

CHAPTER 1

INTRODUCTION

A human being is an amazing and complicated system. The level of grace and complexity becomes apparent when one asks a machine to perform a task completed so simply by a human, such as object manipulation. A list of all the variables and information for which a robotic manipulation system would have to account would be quite lengthy. Yet humans are able to manage this load while performing such tasks nearly flawlessly, despite having to operate in unstructured environments. While it is unreasonable to believe that robots will reach levels of recognition, proprioception, and control comparable to that of humans anytime soon, it seems valid to draw upon a human's innate abilities for motivation in machine control.

The goal of this work is to combine a rigorously formulated motion planning technique with fuzzy logic to provide operational flexibility to a set of robot manipulators *via* end-effector/object force feedback and closed loop control to effect object manipulation. For this purpose, *manipulation* is defined as a preordained reconfiguration of an object by the manipulators.

Looking to nature for engineering inspiration is certainly not a new idea. It has been practiced ever since humans began to observe their environment to better cope with their surroundings, which is to say ever since there have been humans. One great observer of nature, Leonardo da Vinci, expressed it this way: "a bird is an instrument working according to the mathematical law, which ... is within the

capacity of man[*sic*] to reproduce.” [78]. At each step, this work will attempt to emulate a biological system, with the key components being haptic feedback and a fuzzy supervisor. The force sensors provide a rudimentary, haptic interface for force closure and contact-location feedback. A fuzzy system acts as a supervisor for the otherwise open loop motion planning algorithm called Steering-Using-Piecewise-Constant-Inputs (SUPCI) which is applicable to smooth, underactuated, driftless, nonlinear systems. A nonlinear approach is necessary because driftless, underactuated systems cannot be controlled when linearized.

Humans come equipped with fine visual systems. However, machine vision systems tend to be expensive in terms of hardware, robustness, and processing power. Faster computers have reduced the last issue, but cost and robustness are concerns, especially when viable alternatives exist. Implied in the above paragraph is that, in close quarters, vision is not a prerequisite for object acquisition and manipulation. Humans are proficient at identifying and manipulating objects they are unable to see. In an experiment by Lederman and Klatzky [37] subjects were blindfolded and asked to identify 100 common objects. The result was near 100% accuracy and recognition in 2–3 seconds. How do blindfolded humans “recognize” objects? At the engagement level, proprioception and haptic feedback help to provide humans with a major advantage over robots for manipulation tasks. Humans use information from skin, muscle, tendon, and joint receptors to perceive objects [37]. This ability allows a human to manipulate an unknown object without needing to view the object. At the same time, the nerve endings in the fingers send information about an object’s weight, topology, and geometry to the brain, while the muscle system adapts locally to disturbances, closing a sophisticated control loop. The importance of proper finger coordination is evident in the example of screwing in a light bulb. For this application, opposing fingers are used to provide a substantial

enough couple moment to rotate the object, while regulating the normal force to prevent slipping or crushing. In addition, humans are adaptive and can perform manipulation tasks on a variety of objects and in a variety of work spaces. Modern robots cannot come close to this kind of dexterity or flexibility.

Industrial robots can perform repetitive, non-manipulative tasks such as stamping, spot welding, and soldering with great repeatability [7]. While these have proved useful automation tools, current robots are outdone by their human counterparts when it comes to the tasks of recognition and manipulation. In addition, robots often require exact knowledge of their surroundings and of the object to perform tasks. The distinct advantage robots have, however, is the speed with which they can perform tasks, the strength required to perform heavy tasks, and the stamina to perform tasks for long periods of time.

Current limitations on robots no doubt stem from the specific-use mentality of the application, but, as the limits of automation are pushed, it seems reasonable to assume robots will be asked to perform fine manipulation of complex objects in uncharted environments, perhaps in performing search-and-rescue or data collection in a hazardous environment. In the latter, researchers are likely searching for “interesting” objects to examine, for example, a rock formation on Mars. If “interesting” is a function of geometry, would sonar work just as well as vision for identification? If so, the focus shifts to using task-specific sensors where they are most appropriate. For example, an autonomous vehicle equipped with a robotic arm may use sonar to identify an object to query, use haptic feedback to manipulate the object, and use vision to extract interesting topological characteristics of the object.

Increased autonomy will likely also require development of new grippers. Already, work toward more general end-effectors has been done. Most gripper designs incorporate from two to five fingers although continuum manipulators, modeled af-

ter elephant trunks, are very intriguing (see [20]). The most simple — the two-finger gripper — is the type often used to perform non-manipulative tasks. However, functionality also depends on the number of degrees of freedom (DOFs) of the finger designs. Increased DOFs allow grippers to generate more grasp types. Of course, there is a trade-off between the number of DOFs and complexity of the kinematic analysis and of the physical gripper and the accompanying dynamic control. Most three-finger grippers exhibit anywhere from three to 12 DOFs [63]. Four-finger grippers effect manipulation by allowing the fourth finger to reposition itself while the other three fingers provide a stable grasp. While common sense seems to dictate that more gripping fingers are better, this is not always the case. Yates [83] introduces a three-finger gripper to manipulate a cylindrical object. One finger is allowed to slide in a curved slot, adding one DOF. This provides manipulation levels similar to that of four-finger grippers.

Gripper kinematics, however, is only a small piece of the puzzle. The light bulb task mentioned above, requires a plan for orienting the bulb so it can be installed, information on the material so it is not squeezed too tightly and crushed, force and torque feedback in three dimensions so the installer knows if she is squeezing the bulb hard enough to effect rotation and to know when the task has been completed, and a type of inverse kinematics to know where to place her fingers. In general, the amount of information a human receives from her sensors, filters, and processes is staggering. By comparing this to the task of equipping a robot with appropriate sensors to provide equivalent information, discernment abilities, and processing power, it becomes clear as to why the manipulation task is so easy for humans and so difficult for machines.

Obviously, when it comes to interaction between an end-effector and an object, position control is insufficient since the contact constraint may preclude position

attainment. Ultimately this would be damaging to actuators since the controller is constantly trying to push against rigid joints. In this case, many researchers apply hybrid position/force control which requires information about contact force (See [8, 49, 74, 82, 86]). Natale and Villani [49] place force/torque sensors at the wrist to trace an object while maintaining a prescribed force profile. Mohammad *et al.* [86] use force feedback from tendons to control a tendon-based manipulator. Yao and Tomizuka [82] assume contact forces can be measured while Wang *et al.* [74] provide a method to calculate force at the end-effector. The latter, however, requires exact knowledge of the robot parameters, joint torques, joint accelerations, and assumes no external disturbances. In addition, the above referenced body of work studies dynamical systems. As such, it is not directly applicable to this work since the approach here is a kinematics analysis. The reason for a kinematics approach is twofold. First, a kinematics' viewpoint reduces the size of the space to consider since accelerations and the forces that cause them are not considered. This approach is justified by viewing manipulation as a quasi-static task. Second, the kinematics analysis is more amenable to analytical solutions for complex systems and for systems with intermittent contact. None of the studies above deal with manipulation characterized by intermittent contact. In fact, Wang *et al.* [74] refer to simple planar engagement of an object as manipulation in direct contrast to the definition here.

To accomplish intermittent contact, it seems reasonable to place sensors nearer to the point of interest. Again, the motivation for this is biological. In humans, haptic information comes from sensors on and under the surface of the skin. This researcher suspects if the eye were more rugged some modified version of them would exist on human fingertips too. In addition, less interpretation is necessary to

process data when it is received at the interface rather than higher up, at the wrist, for example, as is done with some robots.

While closed loop control *via* haptic feedback has been mentioned, another potential ally is compliance. Compliance is characterized by the amount of deformation a body undergoes when a force is applied. Obviously, human finger pads are compliant, and all bodies are compliant to some extent. This may aid in manipulating objects, especially those with points or edges since, depending on the size of the object, the surface of the fingertip deforms around the discontinuity [11, 16, 46]. This view of compliance differs vastly from the majority of the research which treats compliance as displacement between rigid bodies, which is useful in its own right. For example, compliant end-effectors can compensate for inaccuracies during position control, thus allowing insertion tasks to be accomplished [69]. In fact, ATI Industrial Automation [5] makes a robot tool adapter called a compensator remote center compliance device. Its function is to deform to aid in peg-in-hole type applications in which the hole is misaligned. In addition, depending on the application, compliance can eliminate the need for sensors or feedback [20] and ensure safety during robot/human interaction [40].

Research on compliance as understood here has been isolated to kinematics. Shortly after publishing work on contact evolution equations assuming rigid bodies in contact [45], Montana [46] extended his work to compliant objects. The main difference is that compliant surfaces make contact over an area rather than at a single point. The equations developed are identical to those developed for the rigid-body case except that the relative velocities between the two objects now include an additional term to account for velocities due to compliance. However, it seems unfortunate that Montana also decided to maintain that relative motion along the surface normal to the two objects must still be constrained to zero when it is appar-

ent that this constraint no longer holds for compliant surfaces. It is quite possible for displacement between compliant surfaces to occur along the contact normal without the surfaces breaking contact. In addition, he notes that these deformed surfaces give rise to nonorthogonal coordinate maps. His solution is to define additional coordinate charts which map from the rigid to the deformed surfaces. Perhaps a better solution would have been to rederive the geometric parameters to reflect nonorthogonal maps [56].

Montana also performs an experiment in which an array of tactile sensors is used to measure the contact surface. The sensor array is mounted on a center-of-compliance device to introduce compliance, but the contacting object is still rigid. He then calculates the contact center to be the centroid of the normal forces measured by the array.

Since Montana's work, there has been relatively little research done in the area of compliance kinematics, but in [11] Chang and Cutkosky present experimental results on the reaction of various compliant materials. The experiment consists of measuring the distance it takes a deformable cylinder to roll around a rigid cylinder under various contact forces. This distance is then measured against the theoretical distance based on the geometry of the cylinders under perfect rigidity assumptions. The results show the rolling distance is not only a function of the contact force but of the material as well. Rolling distance increases or decreases based on how the cylinder's perimeter is affected under loading. Incompressible materials tend to "bulge" in their unloaded directions, thus increasing the rolling distance whereas compressible materials tend to compact locally, effectively resulting in a smaller-radius cylinder, and decreasing the rolling distance. The impact of these results on compliant manipulation is that geometry information could be adjusted based on

material properties and the amount of contact prior to calculating joint trajectories for manipulation.

As an extension of the above, few researchers have attempted to exploit compliance for manipulation tasks. In the precursor for this work, Wei [76] assumes objects and fingertips are rigid. Natale and Villani [49] model object compliance by allowing end-effector motion normal to the object during contact. Their finger model, however, uses frictionless point contact. DeSchutter and Van Brussel [14] effect compliance by modifying the trajectory of the end-effector based on contact forces.

Many authors have previously recommended imbuing robots with human abilities (See [26, 29, 37, 41, 42]). Hershkovitz *et al.* [26] suggest finding objective functions that relate to human grasp in terms of muscle effort, finger force, and force distribution. Lederman and Klatzky [37] suggest biological approaches to sensor-based robotics are complementary to analytical methods. Reconciling such combinations is a key issue for behavior-based systems. The underlying issue is how to guarantee performance from systems that are not completely analytical.

Of behavior-based, or artificial intelligent applications, fuzzy logic is a natural choice for manipulation tasks. It should reduce the amount of calibration required due to its empiricism. Consequently, the controller will work with similar but physically different systems, different objects, or different numbers of fingers. Linearization is impractical since large joint angles must typically be swept out during grasping and manipulation tasks. Young and Fan [84] suggest fuzzy logic is an excellent representation for biological systems due to their shared empirical properties. In addition, evidence suggests that the brain uses a set of quantitative rules to determine activation levels in muscle synergy [79]. Finally, fuzzy logic fits well in a supervisory role [53]. This is also reminiscent of the human neuromuscular

system. Electromyographic (EMG) data has shown that various muscle synergies can occur for the same task. This suggests a hierarchical control with the synergy occurring at a high level and the participating muscle activity at a low level [79]. Corroborating research has suggested that the intelligence of the neuromuscular system is distributed between the nervous system and the muscular system. Before sending control signals to the limbs, the muscle system locally adapts signals from the brain to account for changes in load, movement, and environment. This enables the system to be insensitive to load variation as well as to dynamically compensate for multi-joint movements [84]. Figure 1.1 depicts this structure.

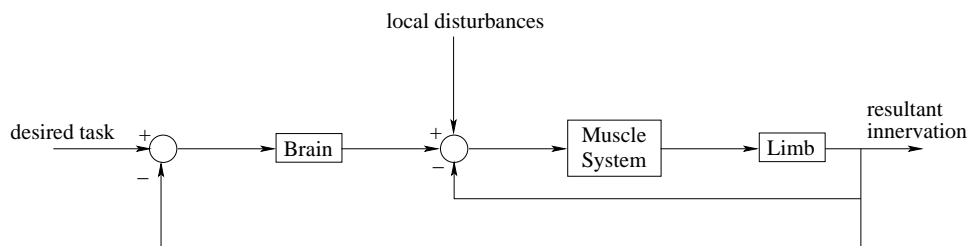


Figure 1.1. Biological Control Architecture

While fuzzy logic is model-free, much work has been done in developing analytical tools for motion planning. The motion planning algorithm used here is attributed to Lafferriere and Sussmann [34] and Goodwine [19]. The previous presents a method of motion planning for smooth, underactuated, driftless, nonlinear systems, while the latter extends the method to discontinuous systems, for example, cases involving intermittent contact or engagement, later referred to as *stratified*. One disadvantage of the motion planning algorithm in [34], resulting in the necessity to incorporate feedback control in the first place, is that the method is open loop and, therefore, highly susceptible to modeling errors. The advantage is that analytical systems

are amenable to analysis such as controllability; this is in direct contrast to fuzzy systems.

Quantifying or guaranteeing performance remains a drawback of soft computing techniques, and may be a key issue in the push for developing hybrid controls which is characterized here as combining analytical techniques with soft computing, specifically fuzzy logic. Work in this area is being done using model reference [30] and proportional-integral-derivative (PID) equivalents [15, 68]. In fact, basic fuzzy logic structures typically resemble proportional and integral or derivative forms [80]. Much work in this area assumes a specific structure of the fuzzy system so analytical analysis can still be performed. In addition, robust control techniques include uncertainty specifications. So, this may provide some direction for hybrid development.

1.1 Contributions of this Research

The goal of this work is to effectively combine mathematically rigorous but open loop motion planning techniques with fuzzy logic to provide operational flexibility to a set of cooperating robot manipulators acting as fingers to dexterously manipulate smooth and nonsmooth objects. Throughout, enhancements to the open loop analysis are biologically motivated. This is achieved through three specific goals: first, by implementing haptic feedback; second, by eliminating the need for multi-robot calibration; and last, by fusing analytical with non-model based techniques for nonlinear control. In addition, this work presents a technique for online object compliance classification, and introduces the **compliant finger** to the literature on finger models.

While biological motivations to machine intelligence are appealing, it is necessary to balance the desire for embedded systems with ease-of-use, processing speed, and

environmental flexibility. A robot affixed with force sensors on its end-effector is no more an accurate representation of haptic ability than an artificial neural network is of human cognition. An attempt to do more may render a system inoperable from a practical standpoint.

The components used to instantiate the basic premise are pre-existing, but they will be combined in a way that brings operational flexibility to the robotic manipulation task. In the sequel, the closed loop block diagram for the manipulation task shown in Figure 1.2 is systematically constructed. Notice the similarity to the biological control system shown in Figure 1.1 to adhere to a biomimetic approach. Specifically addressing the low-level control of the robots, the PID controller is treated as a black box; it is programmed on the motion control boards. Although, the controller gains are adjustable, it is assumed the PID controller is sufficient to achieve its objective. Wei [76] has previously confirmed this assumption.

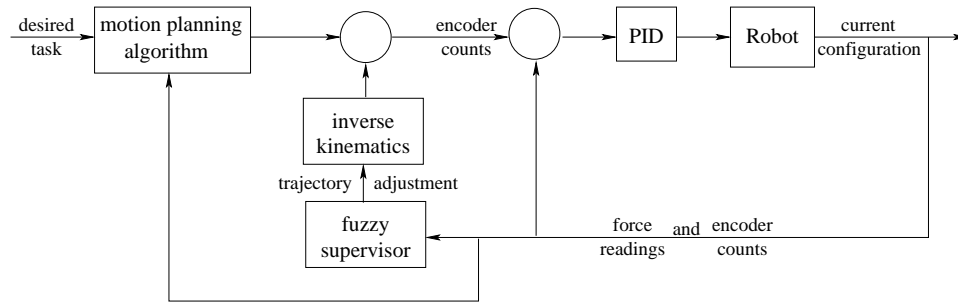


Figure 1.2. Control Architecture for the Manipulation Task

1.2 Organization

The remainder of this dissertation proceeds as follows: Chapter 2 provides information on the precepts of planning. Chapter 3 provides background on the theoretical framework of motion planning, stratified systems, robot kinematics, grasping, and fuzzy logic. Chapter 4 provides examples that bring to light the concepts of

Chapter 3 to move from “the math” to a practical application of it. The methods used to carry out the experiments and preliminary results are given in Chapter 5, including an overview of the testbed, associated hardware and software, and logic approaches. Finally, Chapter 6 presents experimental results, discusses the efficacy of the approach, and provides a retrospective of the work.