subsequent experiments the user was not seen to perform very well in other similar paradigms, especially with respect to finding parameters for the sEMG processing that allowed the user to return to the rest area. This user may just have too much random activity in that area for the processing pipeline we have utilized. A second problem was that the online reachability tester is fairly slow using the CBiRRT planner, and thus new available grasps appeared slowly. This caused relatively few reasonable grasps to be available, and so the user had more trouble because he had to iterate through more grasps which were not reflective of their intent while looking for a reasonable one. While indicating poor regions for grasping by shading the display hand was somewhat effective at helping the user avoid long waits in regions that were doomed to failure, it was not sufficient near border regions where grasps were possible but unlikely because of occlusions.

5.3 Further Refinements

Our initial results showed enough efficacy of this system that we developed a second prototype using a smaller, lower weight robotic arm, the Kinova Mico, which is suitable for mounting on a wheel chair. We also sought feedback from our colleagues at the Columbia Medical Center who worked with this same sEMG device in stroke patients. Their advice was that our user interface needed further streamlining. We also sought to resolve the online reachability checking issue by integrating a faster planner.

5.3.1 Adaptations For the Mico Manipulator

The Kinova Mico arm is a six DOF arm with a two finger gripper. The fingers use a passive underactuation mechanism and is capable of both enveloping and fingertip

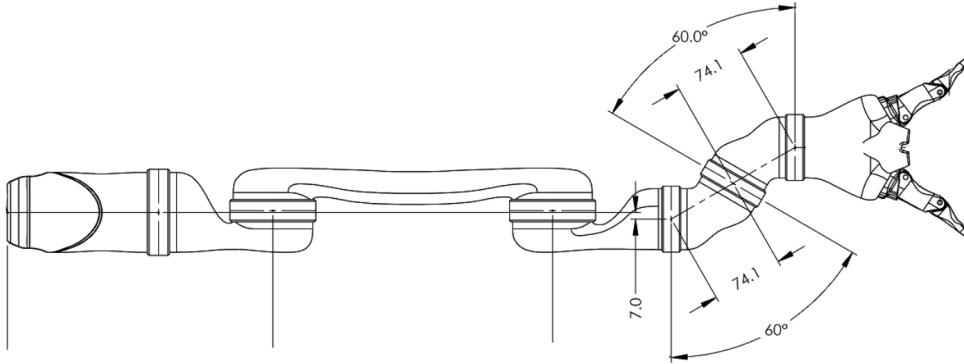


Figure 5.7: A diagram of the kinematics of the Mico arm. The 60° offsets of the the final two arm joints is very unusual, and causes difficulties for some robotics libraries.

grasps. These fingers are made of a hard plastic which has relatively little friction. The transmission of the underactuation mechanism is designed such that the fingertips remain perpendicular through most of the range of the finger's motion. In order to plan grasps in GraspIt! for a such a gripper with a small friction coefficient, it is necessary to strongly bias the planner towards keeping the fingertips very well aligned to the surface of the object. The simplest way to do this is to add a strict filtering layer to the grasp quality metric which only performs the second stage of grasp analysis, which tests for force closure of the final grasp, when the virtual contacts are aligned to within 3° of the normal to the nearest surface. Because the finger closing does not change the fingertip angle much during the closing process and there is very little friction, performing the second stage is not likely to succeed unless the surface alignment is good to begin with.

Additionally, the CBiRRT planning pipeline uses an inverse kinematics library, described in [Len *et al.*, 2010] that is incompatible with the unusual 60° offsets of the Mico Arm (see Fig. 5.7 for an illustration). Without this library, the filtering pipeline is slightly slower and less reliable. Given our previous insight that the online reachability testing is a bottleneck for the online grasp refinement, this motivated us to explore a variety of different planners integrated with the MoveIt! planning environment (see [Sucan and Chitta, 2013]).

5.3.2 Improved Online Reachability Checking

MoveIt! provides an interface to the OMPL planning library by [Şucan *et al.*, 2012], which integrates a number of planners which have very different performance properties. In order to investigate which one is appropriate to grasping in the cluttered scenes with the Mico Arm, we captured 10 scenes similar to that in Fig. 5.12 and ran the online reachability checker on the set of default grasps for each of the objects in the scene. Since many of the grasps in the online planner tend to be very similar, we perturbed the grasps by a +/- 0.005 m in each direction, testing 60 grasps for each of three objects for each scene. In order to take advantage of this proximity, we implemented a plan caching scheme which stores the start and end point of the arm trajectory in a nearest neighbors lookup tree. When planning a new trajectory for online analysis, we first attempt to plan from the end of the nearest endpoint. If that fails, we retry from the original starting position. If this second attempt succeeds, the planned path is inserted into the cache. For the actual arm motion, we retry the planning until it succeeds from the original starting location, so long as a valid cached plan exists. This is because smoothing such plans to remove the excess waypoints introduced by the initial segment from the cached plan is still an open area of research that we did not wish to address in this work.

We did a parameter sweep of the allowed trajectory segment length from 0.01 to 0.1 in steps of 0.01 with allowed planning times up to 20 seconds. The SBL and PRM planner had around the same rate of success using the caching scheme, succeeding in 43% of the grasps, and the PRM had the fastest planning for the caching version of the planner, with an average planning time of 5.5 seconds for arm motions in which the caching fails, and 0.1 seconds when the cache succeeds. However, when not using the caching scheme, the SBL planner’s success rate dropped to 30%. So, for the online reachability verification, we used the PRM planner with a segment length of 0.05, while for producing the actual grasp on the robot we used the SBL planner. These changes removed the online reachability checking as a bottleneck for the online grasp refinement stage of the pipeline.¹

¹Although MoveIt! includes a benchmarking suite for determining the optimal parameters for a set of problems, it cannot be used with MoveIt!’s pick and place grasping pipeline, which handles the approach

5.3.3 Further UI Improvements

In our previous pipelines, the two 'continuous' inputs which shifted the hand around the object were not part of the pipeline guide display which showed the user which phase they were in and what their inputs would do. In every phase of the pipeline, they always did the same thing. However, in this version of the pipeline the purpose of these inputs can also change in each stage. In addition, our previous test user and our collaborators at the Columbia Medical Center indicated that there should be a clearer differentiation between the augmented reality region containing the grasp planning scene and the rest of the UI and fewer grasp options presented during the parts of the pipeline where they are not needed.

In this version, the UI window is adaptive, changing more to suit the needs of each stage of the pipeline. The grasp previews are integrated with the pipeline guide display, and the pipeline guide areas also function as GUI buttons for the experimenter to use when familiarizing the subject with the UI. Each of the targets now has a corresponding color coded button. These new UI elements are shown in Fig. 5.8, Fig. 5.9, and Fig. 5.10. This version of the UI is more dynamic, with the layout of the guide window on the right side of the screen changing as the user progresses through the pipeline. While this may seem like unnecessary complexity, the UI is more visibly different in each stage and less extraneous information is presented. This seems to help subjects keep track of what stage they are in and what its purpose is.

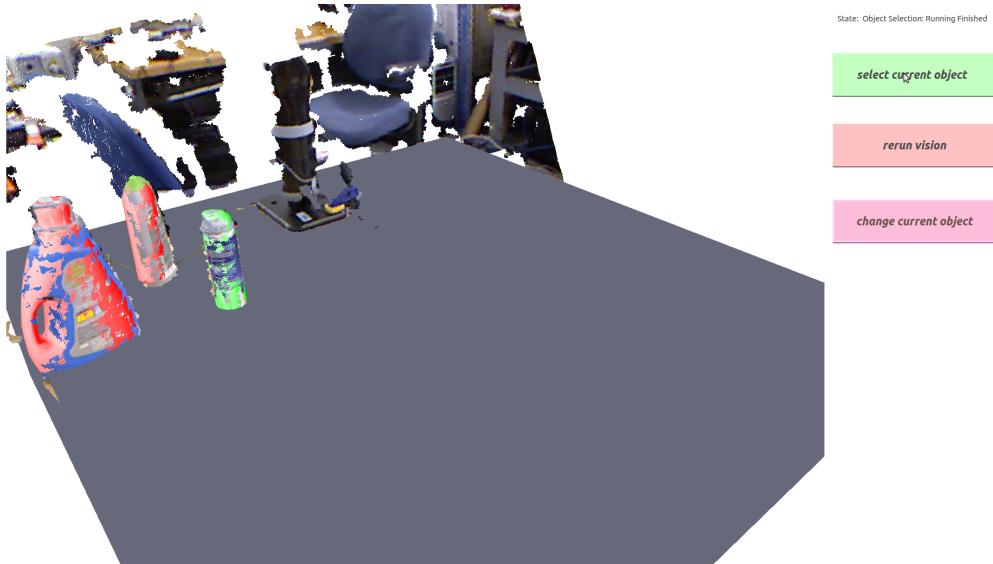
5.3.4 Updated Pipeline

The updated pipeline is slightly shorter and makes more varied use of inputs 3 and 4.

Object Recognition and Selection: This phase combines the first two phases of version 3. To select an object as a target, the user sends input 2. To cycle to the next object in the recognized object list the user sends input 3, which will continuously iterate through the grasps until the user leaves the rest area. To rerun the object recognition system the user sends input 1. While the recognition system is still running, the whole screen is

and lift phases of the path planning, or with robots that have some joints with continuous joint ranges. As such, we implemented our own, less comprehensive optimization script.

Figure 5.8: The Object Recognition and Selection state user interface



(a) The object selection and recognition state. The user can cycle through the objects at a rate of 2 per second by sending input 3. Selecting input 1 goes to the next state.



(b) Sending input 2 triggers the object recognition state and highlights the background in red while the recognition is running.

highlighted in red and it is not possible to proceed to the next phase until the recognition finishes.

Initial Review: As in the pipeline version 3, the user is presented with a list of pre-planned grasps from a precomputed database. As illustrated in Fig. 5.9a, the currently selected grasp is shown in the window of the top of the guide area, with the color of the background again indicating the results of the online reachability checker. The next grasp is shown in the bottom of the window. Input 1 begins the online refinement stage, input 2 skips to the Final Grasp Review stage. Input 3 will iterate through the available grasps, whereas input 4 will return to the Object Recognition and Selection Stage.

Grasp Refinement: This phase is the same as version 3, but with the first grasp shown in the top of the window and the next grasp shown on the bottom. Input 1 proceeds to the Final Grasp Review stage, input 2 aligns the hand to the next grasp and brings it up to the top window. Inputs 3 and 4 rotate the hand around the object as previously described.

Final Grasp Review: This phase is similar to version 3, but adapted as previous stages to have only two grasps, the top showing the current selection and the bottom showing the next selection. Input 1 proceeds to the Grasp Choice Confirmation stage, input 2 aligns the hand to the next grasp and brings it up to the top window. Inputs 3 and 4 rotate the hand around the object as previously described.

Grasp Choice Confirmation: This phase is similar to version 3, but with only the selected grasp shown in the grasp preview window. The user sends input 1 to go back to the Grasp Refinement stage and input 2 to send the grasp for execution on the robot.

5.3.5 Validation

To validate these design decisions, we tested our pipeline on 5 naive subjects, 2 male and 3 female, ages 22-30. All testing was approved by the Institutional Review Board of the Columbia University under Protocol AAAJ6951. To simplify testing of the UI, we did not attempt to train the subjects on the two dimensional version of the user interface. Instead, the subjects were given a similar user interface, but the cursor is constrained to move towards the target representing the 'selected' input, which is outlined in green

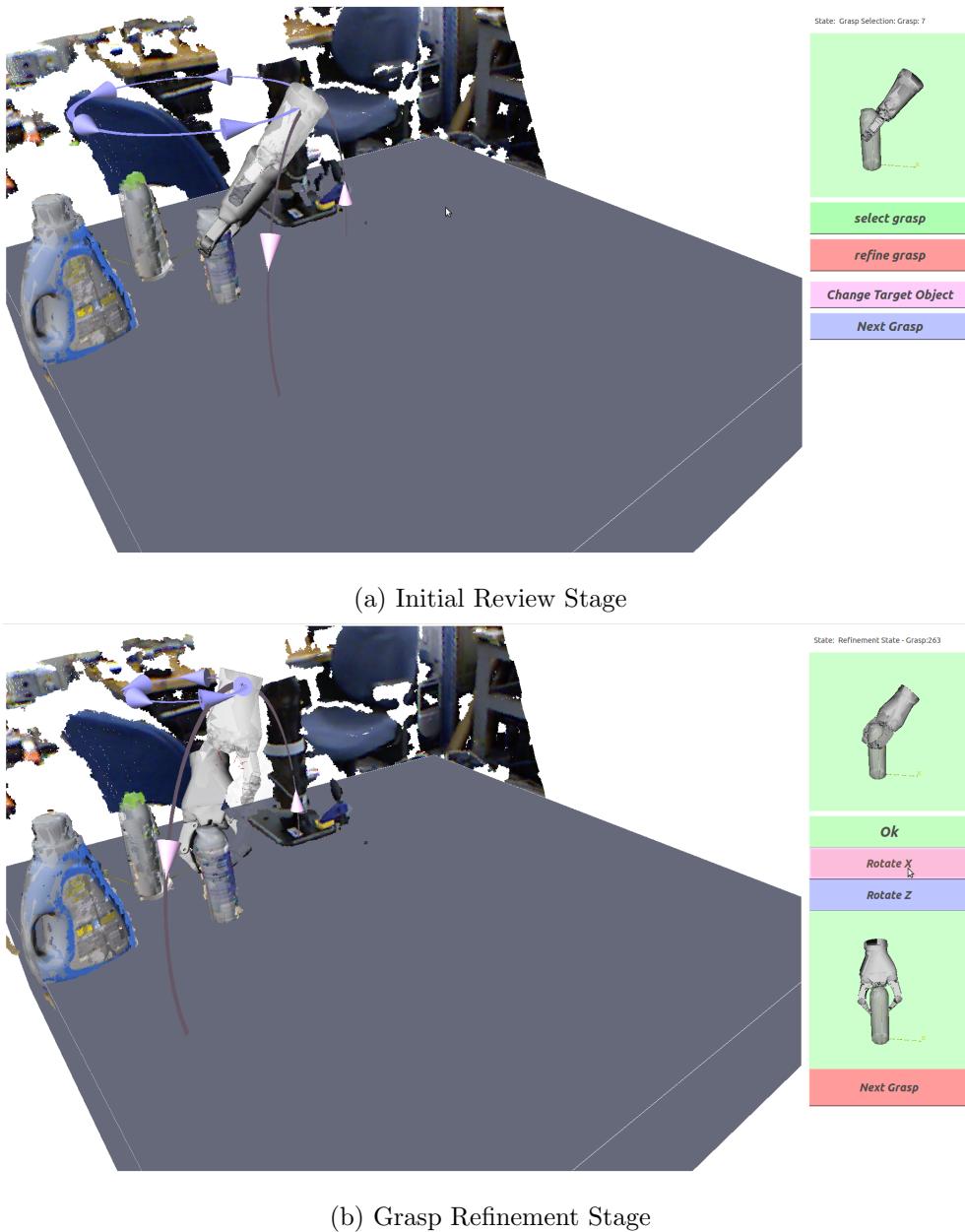


Figure 5.9: The UI in all of the second and third of the pipeline. The buttons on the right function as both guides for the result of hitting the color coded input options that will be presented to the user, as well as buttons that the user and experimentor use during the training stage

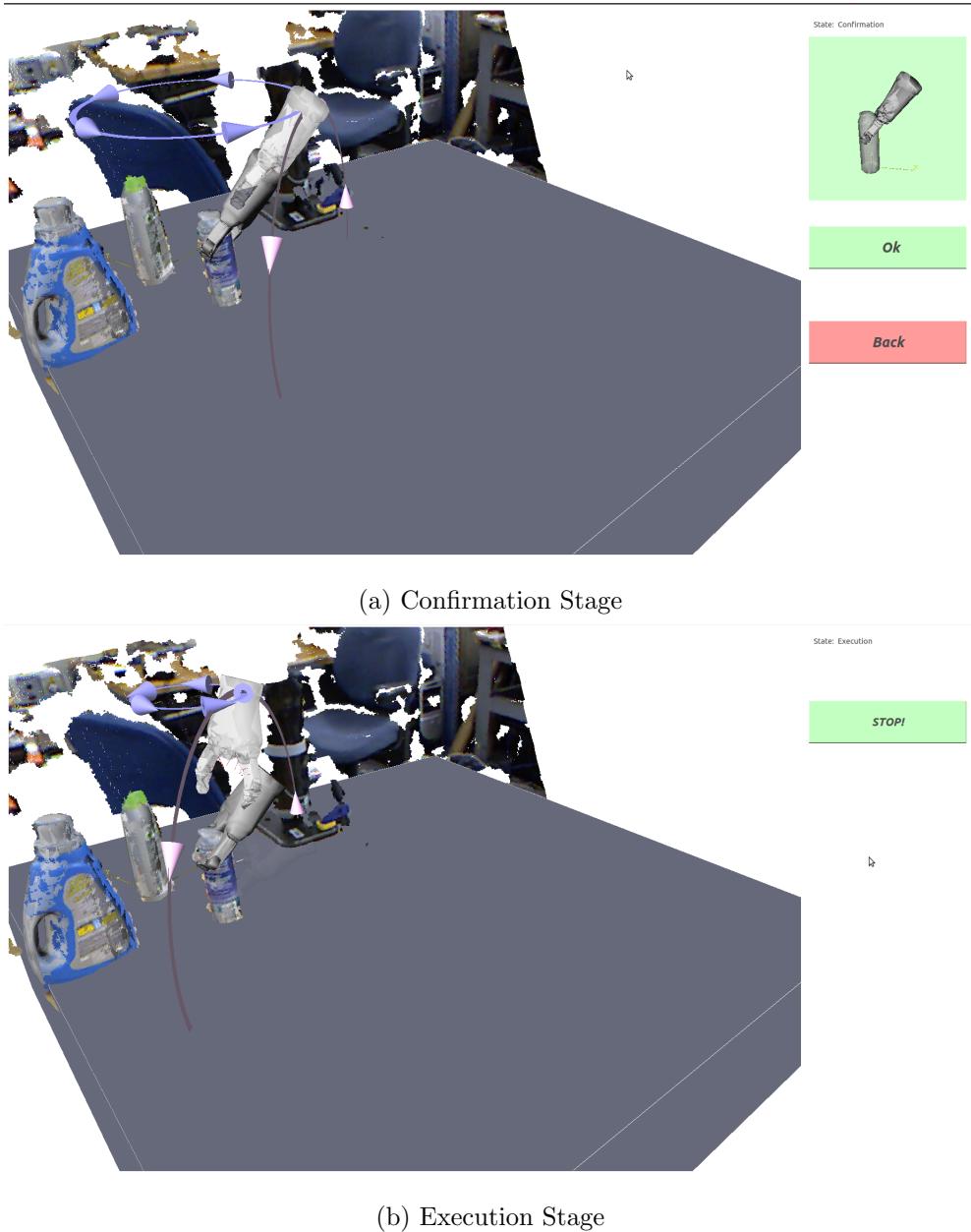


Figure 5.10: The final two stages of version 4 of the BCI grasping UI. This version of the UI is more dynamic, with the layout of the guide window on the right side of the screen changing as the user progresses through the pipeline. While this may seem like unnecessary complexity, the UI is more visibly different in each stage and less extraneous information is presented.

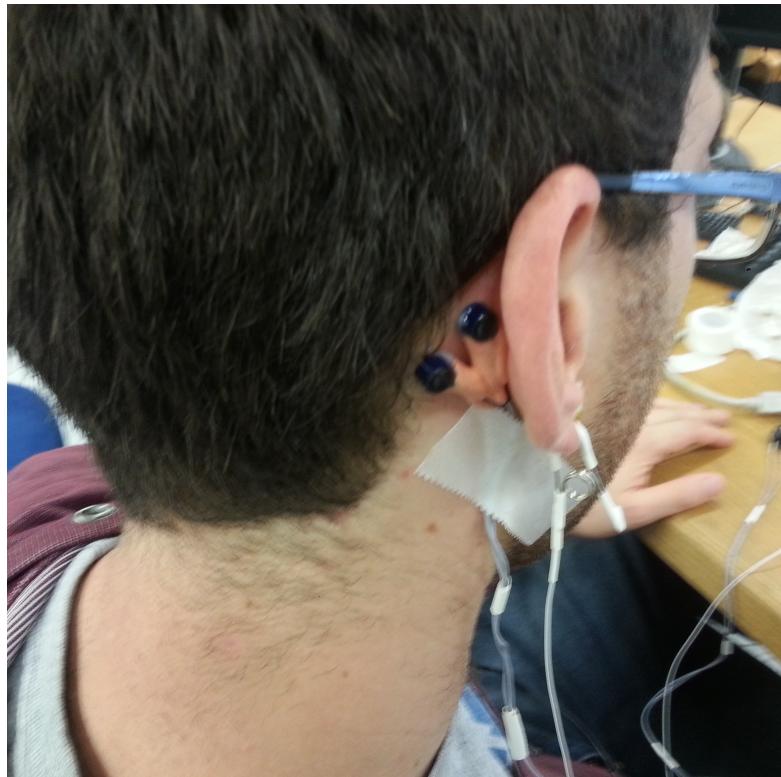


Figure 5.11: The sEMG system setup for the updated pipeline experiments. In these experiments, we placed the sEMG device behind the ear of the subject to measure contractions of the PA muscle. In order to stabilize the device and reduce noise due to motion of the wires, we stabilize the electrodes by wrapping the head of the electrodes in Silly Putty brand silicone putty.

as shown in Fig. 5.12. In order to switch which target is currently 'selected', the user leaves the rest area and returns to it without hitting a target. This cycles the 'selected' target forward by one. This change allowed us to focus on testing improvements the user interface and grasp planning pipeline without needing the more extensive training necessary to train a subject to achieve full 2D control over the cursor.

5.3.5.1 sEMG Device Setup

In these experiments, we placed the sEMG device behind the ear of the subject to measure contractions of the PA muscle. In order to stabilize the device and reduce noise

due to motion of the wires, we stabilize the electrodes by wrapping the head of the electrodes in Silly Putty brand silicone putty, as shown in Fig. 5.11. We find the correct placement of the device by asking the subject to clench their jaw gently and raise their eyebrows. We place the electrodes where we find a large response to eyebrow raises and little response to jaw motion.

5.3.5.2 Training

sEMG Device: Each subject was trained on the sEMG user interface without the grasp planning system. In the training system, shown in Fig. 5.13, the user is given a 'desired' target highlighted in red which is randomly selected at the beginning of each trial. The user is then instructed to cycle the 'selected' target until it overlaps with the 'desired target', which is then shown in gold. The subject was asked to perform sets of 30 trial blocks until they successfully completed at least 29 of the 30 attempts. This took at most 2 blocks of trials for any subject, with subjects who already had some ability to move their ears frequently succeeding in their first block.

Grasp Planning Interface: To familiarize the subject with the grasp planning system, we manually showed the subject three examples of grasping objects, once short circuiting the online planning and twice allowing the online refinement to run. Then we allowed the subject to guide the pipeline themselves five times, twice without the online planner and three times with it. Then we repeated the training allowing the subject to guide the planner to pick up the large detergent bottle five times in whatever direction they chose using the UI through the on screen button interface.

5.3.5.3 Task

We placed the objects on the table in proximity to one another as shown in Fig. 5.12. We asked the subject to grasp each object three times, the first time from any direction they deemed reasonable, once from the side, and once from above. For each object, the placement of the objects and grasps in the database were such that either the side or top grasp required the online grasp refinement. Since the workspace of the Mico arm is not very large, this was not difficult to accomplish.

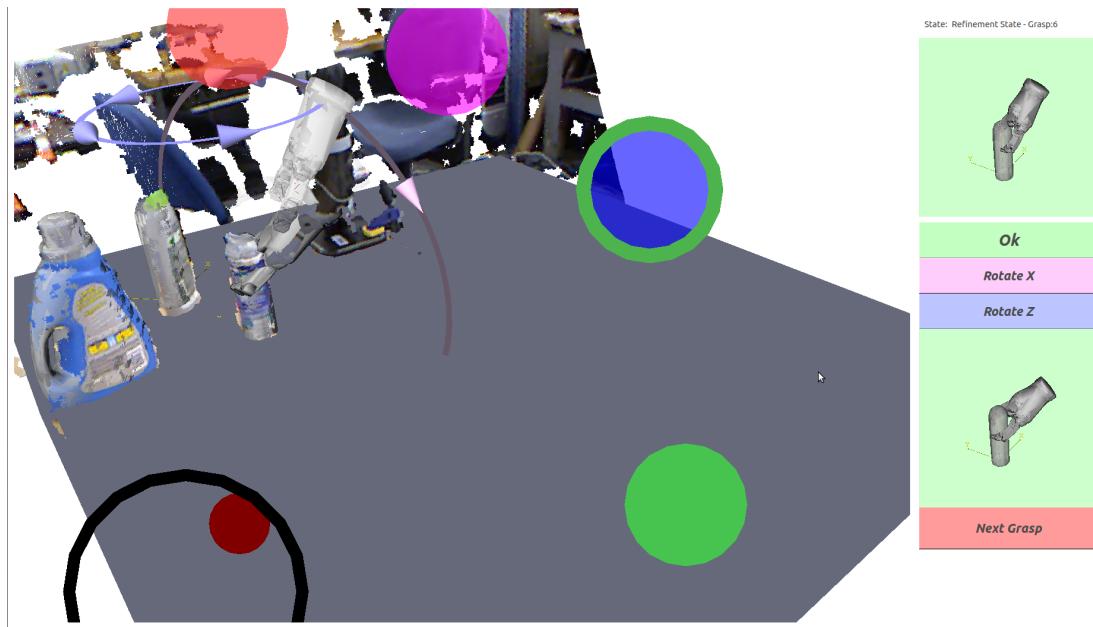


Figure 5.12: The sEMG interface overlaid on the planning scene with the selected target highlighted in green.

5.3.5.4 Results

The results of the experiment for 5 subjects are tabulated in Tab. 5.2. On average, the subjects were successful in grasping 82% of the objects within 92 seconds of the first time their cursor left the rest area. With respect to speed, results are comparable, and indeed somewhat better than the amount of time it took subjects to grasp objects with the Emotiv EPOC, even though the subject may have to iterate over the possible options before selecting them. Subjects 2 and 3 were the best able to control the cursor, having previously been able to move their ears already, and also performed the best in these experiments. These results indicate that the underlying planning system is providing options that the less capable subjects are not exploring because they are having more difficulty with the UI.

For the shampoo bottle, there are relatively fewer grasps that can succeed as compared to the rotationally symmetric shaving gel bottle and the taller, sloping detergent bottle. The only feasible grasps from the side for the shampoo bottle are directly from the side, aligned with the wide axis of the bottle, as demonstrated in Fig. 5.14. This

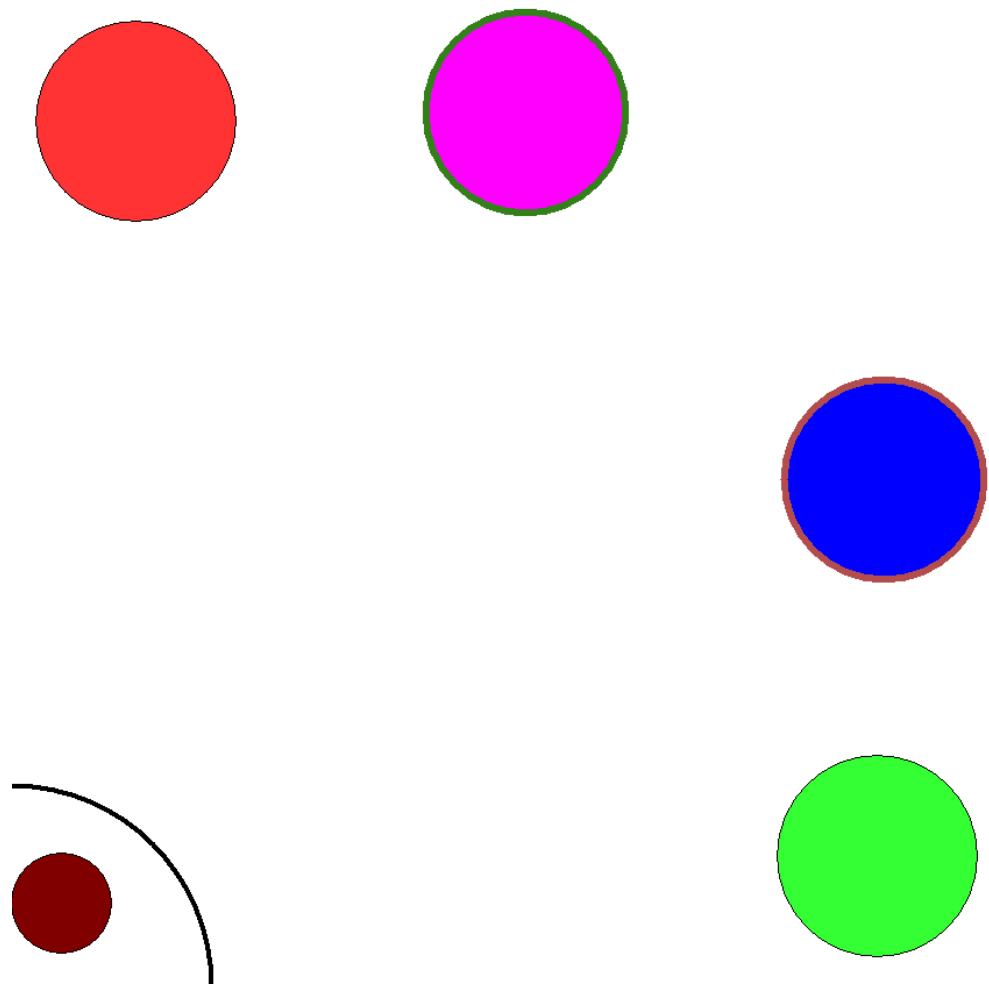


Figure 5.13: The training version of the sEMG interface in Matlab, showing the desired target outlined in a thin red band, and the selected target in outlined green.



Figure 5.14: A typical grasp of the shampoo bottle from the side in the cluttered scene. Note that the hand is just able to fit between the other objects to grasp the desired target. Note that the ability to plan this grasp in such a restricted environment is an indication that this system is very successful at handling the cluttered scene.

narrow feasible region and the potential for many collisions with the other objects in the scene during the reaching motion to this region makes this a particularly difficult grasp, especially when the clearance around the grasp is as tight as it is in Fig. 5.14. Without the partial plan caching implemented in the online trajectory planner, planning grasps to this region using stochastic, sampling based planners is extremely unreliable. With the caching scheme, this grasp was successfully found 100% of the time, although the planning time is somewhat longer than the other grasp tasks.

5.4 Conclusions

Through this work with the UC-Davis sEMG device, we have pushed the boundaries of what can be accomplished with a minimally invasive, facial muscle driven input. First, we extended our basic system design to a more complex environment with multiple objects in close proximity to one another. This involved augmenting the user interface with additional stages to select the desired object, adding an online reachability tester, and producing a new UI with a dedicated interface including a cleaner UI with an integrated sEMG driven option selection overlay. After initial validation of the interface on an impaired user, we developed a series of improvements to the user interface, the online grasp planning, and online reachability tester to address the most challenging issues that caused our initial user to take up to eight minutes to make a single grasp selection. We developed a novel control paradigm for testing these changes which allowed us to validate the updated system on naive users without the extensive training necessary to train an individual to develop full 2-D control. This study serves as a pilot to validate the design choices of the system on a path towards more experiments with impaired users. Even though this paradigm requires the user to make up to four motions for selections which had previously required one, we observed that users took on average 1/8th the time to make grasp selections in the latest version of the sEMG driven planner. We did not explicitly measure how long the users spent in each stage of the pipeline, but one of the most costly phases was observed to be the grasp refinement stage, when it was used. In order to improve performance in this stage, we would have to improve the performance of the collision detection system, which is the dominant cost of the simulated annealing driven grasp refinement. Overall, the majority of the failures to grasp an object were caused by the difficulty of grasping cylinders along the major axis with a gripper, represented by grasping the detergent bottle or shaving gel bottle from above. In these grasps, squeezing the gripper can easily cause the object to be ejected. Subjects cannot seem to learn to expect this behavior without having experienced it a number of times, as they do not have a good sense of the friction properties of the gripper. To improve this behavior, we would have to implement a more complex feedback controller during the grasping process. It is also likely that with greater experience, the

subjects would have been more familiar with the kind of grasps that cause ejection.

This work demonstrates one the first EMG driven grasping systems that we know of that allows a user to grasp an object in a somewhat cluttered scene, or integrates user intent with the intermediate level of control we have proposed. The sEMG device itself is very minimalistic, and could itself be embedded in the frame of a pair of glasses, which makes this device a real candidate for evolving to a consumer level product. Future work for this paradigm will be to refine the training paradigm to make learning 2D control over the device easier, exploring new control paradigms, and extending the user interface to control the locomotion of a motorized wheel chair or mobile manipulator assistive platform. We have also begun some exploration towards more complex grasp quality measures that integrate more complex artificial intelligence techniques such as “deep learning” which may have less reliance on the accuracy of the object recognition system.

One remarkable thing about the assistive grasping paradigm which we have developed through this work is its flexibility. Thus far, I have described the iterative development of this user interface through two different user interface devices and two different robotic manipulators. In the final chapter, we will describe how with a few further improvements, the system can extend to a completely different input paradigm with much higher latencies and lower accuracy in the user interface.

Grasp	Subject	Success	Time	Grasp	Subject	Success	Time
Detergent Bottle Top	1	Yes	75	Shampoo Bottle Open Choice	1	Yes	93
	2	Yes	53		2	Yes	121
	3	No	45		3	Yes	63
	4	No	122		4	Yes	95
	5	Yes	135		5	Yes	117
	Mean	60%	86		Mean	100%	98
Detergent Bottle Side	1	No	66	Shaving Gel Top	1	No	83
	2	Yes	40		2	No	123
	3	Yes	52		3	Yes	112
	4	Yes	80		4	No	139
	5	Yes	85		5	Yes	97
	Mean	80%	64		Mean	60%	111
Detergent Bottle Open Choice	1	Yes	50	Shaving Gel Side	1	Yes	65
	2	Yes	57		2	Yes	52
	3	Yes	53		3	Yes	57
	4	Yes	135		4	Yes	88
	5	Yes	128		5	Yes	92
	Mean	100%	85		Mean	100%	71
Shampoo Bottle Top	1	Yes	151	Shaving Gel Open Choice	1	No	73
	2	Yes	72		2	Yes	59
	3	Yes	60		3	Yes	76
	4	No	126		4	Yes	81
	5	No	104		5	Yes	85
	Mean	60%	102		Mean	80%	75
Shampoo Bottle Side	1	Yes	134	Average Perfor- mance	1	66%	87
	2	Yes	95		2	88%	75
	3	Yes	132		3	88%	72
	4	Yes	164		4	77%	114
	5	Yes	143		5	88%	109
	Mean	100%	133		Mean	82%	92

Table 5.2: Results from Experiment 3. On average, the subjects were successful in grasping 82% of the objects within 92 seconds of the first time their cursor left rest area.

Chapter 6

Incorporating an EEG based Paradigm

6.1 EEG Option Choice Paradigm

6.1.1 Introduction

This chapter describes work towards extending our shared control framework to an EEG input based paradigm with different constraints than that demonstrated in Chapters 4 and 5. This is different in a number of important respects. The modality is completely EEG based and uses a device to capture EEG signals which is not low cost, although its capabilities are basic enough that it may be possible to replicate these results with a low cost device. Although the pipeline remains largely similar, the interface paradigm is significantly different because as new options are generated by the pipeline, new decisions from the user are requested by the system at a specific time, rather than being at the discretion of the user. In this paradigm, the EEG interface is used to recognize the user's preference among a set of options presented by the planner. The EEG signal classifier is fast and simple to train, requiring a half hour training period before the test session. The system as a whole requires almost no learning on the part of the subject.

Using an EEG based paradigm is of interest because it may be accessible to some individuals that do not maintain sufficient control over their facial muscles to use the

other input devices we have tested. It may also be simpler for some users, since the user’s role in the system is much more passive. Additionally, the different constraints of the novel paradigm allow us to explore how to make the underlying planner more flexible and robust.

6.1.2 EEG Input Device

We implemented this system using a B-Alert X10 EEG system from Advanced Brain Monitoring (Carlsbad, CA), borrowed from Paul Sajda at the LIINC lab. This EEG input device provides 9 electrodes positioned according to the 10-20 system and a pair of reference channels. More information on this system can be found at [<http://www.advancedbrainmonitoring.com/xseries/x10/>]. The cost of this device is on the order of \$10,000 as of the time of this writing¹. As can be seen in Fig. 6.1, the cap and device are relatively minimalistic, and can be comfortably worn for an hour at a time without requiring re-wetting or reseating of the electrodes. With the advent of the OpenBCI project (www.openbci.com) and similar efforts towards low cost, open hardware EEG devices, a low cost solution with similar capabilities may be on the horizon.

6.1.3 One-of-many selection

The EEG interface presented in this work is based on an ‘interest’ detector which can be used to provide a one-of-many selection between various options. This ‘interest’ signal paradigm is based on the work in [Pohlmeyer *et al.*, 2011a]. The options are presented as a stream of images, and the subject is primed to look for particular images that suit some criterion. This paradigm is known as *Rapid Serial Visual Presentation* (RSVP). Spikes in EEG activity which correlate with ‘interest’ are connected with the image that was presented at the time the EEG activity was evoked, which is then used to derive the user’s desired input. In order to grasp an object using this system, pipeline version 3, which was presented in section 5.2.2 has been adapted to produce visual representations of all of the options available to the user. Some options which cannot be visually represented, such as redoing a previous state, are presented as white text on a black background.

¹Pricing information on this device is generally unlisted and given on an “at request” basis

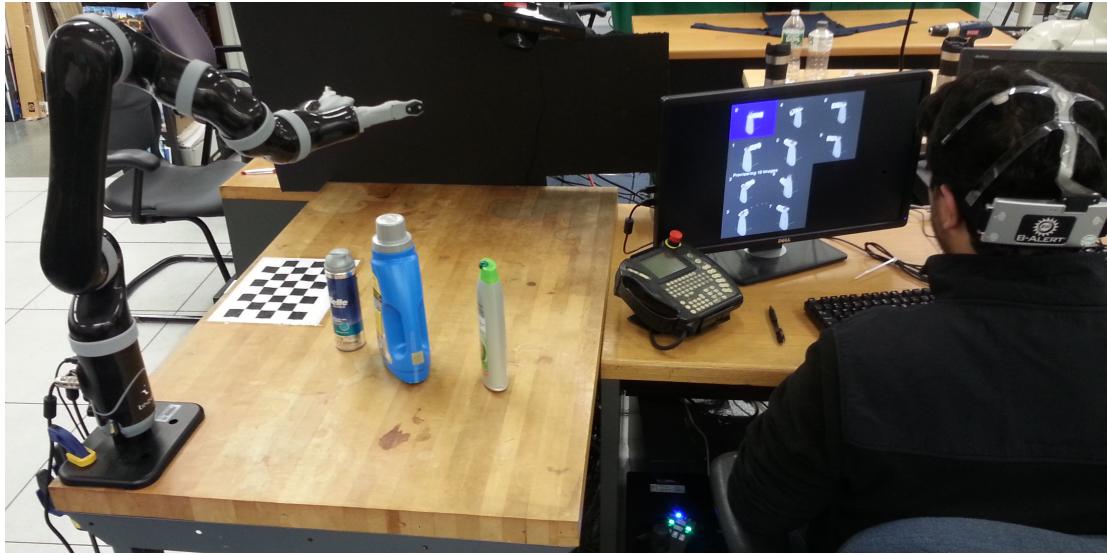


Figure 6.1: The subject wearing the B-Alert X10 EEG device while guiding the system through the grasp refinement stage. The EEG user interface can be seen in front of the user, and differs significantly from the one demonstrated in the previous chapters in that it is not presented directly from within GraspIt! This visualization is simpler so that the user will be able to distinguish between options quickly enough for the RSVP paradigm.

Previous work with this RSVP paradigm has asked the subject to look for objects of a particular category, which is a very natural task and which requires minimal explanation to the user. In our system, the images represent actions that are suggested by the grasp planner implemented by the Mico Robot, which the subject may not have previous experience with. In this case, the subject must be given time to analyze the options and primed to find the features which make their desired option visually distinct from similar options. To make this easier, the user is first presented with a *summary pane* which shows all of the options that will be in the visual stream. This allows the user to pick out particular features to watch for during the presentation stage. This is illustrated in Fig. 6.2, which shows the *summary pane* containing a grid of all of the options, which are then shuffled and presented to the user. In Fig. 6.1, you can see the subject reviewing the options in the *summary pane* before the serial presentation of the options. One major advantage of this paradigm is that it generalizes a single interaction across all phases

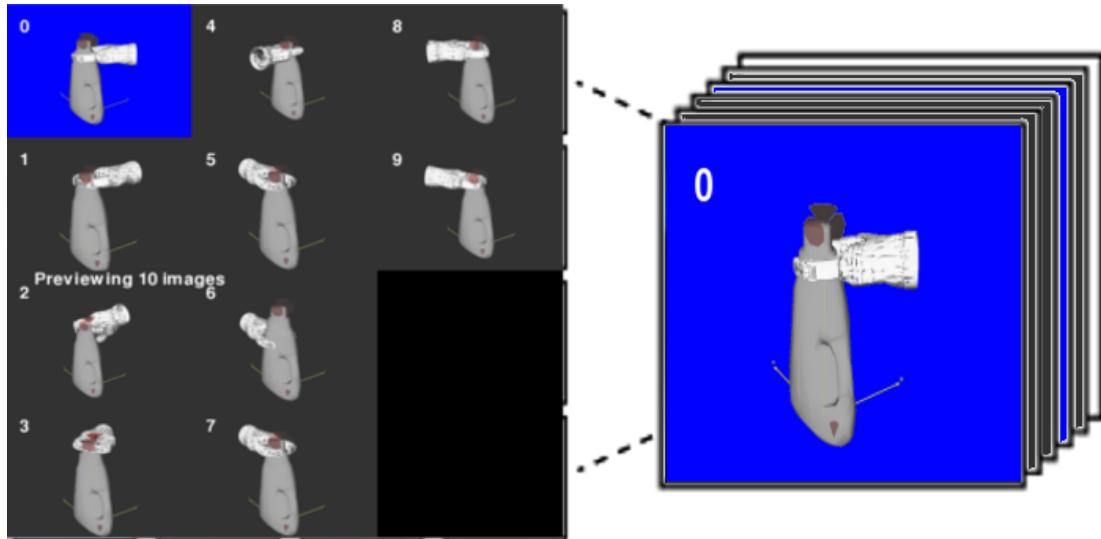


Figure 6.2: The grasp planning system compiles a set of images representing potential actions, for example a set of grasps as seen in this image. The image options are tiled together to form the summary pane seen on the left, which lets the user pick out the one that reflects their desire. The images are then shuffled, with repetitions, into a stream that is serially presented to the user.

of the grasp planning pipeline. The system only has to be trained to recognize the “interest” signal for each subject. Afterward, the subject’s interaction with each phase is the same, and the system does not require training for each phase. This is in contrast to the sEMG driven pipeline, where each individual action selection affects the system in a different way, which produces a higher cognitive burden on the user.

6.1.4 EEG Interest Metric

The EEG interest metric is based that used in [Pohlmeier *et al.*, 2011b; Sajda *et al.*, 2010; Gerson *et al.*, 2006], which is based on the P300 signal. The P300 signal is an increase in measured EEG activity which has been observed approximately 300ms after an item of interest is presented to the user. This interest measure assumes that the P300 signal resulting from a particular image varies with a resolution of 100ms. For each block, it examines the time period from 100ms to 1200 ms after the input stimulus as separate 100ms blocks, combined in a linear model:

$$y_{sn} = \sum_i w_i x_{in} \quad (6.1)$$

where each x_{in} is the reading at a specific electrode i at some time period n . The weights w_i are learned from the training data so as to maximize the difference between target and non-target images using Fisher linear discriminant analysis. The resulting values (y_{sk}) from each time window are then combined in a weighted average over the time windows

$$y = \sum_k v_k y_{sk} \quad (6.2)$$

where the weights v_k are determined by applying logistic regression on the training data.

In training, we additionally compute summary statistics for both target and non-target images, which are used later to normalize the individual readings per trial.

6.1.5 Choosing Options

To generate the RSVP sequence, the system randomly selects each option to appear between three and seven times. The sequence is then randomly ordered so that the same option does not appear in two consecutive presentations. If there are less than five options, the system will automatically fill in distractor image options to make this constraint more feasible. These are generated procedurally based on the phase of the experiment.

The images are each presented at 4 Hz, and EEG scores e_i for each image i are assigned. We aggregate each of the n images by their option, and determine whether the user has made a selection.

To test if a selection has occurred, we sort the images by their EEG scores, and then split it into a group of size x and $n - x$. We vary x to maximize the change in the average EEG score:

$$x^* = \arg \max_{x \in [1, n]} \left(\frac{1}{n} \sum_{i=1}^n e_i - \frac{1}{n-x} \sum_{i=x+1}^n e_i \right) \quad (6.3)$$

If $x^* > \max(0.1n, 5)$, we determine that the user had not made a choice. In practice, this is a highly reliable means of checking whether the user was paying attention and attempting to make a selection.

If $x^* \leq \max(0.1n, 5)$, we use each of the images which are sorted in the top x^* positions as a vote; the option with the most votes is selected. If there are options with an equal number of votes, the tie is broken by the option with a better average EEG score.

This paradigm has been demonstrated to be robust for selecting objects by category in previous work by [Sajda *et al.*, 2010]. Its main strength in this pipeline is in the grasp refinement stage, in which many reasonable options are presented to the user and many of them may represent the generic grasp strategy that the user has in mind. This is the phase in which there are the most options and where the selection needs to be fastest, and so the ability to take advantage of the inherent ambiguity of the problem is valuable.

6.2 EEG Option Choice UI

6.2.1 Grasping Pipeline

There are four states that the user progresses through when attempting to formulate a grasp, *Object Selection*, *Grasp Selection*, *Grasp Refinement*, and *Confirmation*. The pathway is illustrated in Fig. 6.3.

6.2.1.1 Object selection state

In this stage, an object recognition system is used to retrieve models from a database that fit the scene. An image representing selection of each object is generated as shown in the “summary pane” in Fig. 6.4, with the target object highlighted green in each potential selection. Between the various images only the highlighted object changes. An additional state is presented that allows the user to run the recognition system again. If fewer than eight objects are detected, additional distractor images of the scene with no highlighted object are generated to act as distractor images which help establish the background level of EEG activity. The user is instructed to look for the object they

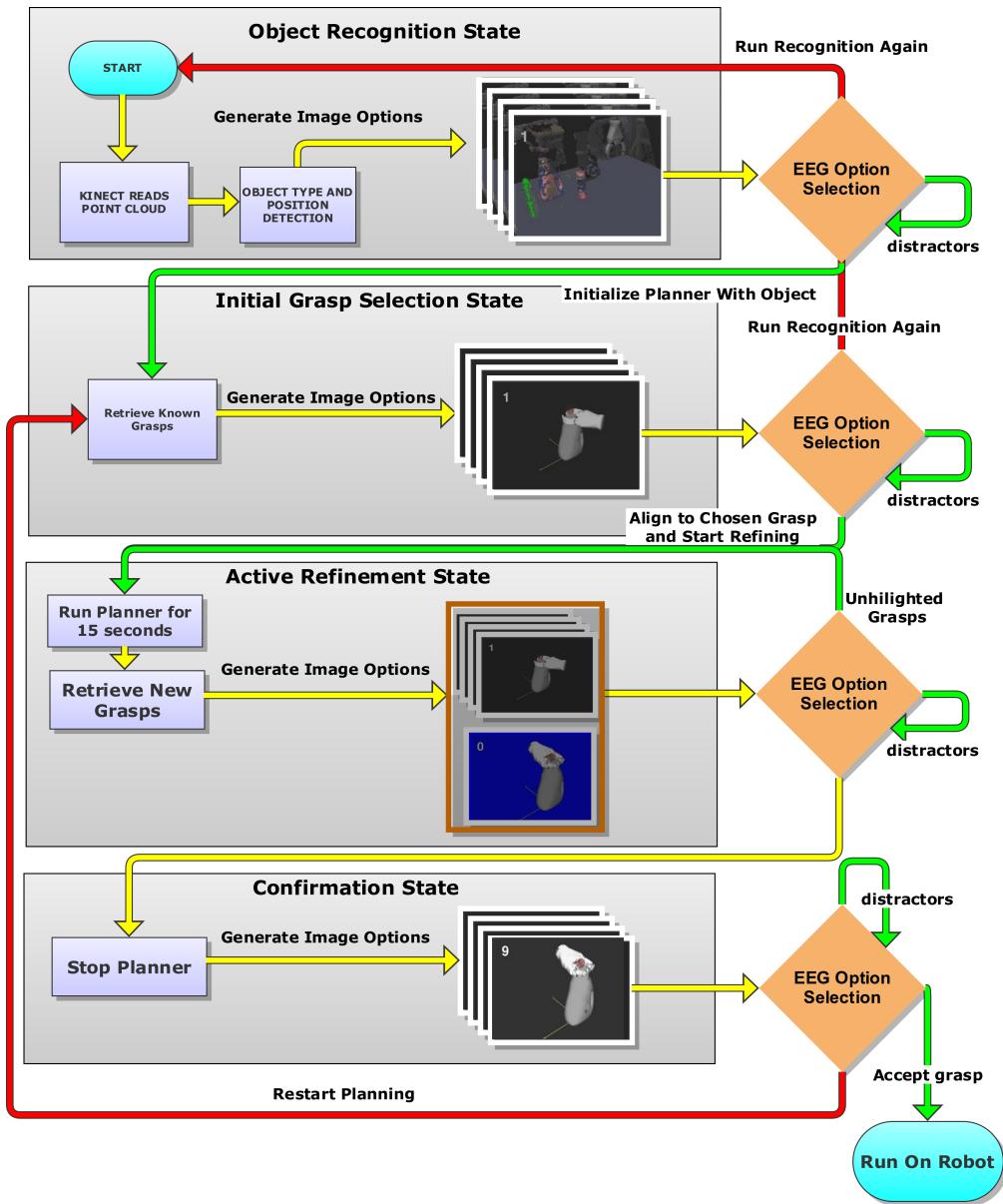


Figure 6.3: A diagram outlining the EEG RSVP driven grasping pipeline. In each phase, a series of images is generated representing the available options, as described in Section 6.2. A summary pane of the image options generated at each phase is presented in more detail in Figs. 6.4 - 6.6.

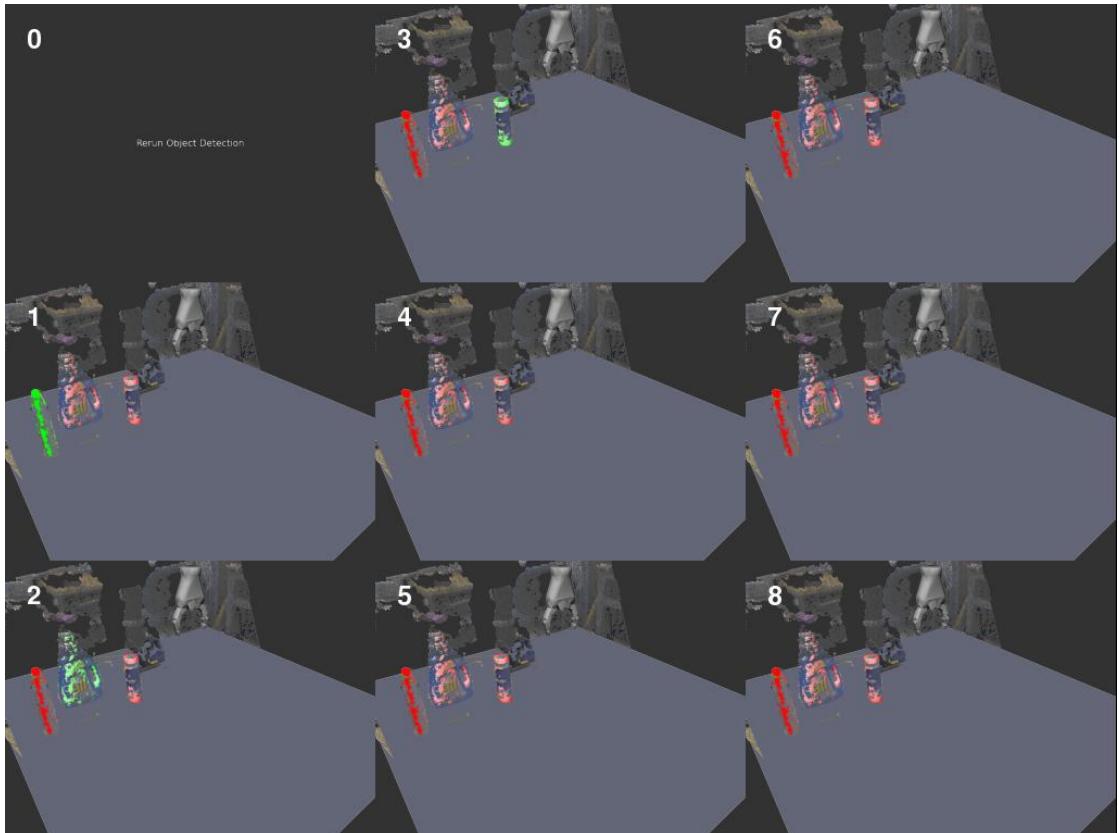


Figure 6.4: The “summary pane” for the object selection phase. As in the previous pipelines, the green object is the one which will be grasped if the image is selected. The text option will rerun the object detection. An image of the grasp planning scene without any highlighted object is used as a distractor image.

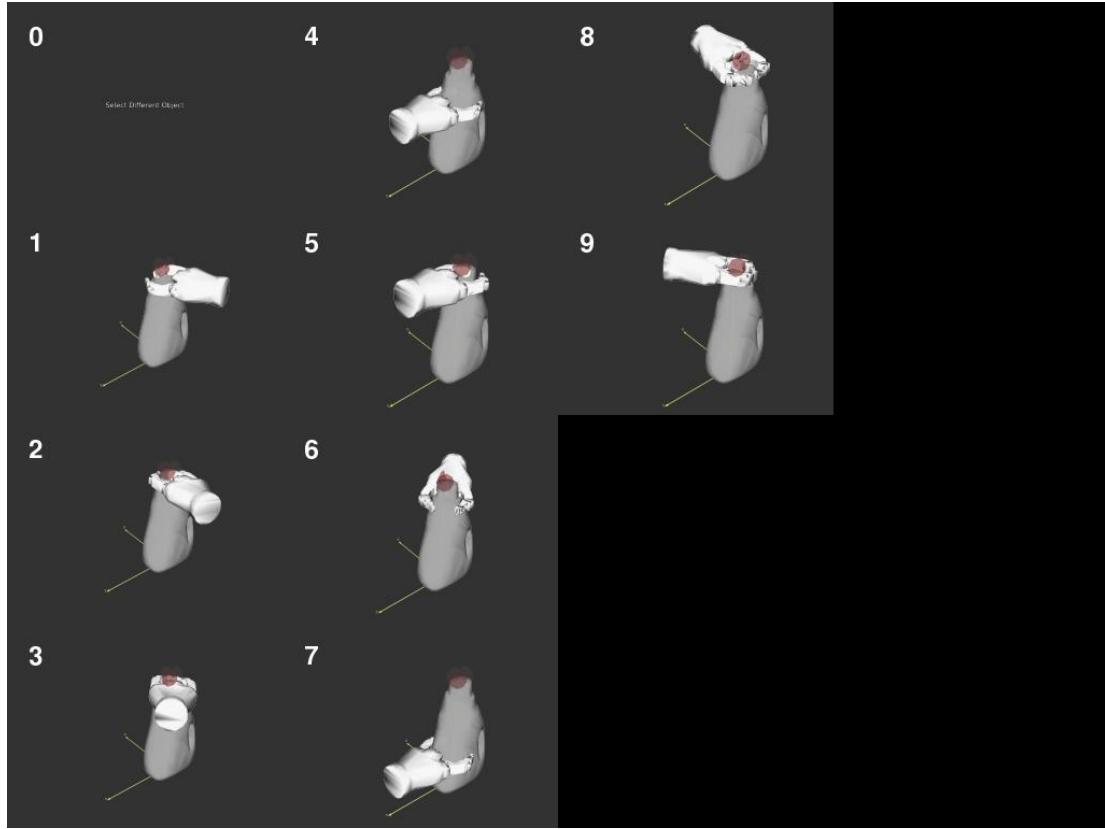


Figure 6.5: The “summary pane” presented during the grasp selection stage. In this view, the robot hand and target object are rendered without the rest of the scene to minimize the similarity between each image. The text option will return to the previous phase after rerunning the object detection system. If fewer than eight grasps are available, additional images with no hand rendered are generated automatically.

want to grasp as the image stream is shown.

6.2.1.2 Grasp selection and refinement states

Once the object is selected, the system moves into the grasp selection state. The user’s interaction with the grasp selection state and refinement states are very similar. An example of the “summary pane” for each these phases is shown in Fig. 6.5 and Fig. 6.6. In the grasp selection state, the set of preplanned grasps is retrieved and placed in an arbitrary order. In this stage each of the grasps is visually distinct, and supplies the

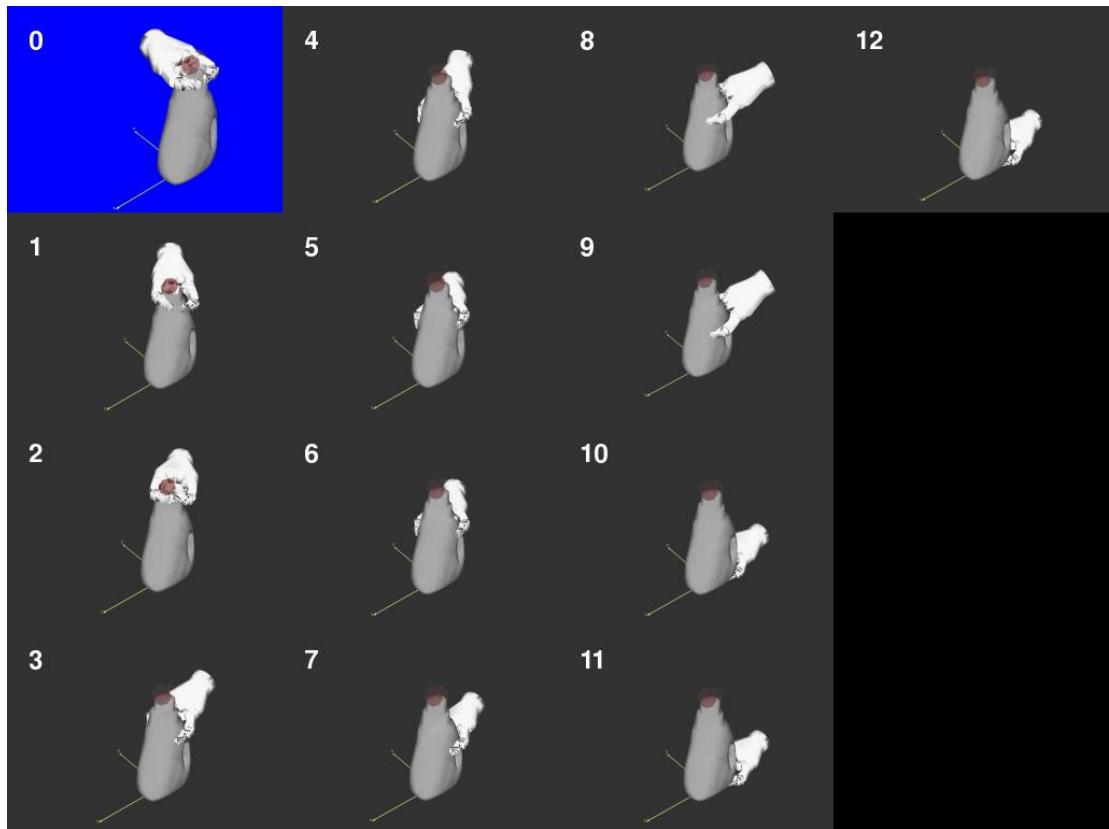


Figure 6.6: The “summary pane” presented during the active refinement stage. The grasps are rendered just as during the grasp selection phase, except that the 0th grasp is rendered on a bright blue background if it is reachable. If fewer than nine grasps are available, images of the target object with no corresponding grasps are added to make up nine options.

planner with an approach angle to start with. One additional text option is presented - “Select Different Object”. Choosing this option goes back to the object selection stage. When any grasp is detected as a valid selection, the system enters the grasp refinement state. If fewer than eight grasps are available, additional images with no hand rendered are added.

In the grasp refinement state, the online planner begins populating the grasp list with more grasps that are similar to the one selected in the grasp selection state. Every 15 seconds, the available grasps are presented to the user. The user’s selected grasp is then used to set the approach direction and hand state used to seed the planner. The reachable grasp with the highest quality score is also sent as an option highlighted in blue. If no reachable option has been found yet, no highlighted grasp is option is presented. If this option is selected, the displayed grasp is *selected*, and the refinement state ends. As grasps are generated, only 5 grasps are allowed in the grasp list with an approach direction within 20° of the generated grasp. If more grasps are in the region, the oldest grasps are penalized and moved to the end of the list, behind grasps that have a different approach direction. This forces some heterogeneity to remain in the grasps that are presented to the user. This way, if the current grasps do not represent the approach direction that user wants, the user can ‘walk’ the grasping point and direction to a desired approach direction, even if it is not initially represented in the options.

In this phase, we also take advantage of visual ambiguity. For the list of options sent to the user, we also generate a symmetric *similarity* matrix S where each entry $s_{i,j}$ holds the dot product of the approach direction of grasp i and j . The selection measure is then modified to select the choice index c that maximizes the sum of the scores of the weighted measure. Given a function $M(i,j)$ which is 1 when the stimulus response j is measured in response to stimulus i and 0 otherwise, we calculate the choice index c as:

$$v_i = \sum_{j=0}^n M(i, j)e_j \quad (6.4)$$

$$V = [v_1, v_2, \dots v_n]^T \quad (6.5)$$

$$C = SV \quad (6.6)$$

$$c = \text{maxrow}(C) \quad (6.7)$$

This reduces the number of ambiguous selections that occur when the user has no strong preference among several grasps with very similar approach directions, which was a common occurrence among some of our prototype subjects.

6.2.1.3 Confirmation State

In the confirmation state, the user is shown the image representing the grasp again along with a distractor image presenting the target object with no associated grasp. The user is also presented with the text option “Go Back-Replan” to return to the object selection phase. Selecting the grasp again confirms the grasp for execution and proceeds to the execution state.

6.2.1.4 Execution State

In the execution state, the user is presented with only three text options - “Restart Execution” which restarts the execution if it has failed, telling the robot to return to its home position and attempt to grasp again, “Stop Execution” which stops the robot from continuing the execution and returns to the confirmation state, and finally a set of distractor images showing the object with no hand rendered and added to make a total of ten options.

6.3 Experiments

We have validated this system on three unimpaired subjects, 2 female (ages 30 and 65) and one male (age 22) asking them to lift each of the objects presented in the experiments in Sec. 5.3.5.4 three times from either the top, from the side, or at their own discretion.

All testing was approved by the Institutional Review Board of the Columbia University under Protocol AAAJ6951, which also covered the experiments in Chapter 5.

6.4 Classifier Training

The classifier weights described in Eq. 6.2 must be retrained every time the headset is reapplied to the user. During the training phase, the user is shown a block of 40 images. 38 of these images are selected uniformly from a set of fifteen object models similar to those presented during the object selection phase, while the remaining two are marked as target images and selected from a set of four images of bowls. Unlike the object selection phase, however, these object images are presented one at a time, without the other objects visible. There is also no summary pane, as the images would be too small to practically see. Instead, the subject is shown the set of four potential target images. All of the images together are shown in 6.7.

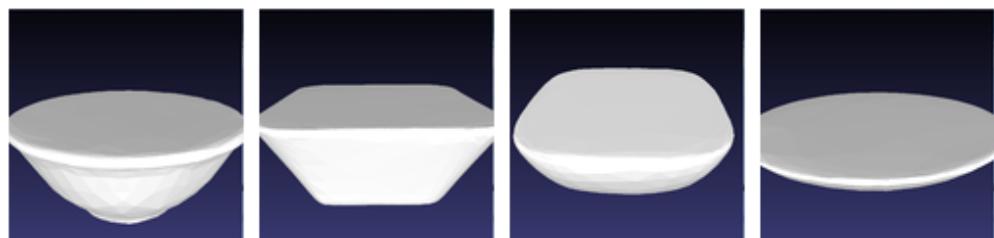
In each block, the subject is told that there will be exactly two target images, and is asked to search for them in the sequence. After a block of images has been presented, the user is also shown the location of the two target images in the sequence and, separately, where the classifier placed those images in a list sorted by detected interest level. The results screen is shown in 6.8. The user is presented blocks at a self-paced rate until at least 20 blocks have been presented, and the user is able to consistently place the two target images in the top three sort positions. The latter condition is usually fulfilled before the former.

6.4.1 Subject Training

To demonstrate how the system works, the subject is shown the system running in a keyboard driven mode, where after the image stream the subject is able to press a key that indicates their chosen option. We allow them to walk through the stages of the grasping procedure as many times as they ask, (always less than 5), while explaining what is being visualized at each step.



(a) The distractor images.



(b) The target images.

Figure 6.7: These are the images presented to the subject during the training of the classifier. These objects are taken from the same dataset and include the objects that will be grasped during the experiment. The subject was asked to look for images of plates or bowls. (a) *Top*: The non-target images. (b) *Bottom*: The target images.

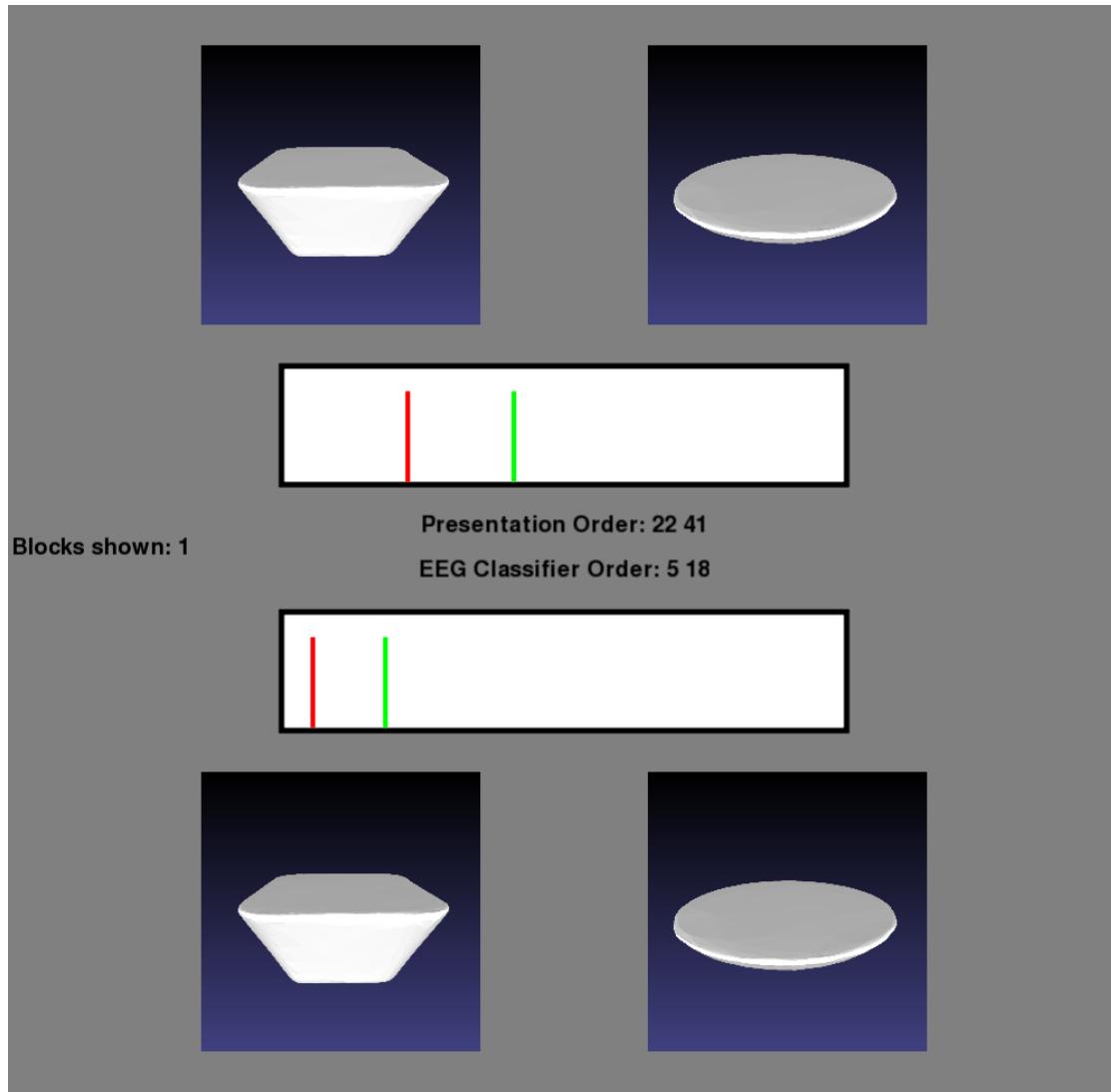


Figure 6.8: The results screen during the training, which shows the subject the presentation order, which is the order in which the plates appeared in the image stream, and the score after the EEG classifier is run on the images, which is lower when the classifier is better. This image shows the results after the first training block.

6.4.2 Results

The results of this experiment are summarized in Tab. 6.1. The subjects were always successful in selecting reasonable grasps that lifted the object, but the system did not always detect the option that the subject wanted correctly. The third column describes the number of misselections, which represents the number of times that the user inadvertently selected an option. Because the pipeline allows stepping back through each phase, this is not fatal. Detected selections of a “distractor” image are not considered misselections, because they do not elicit any actual action that changes the state of the system. The fourth column describes the number of iterations of the “grasp refinement” stage the user accomplished to find an acceptable grasp. The task duration is reported in 15 second increments because it was measured manually with lower accuracy than of previous experiments.

When grasping the detergent bottle, Subject 1 chose to attempt to grasp the handle of the object starting from a top grasp, eliciting the ‘walking’ behavior described in Sec. 6.2.1, which necessitated a large number of iterations of the refinement state. The largest number of misselections come from the users accidentally selecting the option to rerun object detection in the “object selection” phase. Misselections of the wrong grasp during the “active refinement” stage when the user actually wanted to accept the currently best grasp and leave the stage also occurred, but these mistakes are quickly recoverable since a similar grasp is likely to be present in the next set of grasps.

6.4.3 Conclusions

These results are encouraging, and demonstrate that a relatively fast and effective pipeline using only EEG based is workable. There were some issues that were revealed during this experiment, specifically in terms of how the images are generated representing more abstract concepts like the text based image options and the “selected” grasp during the “grasp refinement” stage.

The most common misselection was the command to redo the object detection during the “object selection” phase. This is probably because the difference between the images representing object selections and the text option image is large and somewhat startling,

which elicits a reaction from the subject. A similar issue was seen in the initial attempt to use the system with Subject 2, who selected the blue image option every time it was presented in the “grasp refinement” stage, until the brightness of the background was reduced by 50%. After this modification, the subject had no trouble making the correct selection in the “grasp refinement” stage. Also perhaps similarly, subject 2 sometimes had trouble making the correct selection in the “confirmation” stage, possibly because the distractor images were too similar, which makes the task too different from the one that the classification system is trained on.

There is an enormous space of design parameters than can be explored that may resolve some of these issues to produce a more robust system. One option would be adapting the thresholds used by the classifier based on the content of the image options. Another option would be to modify the training set of images to be more similar to the images presented in the task stage. While the current training regime has proven to be somewhat generalizable, it may not be adequately representative of the responses that are elicited by large stimuli like the blue background of the “selected image.” Finally, some calibration procedure for modifying the images based on the responses they elicit from the user may need to be incorporated into the training regime.

The extension of the online HitL planner to this EEG based image streaming paradigm has just begun. In its current implementation, the subject decisions are elicited at fixed points of the pipeline. Future work will move towards attempting to integrate the EEG data in a more real-time strategy, perhaps being fully embedded into the augmented reality environment.

Finally, another approach to be explored in the future may be to combine the approaches presented in Chapters 5 and 6. This multimodal strategy would incorporate an EEG based classifier for directing the planner towards the users preferences while a facial EMG input is used to signal discrete decisions. Such a system would address the shortcomings of each individual modality - allowing the system to quickly filter reasonable options. In such a filter, accuracy may be less important so long as the filter is somewhat conservative. Integrating the EMG input would allow the user to signal discrete commands quickly with high confidence. For stages such as confirming the fi-

nal selections, which affect the state of the robot and may result in inappropriate or potentially damaging behaviors, this more robust selection may be more important.

Grasp	Subject	Misselections	Refinement Iterations	Time(s)
Detergent Bottle Top	1	0	1	120
	2	2	3	150
	3	1	2	135
Detergent Bottle Side	1	0	1	120
	2	1	2	135
	3	0	1	120
Detergent Bottle Open Choice	1	0	10	270
	2	0	2	135
	3	3	5	180
Shampoo Bottle Top	1	0	1	135
	2	0	1	120
	3	0	1	150
Shampoo Bottle Side	1	0	1	120
	2	1	1	135
	3	0	2	135
Shampoo Bottle Open Choice	1	1	1	210
	2	1	3	120
	3	0	1	150
Shaving Gel Top	1	0	2	180
	2	1	1	120
	3	0	2	135
Shaving Gel Side	1	1	2	135
	2	0	1	120
	3	0	2	150
Shaving Gel Open Choice	1	0	2	120
	2	0	1	120
	3	0	2	180

Table 6.1: Results from Experiment 5. The subjects were always successful in selecting reasonable grasps that successfully lifted the object. The third column describes the number of misselections, which represents the number of times that the user inadvertently selected an option. Because the pipeline allows stepping back through each phase, this is not fatal. The fourth column describes the number of iterations of the active refinement stage the user selected to find an acceptable grasp.

Part III

Conclusions

Chapter 7

Conclusions

In this thesis, I have presented a series of iterative improvements made to develop the work presented in [Ciocarlie and Allen, 2009] into a practical, integrated system for human-in-the-loop grasping. We began by developing a sampling based approach to improve the robustness of grasps produced by this planner. From a more robust planner, we begin implementing a series of experiments to develop and validate a user interface that can be used with simple interfaces. We have validated the flexibility of this interface using three different input modalities and two different robotic manipulators. Through each iteration of the system, we sought to simplify the user interface while improving the robustness and speed of performance. The results presented in chapters 5 and 6 demonstrate capabilities that have never been shown through similar low throughput, noisy interfaces before, allowing a user to interact with complex scenes relatively quickly using brain-computer interfaces.

We have validated each stage of our design through experiments with users. Generally, robotics software environments are extremely complex, requiring coordination between a large number of components. It is somewhat normal to encounter software bugs, such as the driver for the Microsoft Kinect hanging indefinitely, on a regular basis. When such bugs happen during an experiment with a subject, the subject tends to lose interest in the experiment, and is likely to stop putting in the effort necessary to learn to use the system effectively. Producing a software environment that is stable enough to bring even a small number of subjects through without encountering adverse events has

been one of the most challenging aspects of this research. Additionally, some of these crashes lead to unexpected behaviors that may damage the robots, which are expensive and difficult to repair. Human-in-the-loop robotics experiments that follow an iterative design philosophy are thus relatively rare.

This has only been possible through the integration of a large number of other libraries. The development of this work has coincided with an explosion of open source robotics frameworks, and has benefited enormously from access to the ROS and OpenRAVE frameworks. These software frameworks are used by a much larger population than the custom robotics environments that have often been used in the past, which leads to the identification of many more bugs. Because our system is designed carefully to be modular, we have been able to swap out different components, such as the path planner or robotic manipulator, in order to evaluate many alternatives. Although these frameworks are widely used, it is still a matter of considerable engineering effort to incorporate them into a coherent system. The integrated system presented in this work is the product of multiple researchers that have contributed to this project over the last five years.

The experimental results of the final version of the sEMG driven and EEG driven pipelines demonstrate the flexibility and effectiveness of both the underlying grasp planner and the modular system that we have constructed. This system will form a strong basis on which to begin introducing it to impaired subjects in collaboration with our colleagues at the medical center. The sEMG based pipeline, in particular, shows great promise in its simplicity, and future work may see it integrated into an assistive robotic device outside of the lab.

7.1 Limitations

This work has addressed only a particular subset of the problems that would be faced by an assistive robotic device, the task of acquiring a stable grasp of an object. There are still many challenges ahead for future research in the areas of navigation and manipulation. The challenge of stable grasping in completely unstructured environments also

still remains, particularly in the area of singulating objects that are too close together for planners that do not allow collisions in the grasping process or objects that cannot be clearly seen.

Chapter 3. *Robust Grasping* presents an approach to improving the robustness of the planned grasps to object localization, but it relies on the ϵ_{GWS} , which makes a large number of assumptions and is only a necessary condition for stability - it is not inherently a *sufficient* condition, which in the general case requires accurate models of the transmission of the fingers. There is no widely accepted generic framework for incorporating these concerns. Additionally, we do not consider the problem of controlling the torques applied to the fingers, as many hands to not provide any interface to control the torques directly. Because of these limitations, the robustness filtering which we have implemented biases the planner strongly in favor of enveloping grasps and power grasps, reducing the flexibility of the grasp planner. We did not explore whether this problem could be rectified.

Chapter 5. *Using a Minimal Interface Device* presents a system capable of grasping objects in somewhat cluttered scenes. The object recognition system we have used is only a single view camera that uses only geometric information to recognize objects. When there is significant occlusion of a particular object, this approach will fail. When this happened many times in a row during the experiments, we reshuffled the objects and restarted the trial. Multiple views and contextual information could provide much more robust performance, but development of advanced vision systems is not a focus of this thesis. Additionally, as discussed above, we did not address the problem of singulation. Our system has only been demonstrated on objects that can be grasped without colliding with nearby objects. Singulation is an open area of research, and the state of the art is still too likely to result in damage to the robot to allow experimentation with naive subjects. Finally, in validating the final version of the sEMG pipeline, we did not train the user up to full competency in 2 dimensional control of the cursor controlling the pipeline. Developing a training paradigm that is reproducible is a matter of future research on the part of our collaborators at UC Davis.

Finally, the validation of this system on a larger cohort of impaired users is an

important step that is a matter of future research.

7.2 Future Work

In the time since we published the work presented in this thesis on a sampling based approach to robust grasping, it has been cited by a number of times by authors contrasting the simplicity of the sampling based approach with more mathematically sophisticated or computationally expensive methods (see [Bohg *et al.*, 2014] and [Kim *et al.*, 2013]). However, as of yet no practical, generic method suitable for online planning has been adopted by the grasp planning community. One of the great strengths of this method is that it is purely kinematic, and avoids the complexity and computational cost of dynamic simulation, but this also limits the predictive power of the metric. There is still a great deal of work to be done in this direction.

The planners utilized in this work in both the grasp planning and arm motion planning subtasks are essentially “any-time”, meaning that they return the best result that they have found thus far after a fixed time interval expires. Recent advances in GPGPU computing have the potential to make such planners orders of magnitude more effective. Up to now, implementing algorithms with the complexity of these planners has been largely impractical, however we are beginning to see some library frameworks such as Bullet3 (<http://bulletphysics.org/wordpress/>) that may make some of the most computationally expensive parts of these planners more tractable. When this happens, whole new families of planning algorithms will become “real-time” enough to be integrated in an online planning environment, which may dramatically improve robotic capabilities.

There are two major issues with the current generation of BCI/BMI interface devices that we have explored in this work. The first is the form factor. The Emotiv EPOC and similar headset devices are impractical in their bulk and the expertise needed to keep them working for more than a few minutes. The second is cost - while the Emotiv EPOC system is relatively cheap, we were not impressed with its capabilities. More capable EEG devices have not reached a price point where long term studies with users able to train to use the device over the course of weeks or months have are practical. This

means that all research done using EEG is effectively done on novice users. As cheaper alternatives like the OpenBCI EEG device become available, doing long-term follow up studies to see if users can improve on their ability to use the interface with training is a viable avenue of research that is worth exploring.

The sEMG system is more practical in both respects than any available EEG device. It is low cost and has a form factor that is much more amenable to long term use. However, in its current implementation it is very much a prototype that is held in place by a combination of tape and silly putty. Integrating this device into pair of glasses or goggles would make them a viable alternative input device that may of interest even beyond the field of robotics as wearable computing devices become more common. This advancement will definitely be necessary before the system can be tried in any long term. We believe that a better form factor combined with a much longer term training paradigm in which the subject is able to use the device in their own home for many weeks may be the key to achieving robust 2D control, and perhaps allowing direct user input into some aspects of the pipeline as though the device were a computer mouse.

Finally, the user interface needs to be extended to a system suitable for long term autonomous running with many more manipulation capabilities that go beyond acquiring stable grasps. We can easily envision a future in which a robotic assistant can be controlled in an augmented reality system to perform arbitrary tasks, such as washing the dishes, the same way that they are in virtual worlds in video games today. There is nothing in particular standing in the way of extending the system we have built so far to an arbitrary activity of daily living, so long as it can be broken down to a pipeline where a small number of options can demonstrate the user's intent. Exploring which manipulations can and should be implemented first is an open area of research.

Assistive robotics is still an emerging field. It is not clear what a commercially viable assistive robotic mobile manipulator might look like, as current prototypes are both too expensive and lacking in robustness. As practical devices become available, it will be important to see how we can create user interfaces that enable whatever manipulation capabilities they can provide. As general artificial intelligence seems to still be a long way off, Human-in-the-Loop interfaces will play an essential role in improving the lives

of those with limited mobility. Given the capabilities of the interface devices available for such individuals, carefully developed task specific pipelines offer a promising way forward in the near term.

Part IV

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