Robotic Manipulation with a Human in the Loop – Accuracy Comparison and Analysis

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ROBOTIC MANIPULATION WITH A HUMAN IN THE LOOP – ACCURACY COMPARISON AND ANALYSIS

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This **Masters Project Paper** fulfills the Master of Engineering degree requirement.

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Robotic Manipulation with a Human in the Loop

Accuracy Comparison and Analysis

Master of Engineering Final Capstone Report

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Abstract

To truly make automation economical, there needs to be a shift in robotic performance: from highly specific at one task to general-purpose across many tasks. Unfortunately, such additional functionality is not cost-effective without a sacrifice in performance. In the case of robotics, it is a sacrifice in accuracy. This paper first investigates an industry analysis of a general-purpose robot to outline its merits and drawbacks as a competitive product. The paper then delves into more technical detail about how to accommodate the robot's lack in accuracy. Specifically, our method of implementation is to have the robot self-detect when it is too inaccurate to proceed with a task and subsequently request assistance from the human. Here, we utilize the fine-grained capabilities of a human, relatively, in synergistic combination with the efficiency of an inexpensive robot.

1 PROBLEM STATEMENT

(Authors: Schweigert, Srinivasan, Sun, Su, Jouppi)

We live in an age of increasing automation, but while we have machines that can open a can, pour a glass of water, or assemble a piece of furniture, the world does not have a machine that is versatile enough to do *all* of these tasks.

Normally, when people think of automation, they think of robots designed to accomplish a very specific task, such as lifting a car-door into a car-frame, over and over again. The newer generation of robots though is the class of general-purpose robots. While such robots have yet to materialize commercially, general-purpose is a great concept. Imagine if families could have a robotic assistant to take care of household tasks or run daily errands. In short, human life would be much more convenient and efficient.

Unfortunately, a major limitation towards reaching such a milestone is the engineering trade-off between cost and performance: with a limited budget of resources, it is almost impossible to add additional levels of complexity without decreasing performance. As such, it has traditionally been challenging to use robots that are both low-cost and versatile in domestic environments because the applications of these robots are limited by their low performance – specifically, their inaccuracy. This is where we decided that the human should come in.

To address this barrier of limited resources, our capstone team has developed a system that is designed around robot-human interaction, where human instructors train and work with cost-effective robots to accomplish a broad range of tasks with high accuracy. Using a set of algorithms that we have developed, the robot learns how to perform a task from a human who teaches it through a series of demonstrations. Following this learning process, the robot evaluates the task and identifies the precision requirements using a mathematical model. And when the robot detects that it is unable to achieve the accuracy required for a certain portion of the task, it requests human assistance. The final outcome is a system that excels across a vast range of duties, due to the combination of both the efficiency of robots working on a large-scale and the precision of humans working on a small-scale.

This revolutionary design of cooperation between man and machine succeeds at tasks that are otherwise impossible for the machine to accomplish alone. In essence, we added in the human as an additional resource to improve the overall performance of the system. This was the rationale behind our capstone project, for we saw an opportunity here to make an enormous technical stride in society's current usage of commercial robots: we took an otherwise unimpressive commodity – the low-cost and inaccurate robot – and engineered commercial value from it in the form of robotic adaptability.

2 INDUSTRY AND MARKET TRENDS

(Authors: Schweigert, Srinivasan, Sun, Su, Jouppi)

Before examining any technical details though, we first wanted to scope out the business potential of our project. Consequently, in an attempt to analyze our strategic position in the market, we evaluated the competitive forces outlined by Porter (Porter, 2008) because we felt that an in-depth analysis of the intensity of these forces will influence our marketing strategies. In other words, analyzing these five forces enabled us to have a better understanding of our industry and shaped our strategies to sustain long-term profitability. Before we begin our analysis however, let us first clearly define both our market and our product.

2.1 Market and Product

We defined our market to be consumer households with the intent that our algorithms accomplish household tasks, such as assembling furniture. We chose to target the elderly and the disabled as buyers of our product because this is a large, growing population with critical and largely unmet needs. Simply put, the elderly population in the United States is growing. While the current number of senior citizens in the US is roughly 40 million, that number is expected to grow to over 80 million by 2050 (Ortman et al., 2014). Additionally, according to US 2010 census data, about 30%, 38%, and 56% of the population aged 70 to 74, 75 to 79, and 80 or over, respectively, live with severe disabilities (Brault, 2012). To further narrow our market though, we chose to focus specifically on affluent elderly-and-disabled individuals as our target customers. This is a reasonable objective because many elderly people have amassed a wealth savings and investments cultivated over their lifetimes. Indeed, according to a Pew Research study, the median net worth of senior citizens in the US is $170,000, which is 47 times greater than that of people aged 35 and younger (Censky, 2011).

The definition of our product is a more complex matter because, at its core, our capstone project involved the research and development of an algorithm that allows a robot to learn a task and cooperate with a human to perform that task; it is not a complete software – or hardware – solution. Unfortunately, while software solutions usually have commercialization potential, algorithms alone do not. In order to take our robot-learning algorithm and relate it to a commercial application, we had to decide what form that application should take and how to take such a product to market. One option was to simply license out our algorithm for others to utilize; we would receive royalties as a result of these sold licenses, and companies could make products or provide services using our algorithm. One major caveat, though, is that our algorithm incorporates ideas presented in externally-published research, so the intellectual property for this method may not lie entirely with us. We therefore chose not to investigate this option any further. Our next option to consider was to sell a software solution for users to install on devices that they already own. However, the “device” in this case would be a full-fledged robot, where, as a point of reference, a Baxter robot from Rethink Robotics – our current hardware-platform of choice – has a set price of approximately $35,000 (Rethink Robotics, 2015). Clearly, it would be ludicrous for people to purchase such costly technology without ensuring that it already comes with the necessary software to function. This left us with our final choice: a “full package”, in which we offer a robotic apparatus preloaded and set up with our software such that a consumer only needs to buy one product, with installation services if necessary. This way, we can market our product directly to our target consumers and eliminate the customer’s barrier-to-purchase that comes from setting up the technology. Thus, we decided on this “full package” as the form for our product: a physical robot bundled with software algorithms that we implement.

We must consider several factors with the decision to market this “full package”. The first is price, and this is largely influenced by the suppliers since we must obtain the proper robotic hardware or components externally. After all, according to an IBISWorld report, the cost of mechanical manufacturing is increasing as the expenditure of raw materials increases, so we opt to purchase a whole robot setup instead of building our own robot from basic components (Crompton, 2014:25). As a result, we would look to Rethink Robotics as a supplier of our Baxter robot, a hardware platform. With a markup from our software and services, selling our product at around $40,000, or at about a 15% markup, is not an unreasonable price point – especially if we were to get an Original Equipment Manufacturer (OEM) discount for Baxter. This provides us with a defined pricing model.

Lastly, we must discuss promotion and place/distribution. As O'Donnell points out, 50% of seniors are not using the internet, so marketing is better achieved through conventional channels such as mail, television, and newspapers (O'Donnell, 2015). Interestingly, O'Donnell also predicts an increased use of social media by seniors in 2020, making social-media campaigns a possibility in the near future (O'Donnell, 2015). Distribution of this product, however, is complicated; while we would like to be able to sell our product online, providing setup services would require a trained professional to be present. As such, we will most likely have to either distribute through local partners that provide such services or create a local presence ourselves, incurring additional costs. With our product, price, promotion, and place now defined, we have all the significant facets of a commercialization strategy. Note that we do not analyze the minimum viable product (MVP) in detail. This is because our research specifically investigates the Baxter robot's ability to learn the task of assembling a coffee table, at which point we will have a decent MVP that performs table assembly. Thus, we have established a viable (if hypothetical) commercialization strategy for our research efforts.

2.2 Competitive Forces Analysis

2.2.1 Power of Buyers

With the market and product definition out of the way, we can begin to evaluate Porter's five forces, the first of which is the power of buyers (Porter, 2008). We deduce this force to be relatively weak, since the large population of potential buyers means that individual buyers do not have much leverage or bargaining power with us in our product offering. Moreover, as we will address later on, there are few – if any – direct rivals in our industry. Thus, a scarcity of competing products only elevates our power, as options are limited for the buyer. Furthermore, the switching costs for complex, robotic solutions would be high; given that the price of these robots with our software would be roughly $40,000, it is not an expense to be made frequently. We imagine that a typical customer will only purchase one such robotic system in their life. Thus, it is not of great concern that customers would switch to using a competitor's domestic robot solution after purchasing our product. Overall, the power of buyers is assessed to be fairly weak, and we do not concern ourselves in mitigating this force.

2.2.2 Power of Competitors

Regarding rivalry within our industry, there are two main classifications of competitors: robotics companies and robotics research institutions. Some of these competitors offer products that are mildly similar to our envisioned product, and they also target similar markets. For example, Clearpath Robotics, a robotics company (Hoover's, Inc. "Clearpath Robotics Inc.," n.d.), offers support to the PR2 robot to perform household chores like fetching food from the refrigerator and cooking it. Alternatively, there are research institutions like the Information and Robot Technology Research Initiative (IRT) at the University of Tokyo working on developing software that allows the AR robot to accomplish household assignments such as cleaning floors, washing laundry, and so on. Fortunately, companies and research institutions like these will only indirectly compete with us because our product differs from theirs in the extent that humans are involved. The robotic systems these competitors are developing are meant to be fully autonomous – the robots execute their tasks independent of any human interaction – while our system is meant to be semi-autonomous, enabling a human to both work with and teach a robot to perform various tasks. This is an advantageously superior method because now the scope of the system is not limited to what the robot can accomplish independently; the scope is broadened to what the robot and human can accomplish together synergistically. Simply put, the generality of our method enhances a robot's utility and flexibility. Apart from offering a unique product though, we also have some advantages over our competitors in terms of hardware costs. To illustrate, a two-arm PR2 robot is priced around $400,000 (Owano, 2011) while a Baxter robot, as mentioned previously, is priced around only $35,000 (Rethink Robotics, 2015), a relatively far-cheaper option. To summarize, since we are working in a fairly new field, there are no true established rivals in this specific area yet. Thus, we can conclude that the force of competitors is weak.

2.2.3 Power of Substitutes

Moving onto the next force listed by Porter, we realize that significant attention needs to be given to the force of substitutes since there are, broadly speaking, quite a number of substitutes to our product. For instance, alternative technologies, like the iRobot Roomba (Biesada, n.d.) – a popular floor cleaning robot, have existed in the consumer market for many years, and these established technologies have a large customer base. Customers are more comfortable with familiar products, so it will not be easy to encourage customers to migrate to a substitute product. Moreover, if we look past the technological substitutes, there are a variety of human-labor alternatives in regards to accomplishing household tasks, such as employing a live-in caretaker or residing in a nursing home. However, similar to our stance against the competitor force, we again have some advantages due to our functionality and low cost. Addressing the concern of alternative technologies, even though products like the iRobot Roomba are popular and functional, they tend to have a limited set of features, such as floor cleaning. Our product, on the other hand, is a more general solution which can be used to tackle a variety of household chores. Along that same line, for many tasks in this set, our robot can be more efficient than a human caretaker due to its autonomous nature. Furthermore, as mentioned previously, our pricing model markets our product at a cost of about $40,000 with an extensive lifespan, while most nursing homes cost up to $80,000 – and that is per year (Ellis, 2013). All of these arguments make our product competitive to existing substitutes, motivating us to divert attention from this force and concentrate on more pressing ones.

2.2.4 Power of New Entrants

In contrast to the mild nature of the forces mentioned previously, new-entrant competition looming over the horizon should be of great concern. For instance, some of the heavy-hitters in robotic research include companies like Clearpath Robotics (McMillan, 2015) and 3D Robotics (Bi, 2015), both of which were founded only six years ago in 2009. It seems that, unlike the issue of existing rivals and possible substitutes, there is indeed a strong force in regards to new entrants. To further illustrate this fact, large corporations with broader goals in the technological field can certainly seep into our industry, such as Amazon with its Amazon Prime Air drones or Google with its autonomous cars. Big players such as these would certainly have the resources to quickly create a new division within their company and fund research in alternative robotic avenues. Furthermore, even our suppliers can be considered possible new entrants, since they both already posses their own hardware and can additionally reverse-engineer our software algorithm that was, in large-part, acquired from public research papers. To summarize then, we see that dangerous incoming players in this industry are: either startups or big companies with other additional focuses, or suppliers that provide our hardware. When combined with the fact that there are no true established rivals yet as mentioned previously, this danger reinforces both the notion that robotics is a relatively new field and that the threat of new entrants is high.

2.2.5 Power of Suppliers

The last of Porter's five forces to address is the threat of suppliers (Porter, 2008). This threat is a complex point that requires careful analysis in our business strategy. To first clarify, we envision robotic-hardware-platform manufacturers as our suppliers. As per our product description, we would take the robotic hardware platforms from companies like Rethink Robotics and Universal Robotics, customize the robots with our specialized software that gives them practical intelligence to work alongside humans, and then sell them to customers. In particular, we would purchase from companies that produce innovative, low-cost robotic hardware platforms upon which we can then build our solution. Our smart software would make up for the inaccuracies in the cheaper hardware with better algorithms and human-in-the-loop collaboration. Since there are currently only a few firms producing such low-cost platforms, these few suppliers have high bargaining power, as we are left with fewer alternate firms from which to choose.

2.3 Market Strategy

We see that presently, of Porter's five forces, both new entrants and existing suppliers hold the most power (Porter, 2008). Knowing this, we can establish our market strategy to mitigate these two forces, strategically positioning ourselves in a superior situation.

To mitigate the threat of new entrants from the suppliers themselves (see Section 2.2.4), we can generalize our software to work across multiple platforms and disincentivize suppliers to enter the market, as they would only be encouraged to produce software across their own single platform. Additionally, to discourage new and small startups from forming, we can both establish strong relationships with suppliers to gain a leg up on others looking to pursue our method of utilizing existing hardware and maintain a high fixed cost – such as a high R&D cost by developing more proprietary algorithms – to deter incomers that have a small amount of seed funding. Finally, we can address the threat of entry from large corporations by realizing that these companies have more overarching goals, so focus on their robotics branch will not be as heavy as on their other branches. As such, we can capture a niche market to detour focus and attention away from us. Fortunately, we have already positioned ourselves in such a situation, in which we target a niche group of customers – the elderly and the disabled. As a result, we see that our competitive landscape as it applies to new entrants can be classified as quite aggressive, but there are indeed routes we can take to dodge much of this aggression.

To mitigate the issue of being locked into a single supplier (see Section 2.2.5), the core strategy is still to generalize our software. This would considerably increase our power, since we would no longer be dependent on any one supplier. Note that as a trend, robotics startups are becoming increasingly common (Tobe, 2013), and we thus anticipate more suppliers coming into the market in the future. As of right now though, suppliers are a strong force that must be considered carefully in our strategy, and we must route efforts to ease this force.

2.4 Market Trends

With an evaluation of competitive forces complete, we end with a discussion of the major trends that influence our project strategy. Aside from the trends of both the changing age demographic of the US – affecting the power of both buyers and substitutes – and the increased interest in the robotic industry – affecting the power of both substitutes and new entrants, another trend to consider is the recent advancement in integrated circuit (IC) technology that has resulted in improved computing performance and reduced cost, resulting in reduced barriers-to-entry and thus further enhancing the threat of new entrants. IC technology has seen consistent improvements in computing power and consistent reductions in cost since their inception. Our industry is directly affected by these advancements; in recent years, more powerful computational devices have generated more robotic technology in the household arena, for engineers are allowed to easily incorporate computing power into the chassis of the robot. This design contrasts with industrial robots, where the computational power is often located in an external computer. The trend is summarized with a concept known as Moore’s law, stating that the computational power of the average IC doubles nearly every two years. This trend has been relatively consistent since the early history of ICs. However, there is disagreement among analysts about how much longer this trend will continue (Hoover’s, Inc. “Home Health Care Services.,” n.d.). The trend has the effect of making our products more functionally efficient and versatile, which reduces the power of substitutes. However, the lower cost of computing technology also reduces the barriers-to-entry in the industry, which increases the power of rivals. Only time will reveal the overall impact that this trend will have.

To summarize, from our strategy analysis, we have deduced that while some competitive forces are certainly in our favor, a few forces bring cause-for-concern and need to be addressed. With adequate industry analysis, we can plan our strategy in order to leverage ourselves into a better position within the market. Summarizing our findings, we have identified within the market both the power of new entrants and the power of suppliers to be strong forces. Consequently, to dampen these threats, we would generalize our software to work across multiple platforms, disincentivizing suppliers from entering the market as well as taking away supplier bargaining power. We would also encourage people to use our product instead of substitutes by having features and functionality that other products do not, at a price point that is not prohibitively expensive.

3 IP STRATEGY

(Authors: Schweigert, Srinivasan, Sun, Su, Jouppi)

Aside from a business standpoint though, we must also consider which legal avenues to take in order to protect our intellectual property (IP): in particular, whether or not our idea is patentable. After all, in many research scenarios such as ours, a patent is the most feasible way to safeguard any IP that is developed. Unfortunately, as this section will argue, patenting our work may not be the most practical path to pursue; however, we do have an alternative strategy better suited to our purposes, in the form of copyright.

We feel that in our more specific situation, the costs of attempting to obtain and enforce a patent far outweigh the benefits, for a number of reasons. One consideration is that the mathematics behind the algorithms we employ are pulled from published research papers, particularly those that deal with robot learning-by-demonstration (Billard et al., 2008). Therefore, the proprietary essence of such research is not ours to claim. By the same token, we cannot patent the ROS (Robot Operating System) software platform upon which we develop because it is open-source and thus, once again, publically available. Most importantly, we do not feel that it is pragmatic to patent the software code itself. This is because software, at its core, is the manifestation of logical deductions, and another group or individual may take a different route of logical deductions to arrive at the same conclusion. Following this train of thought, it is ordinarily quite difficult to obtain and/or protect a patent when the end result can be reached in various ways. As explained by Anthony Klein, an IP attorney at Latham & Watkins LLP, pure software patents remain controversial since “what would constitute patentable subject matter is unclear” (Klein, 2015).

Before investigating an alternative means at protecting our ideas however, it is important that we have the foresight to research whether existing patents overlap with our results. We discovered that the closest patent to our project is entitled: “Method and system for training a robot using human-assisted task demonstration” (Bajaras, 2014). It describes a system for humans to train robots for pick-and-place tasks by moving the robot’s arm while recording trajectory-and-perception data through the robot’s sensory systems. At first glance, it may appear that our project directly infringes upon this patent. However, after delving into the details, this is not the case due to the limited scope of this patent. To give some background on the nature of patents, a patent consists of independent claims and dependent claims; if one does not violate the independent claims, then by definition, one does not violate the dependent claims (Brown & Michaels, PC 2006). Now, many of our project’s similarities with this patent lie in the dependent claims. However, if we can argue that our capstone project does not infringe upon any of the independent claims, then we can legally claim that we do not infringe upon the dependent claims as well – and thus the patent as a whole.

There are two independent claims mentioned in this patent. To quote the first independent claim (claim 1):

> A method for training a robot to execute a robotic task in a work environment, the method comprising: moving the robot across its configuration space … assigning, via the ECU, virtual deictic markers to the detected perceptual features (Bajaras, 2014).

We argue that we do not infringe this claim because our project does not use “virtual deictic markers” – markers are based on a representational paradigm that use “selective attention and pointers … to learn and reason about rich complex environments” (Ravindran, 2007). As for the second independent patent claim (claim 2):

> The method of claim 1, wherein moving the robot across its configuration space includes moving at least one of a robot arm and a robot manipulator attached to the robot arm (Bajaras, 2014).

Our project does not use a single “arm and a manipulator”, but rather a dual-armed Baxter-robot. Hence, our project does not violate any of the independent claims and thus none of the dependent claims. Therefore, while this is the closest patent to our idea, we do not infringe upon it and are therefore not required to license from it. Since other existing patents are even less related, a breach of IP is of no worry to us.

With the threat of similar, existing IP out of the way, we can now begin to pursue an alternative strategy of IP protection. After much consideration, we believe that copyright is the most appropriate option – in fact, this happens to be the choice for many software companies. Of course, copyright does indeed present a few risks since, in general, patents protect ideas while copyright only protects the expressions of ideas.

The first risk is the risk of knock-offs: there are ways around copyright such that people can make products very similar to ours but are not in violation of copyright law. This includes implementing our algorithm through a different tactic – one example is converting our code to a different programming language – as well as merely adapting functions from our program. The point is that copyright does not protect our ideas, making it incredibly easy for others to take our ideas and tweak them to look slightly different in their end product. We would need to mitigate this issue by implementing our algorithm across multiple programming languages to prevent the scenarios where someone claims credit on our ideas based on simple modifications.

The second risk is the risk of undetected duplication. It is the first risk in reverse, where certain competitors are indeed copying our code directly, but we have no way of detecting that they are doing so. The reason for this is that we will generally not have the source code of our competitors to compare to our own; all we will have is the compiled functionality that their code is capable of demonstrating. In that sense, it is near impossible to identify specifically if they have violated copyright. Consequently, it is quite difficult to mitigate this risk.

While copyright does offer less protection than patents, it is nonetheless more feasible and realistic to acquire. For instance, copyright is granted automatically when an original work is created, so registration is not required. This simplified procedure immediately eliminates the time and money that we would otherwise need to spend to obtain a patent. Moreover, the duration of copyright is the life of the author(s) plus 70 years, which is plenty of time for us given the short life cycle of software. Furthermore, copyright offers authors the exclusive rights to reproduction, protects against public displays and derivatives of their work, and establishes a public credibility that can attract investment and customers. Licensing can also present itself as a way to increase profit and expand a business.

To conclude, it appears that pursuing a patent is not the route for us to go. Instead, a more practical approach at protecting our IP is for us to pursue copyright, due to both the more lenient restrictions and more efficient timeline at obtaining copyright.

4 SYSTEM WORKFLOW

(Authors: Schweigert, Srinivasan, Sun, Su, Jouppi)

Shifting gears now to the technical details of our capstone project, let us clarify once more that we developed a general-purpose robotic system that incorporates robot-human interactions. Yet it is difficult to implement generality without first implementing and testing lower-level components. Therefore, as a stepping stone for a starting point, we defined a specific task that we aimed to accomplish: having Baxter assembling a coffee table with the help of human. (Figure 1 shows the workflow of this system.) Having such an aim allowed us to physically manifest an implementation and test of our system.

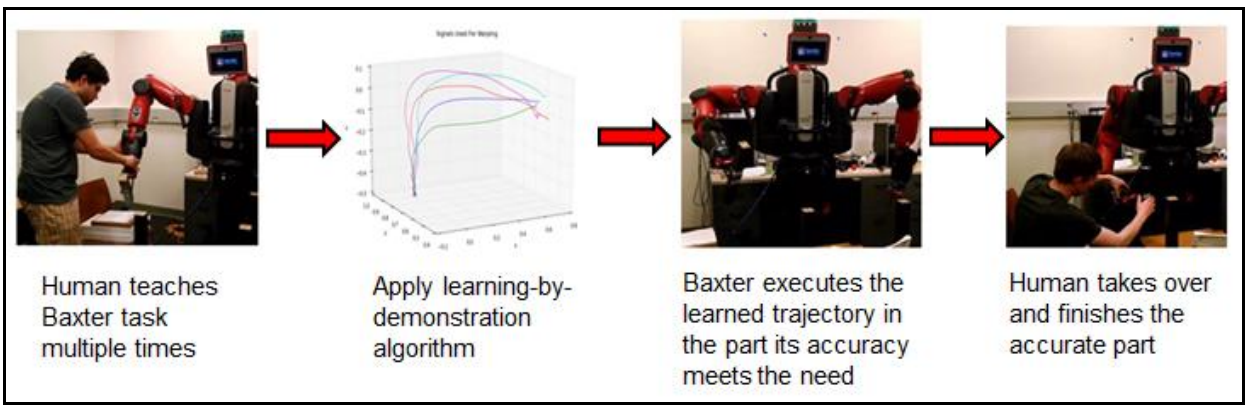

Figure 1: Workflow of System Process

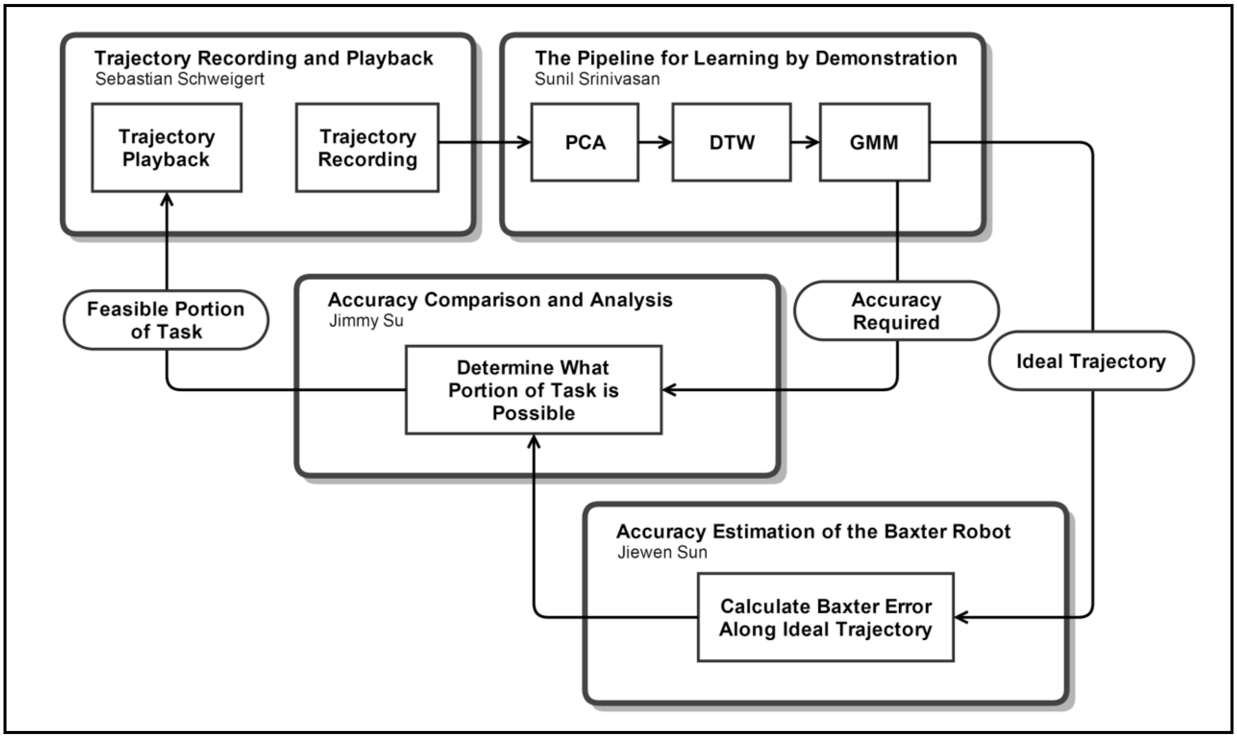

Figure 2: Paper Organization

5 TECHNICAL CONTRIBUTIONS

(Author: Su)

5.1 Overview

Our capstone team created a system that improves the accuracy of a robotic unit. In pursuing a software-related route, we achieved this by optimizing the algorithms that such a robotic unit would employ, in contrast to a more hardware-related pursuit at attempting to fix the robot's inherent mechanical inaccuracies. The fundamental concept is the design of a collaborative system between a human and a robot to accomplish a task: a synergistic combination of man and machine. It is meant to unify the robot's macro-accuracies of large-scale and efficient performance with the human's micro-accuracies of evaluative and finer detail.

Economically, by adding a human into the loop, it becomes more practical to use these low-cost robotic solutions as opposed to their fully-autonomous counterparts.

In endeavoring to accomplish this goal, we deduced that the robot needed to be able to perform a versatile array of tasks, setting the standard for our requirement of a learning algorithm: *learning-by-demonstration* (Srinivasan 2015). This methodology has the human demonstrate to a robot a given task in multiple scenarios, from which the algorithm can extrapolate a generalized solution to the task. Ideally, this learning can be applied to any task, within reason.

Where there is analysis though, there must first come data, prompting the *trajectory recording and playback* (Schweigert 2015) feature that our team implemented. This component was the initial data-gathering process as well as the final data-execution process. All sorts of information was retrieved here in the preliminary stages, including, but not limited to: the joint angles in a robot arm at any configuration, the trajectory that the end-effector (the hand/gripper of the robot) follows, and the time step at each configuration.

Next, once our robot had learned the task, we had to realize that this prior learning was human-assisted and thus that the robot's self-execution was still prone to inaccuracy. This understanding paved the way for the next component of our project: *accuracy-parameterization* (Sun 2015). Accuracy-parameterization allows the robot to determine the portions of the task where it has insufficient accuracy and must subsequently request assistance from the human partner.

The focus of this paper is on the process that was taken to merge the independent components of learning-by-demonstration and accuracy-parameterization. In other words, the overview of this work involves taking theoretical results that have been deduced from experimental learning and comparing the amount of accuracy that a robot needs for a task versus the amount of accuracy that a robot actually has for the task. (See Figure 2 as a reference.) Consequently, if the domain of accuracy that the robot possesses is insufficient, the robot will be unable to guarantee task completion.

5.2 Literature Review

Before diving into what we have built, it is important to first reflect upon the significant contributions that other teams and individuals have accomplished in making our efforts possible.

The work outlined in this paper has roots in the learning-by-demonstration process, an algorithm that has been formally solved (Calinon 2007) and replicated (Billard 2008). The process involves taking trajectory data and running it through a sequence of steps:

1. *Principal Component Analysis (PCA)*: reduce the dimensionality of the data, primarily for the purpose of easier mathematical calculations of uncorrelated data – the dimensionality is then readjusted at the end step once the calculations are complete
2. *Dynamic Time Warping (DTW)*: match the time steps and time intervals of the data in order to synchronize the data to be measured
3. *Gaussian Mixture Modelling (GMM)*: compute an average "learning" trajectory that outputs a mean and standard deviation in Cartesian space at each point along that trajectory, where the standard deviation represents a frequency of the end-effector needing to be at a particular position – **this is our measure of *desired accuracy***

Likewise, our work branched from existing layouts of accuracy-parameterization (Conrad 2000), which accounted for multiple factors such as the mechanical tolerances in joints. Note that by mechanical tolerance, we mean the extent to which a robotic joint can "wiggle": the sturdier the robot, the less it is prone to "wiggle", and thus the lower the tolerance. Taking this one step further, if this process of accuracy-parameterization analyzes input data that defines the robot, then it must output **our measure of *characteristic accuracy*** – the amount of accuracy that our robot of choice currently possesses.

As an aside, *characteristic accuracy* is incredibly beneficial for future analysis, based on the issue of inherent inaccuracies in a robot that may not be feasible overcome, despite one's best efforts at designing efficient software. After all, given the difficulty at reducing robotic tolerances in manufacturing, costs escalate exponentially with higher constraints on tolerance. As Conrad puts it, "High accuracy is the most difficult [parameter] to accomplish" (Conrad 2000).

Speaking from a high-level perspective then, the measurement of accuracy is vital to the future success of robotics because, for some tasks, the outcome of either success and failure gambles on the deviations in accuracy based on tolerance.

5.3 Methods and Design

5.3.1 Materials

Up until this point, the pretense has been that we are composing a universal system that is ready-to-go on any given robot. In reality however, each robotic system has its own nuances, and there does indeed need to be some customization when dealing with different robots. Expanding upon this point then, for our research purposes, we worked with the Baxter robot produced by Rethink Robotics (Rethink Robotics 2015). Figure 3 shows an image of this robot, which is 6'3" with a pedestal (Rethink Robotics 2015). Baxter is pre-designed and commercially available, providing a fantastic hardware base upon which we built our algorithmic solution. To us, the major attractions were that Baxter comes fully equipped with a prior project database, an online community of experienced individuals, and ROS (Robot Operating System) – an open-source operating system that has public documentation. Moreover, when evaluated against possible substitutes, Baxter was one of the most academically affordable robots on the market, equipped with seven joints in each of his two arms that reliably provided a vast amount of data. Indeed, we have made great strides in implementing both learning-by-demonstration (Srinivasan 2015) and accuracy-parameterization (Sun 2015) on the Baxter robot.

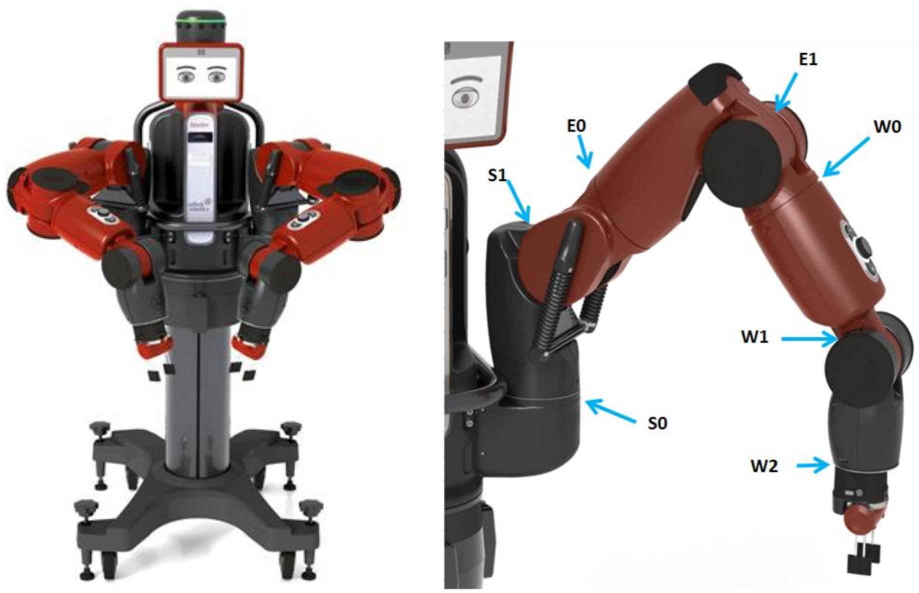

Figure 3: Baxter Robot (Rethink Robotics 2015)

5.3.2 Methods

Our method of choice for comparing our *desired accuracy* versus *characteristic accuracy* was to feed the calculations from the learning-by-demonstration algorithm into the accuracy-parameterization component of our project.

To briefly summarize, the learning-by-demonstration algorithm produces an average trajectory consisting of a set of waypoints in the Cartesian space as well as the standard deviations of those waypoints; this is the output from the Gaussian Mixture Model (Srinivasan 2015). It was important that we employed accuracy-parameterization on the average trajectory that we calculated since it is the “learned” trajectory that Baxter executes. Undoubtedly, it was only logical that we calculated the *characteristic accuracy* along the path that we would realistically follow.

However, there is also an in-between step that we had to first perform. While accuracy-parameterization involves the use of forward kinematics to determine end-effector position from a configuration of joint angles (Sun 2015), we needed to employ the reverse of that method after creating our Gaussian Mixture Model to convert the average trajectories back into joint angles that can be fed into the Jacobian matrix. This mathematical method is known as *inverse kinematics*: a conversion from the Cartesian space to the joint space. (Figure 4 illustrates the distinction between the two spaces as it pertains to a robotic arm.) Inverse kinematics attempts to solve this equation (Equation 1):

$$g_{st}(\theta) = g_d$$

Equation 1: Inverse kinematics equation for a general configuration (Murray 1994)

where g is the configuration of the manipulator, and θ is the set of joint angles where we reach our desired configuration g from our starting configuration. Be aware, though, that g_d scales in complexity with increasing joint angles. For example, for a six-degree-of-freedom manipulator (a robot arm with six joints), Equation 1 expands to:

$$g_{st}(\theta) = e^{\widehat{\xi}_1 \theta_1} \cdots e^{\widehat{\xi}_6 \theta_6} g_{st}(0)$$

Equation 2: Inverse kinematics equation for a six-degree-of-freedom manipulator (Murray 1994)

where $e^{\xi_i \theta_i}$ represents the exponential twist – a value that describes the positional and rotational attributes – at the i-th joint.

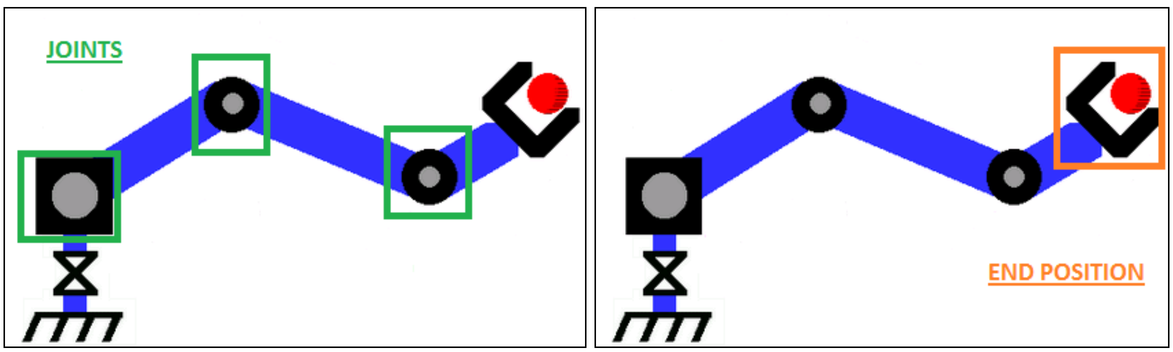

Figure 4: Visualization of robot arm configuration in terms of joint angles (left) or end-effector position in Cartesian space (right)

For reference, the Jacobian is a mathematical construct that assisted in generating our measure of *characteristic accuracy*. In computing this measure, we utilized the Jacobian matrix to account for Baxter's error tolerances with 95% confidence (Sun 2015). However, since the Jacobian matrix takes a set of joint angles – data in the joint space – as inputs, we had an issue due to the fact that our learning-by-demonstration algorithm outputs data as waypoints in Cartesian coordinates. This is why we needed inverse kinematics.

So, to consolidate:

- Data flowed through the learning-by-demonstration algorithm to generate trajectory calculations in Cartesian space, which represented our *desired accuracy*.
- Inverse kinematics converted those calculations from the Cartesian space to the joint space.
- Accuracy-parameterization took the calculations in the joint-space form and outputted our *characteristic accuracy*.

We then finally compared these two quantities to see if Baxter has sufficient accuracy to perform the task at the current configuration.

Be aware that there are two methods of employing the Jacobian. The other alternative to the process that was just summarized was to calculate it on live data coming from the robot. We decided on our method of choice outlined above because the average trajectory is indeed the trajectory we ideally wished to execute, and there would have been less latency if we pre-computed the Jacobian on data from the learning-by-demonstration algorithm rather than on each incoming iterative data point. Note that this is also a separate point from the two methods of calculating the Jacobian – spatial Jacobian and body Jacobian – as outlined by my teammate Jiewen Sun in her paper (Sun 2015).

5.3.3 Design

To cement a specific task for our team to work toward, we considered a variety of ideas, such as having Baxter open a can, pick up trash, put books away on a bookshelf, and sort laundry. Ultimately, we decided on the task of having Baxter build IKEA furniture; more specifically, Baxter was tasked with moving a distant table leg to within proximity of the table surface, then subsequently inserting the peg of the table leg into the appropriate slot in the table. This was the final task-choice since it required a perfect combination of both low-level accuracy (move table leg) and high-level accuracy (put pin in pinhole).

If Baxter had enough accuracy to perform the whole task, then great: the task would have been successfully accomplished without any issue. Unfortunately, this was generally not the case, especially for potions of the task that required more precision than Baxter’s tolerances allowed. We believed that this was likely to be a highly-common scenario given Baxter's status as a low-cost robot. We therefore had to decide what to do when Baxter arrived at a moment where his accuracy was insufficient.

One option, based on our particular task of having Baxter build an IKEA table, involved using haptic guidance: should the robot encounter the high-accuracy scenario at inserting pins into pinholes, the robot would gauge its status based on touch feedback of its current status and adjust motion from there accordingly. In other words, guidance fixtures would be set in place to assist the robot in executing its path (Abbott 2007). This method could possibly bypass the innate-inaccuracy issue mentioned before: if Baxter has too high of a tolerance for the task at hand, then haptic guidance could likely assist in guiding Baxter to degrees of higher accuracy. Regrettably though, this component of our system came at a later stage in our implementation, and time constraints restricted us from exploring this avenue.

Alternatively, if the Baxter robot did not have sufficient accuracy, another approach was to have Baxter stop and request help from the human. In the case of our task at building an IKEA table, if Baxter was too inaccurate to insert a pin into the pinhole, he would stop executing the trajectory and inform the human to take control from there. This method was beneficial in the sense that we minimized the amount of error that a robot exhibits, increasing reliability. After all, it is more dangerous to have false positives – Baxter says he is accurate enough when he is really not – than false negatives – Baxter says he is not accurate enough when he really is. After all, minor positional errors could have produced drastically different results. For instance, if a robot were to pour water from a pitcher into a glass and it does not have enough accuracy but attempts to pour anyways, there is a world of difference between the water ending up in the glass versus possibly ending up on the floor. Furthermore, by adding a human into the loop, many complexities were abstracted away to the human. With no requirement to accomplish the high-precision tasks, the low-cost robot became part of a duality of human-and-robot interaction with high efficiency at accomplishing tasks.

5.4 Results and Discussion

5.4.1 Accuracy Comparison

Though I did contribute in the technical areas of trajectory-recording and accuracy-parameterization, these two areas are more heavily explained in the papers by my teammates: Sebastian Schweigert and Jiewen Sun, respectively. The crux of my work involved unifying these independent components into a single system, where our team was able to achieve meaningful results in a 3-dimensional Cartesian representation: by following our methodology outlined above, both the GMM standard deviations and the Jacobian-tolerance calculations produced data in x-y-z coordinates. Note that from this point onward in the paper, any specific position of the robot arm will be referred to as a *configuration* in this analysis. This means that when Baxter executes his average trajectory, his arm will undergo hundreds of configurations, in a sequential order.

By investigating the results of running a set of recorded trajectories through our accuracy-comparison system, I was able to compare our two types of accuracy. Figure 5 provides an appropriate visualization: we see two isomorphic viewpoints of accuracy measurements at a particular Cartesian configuration. In this configuration, the central blue dot represents the physical location of the end-effector, the green box represents the *characteristic accuracy* – the accuracy constraints that Baxter possesses, and the red box represents the *desired accuracy* – the accuracy that the task requires (see Section 5.3.2). Note that if the green box is ever completely enclosed within the red box, then Baxter's accuracy constraints are tighter than the environment requirements, and Baxter can carry on with proceeding to the next configuration.

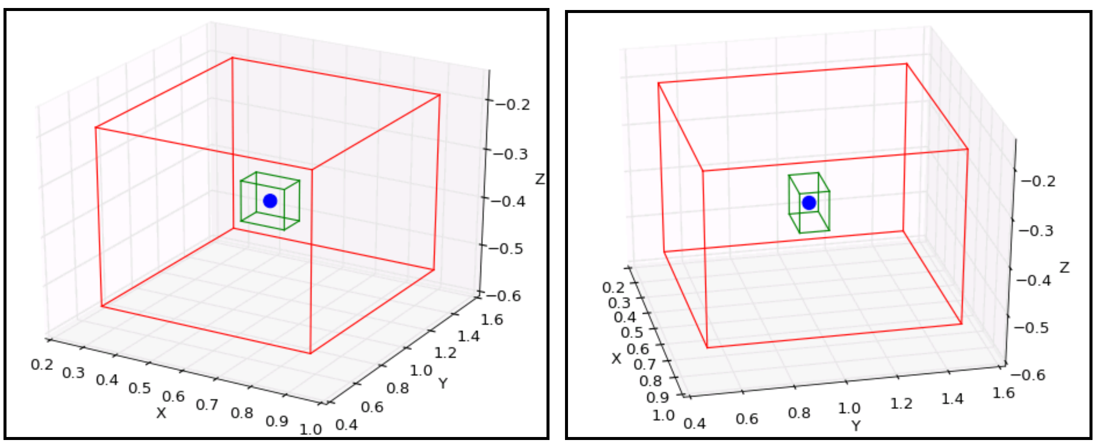

Figure 5: Different isomorphic views of an ***accurate*** *configuration*

In contrast, if the green box ever expands beyond the red box, then our *characteristic accuracy* is too broad for the *desired accuracy*, and Baxter must stop and request assistance from the human. Such a scenario is shown in Figure 6, where the *characteristic accuracy* was not sufficient in the z-direction (we see in the image on the right that the green box vertically extends beyond the confinements of the red box). In other words, this meant that from the coordinate plane of the end-effector perspective, the overall tolerance originating from the tolerance in each of the joint angles can result in the end-effector possibly "wiggling" too much in the z-direction. Consequently, Baxter was not able to guarantee accurate task completion at this stage, and he had to request assistance from the human.

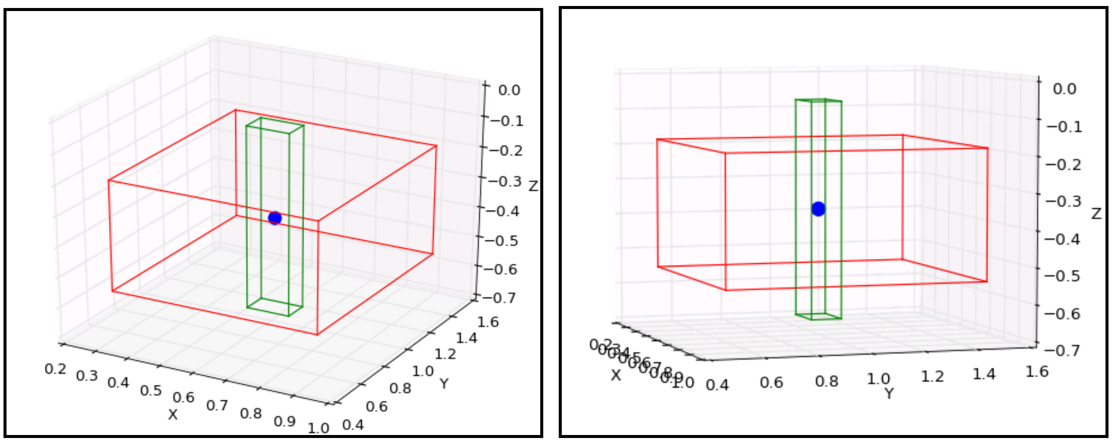

Figure 6: Different isomorphic views of an ***inaccurate*** *configuration*

Remember that these accuracy ranges – visualized as boxes – had been pre-computed for every configuration that Baxter goes through while executing the average trajectory. Thus, the Baxter robot had pre-computed whether it had enough accuracy across all stages in its trajectory, and it asked for assistance when it reached a point where accuracy was insufficient.

5.4.2 Walkthrough

With an understanding of our method now, let us walkthrough the entire process. (See Figure 1 for a visual representation.)

First, the user will train Baxter by guiding it through a task multiple times, all the while recording the configuration in terms of joint angles at sequential time-steps. Our method will then implement forward kinematics to convert those joint angles into Cartesian coordinates. Those coordinates will be fed into the learning-by-demonstration algorithm (DTW and GMM), producing an average "learned" trajectory with standard deviations along the path – *desired accuracy*. That average trajectory will supply the data to the accuracy parameterization model and, using inverse kinematics, will convert those Cartesian coordinates back into joint angles. Accounting for Baxter's inherent joint tolerances, the Jacobian will estimate the accuracy of the end-effector – *characteristic accuracy*. Both of these accuracies will then be compared offline at every configuration along the trajectory, and Baxter will execute the trajectory up to the point where it realizes that it is not accurate enough. (Figure 7 shows a sample execution.)

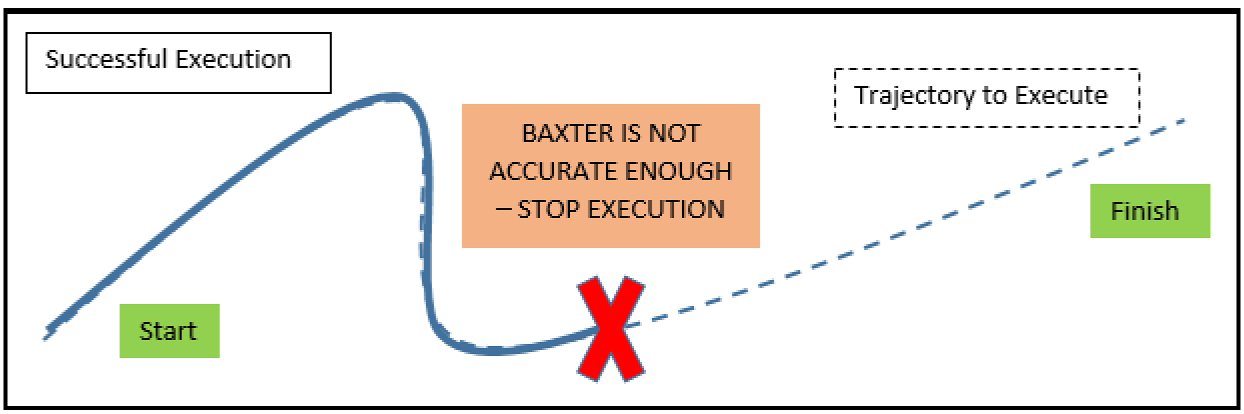

Figure 7: Baxter executes average trajectory path until it detects that it is too inaccurate

5.4.3 Significance

The result is of great significance: here, we are able to say, with high confidence, that when a robot such as Baxter evaluates that it can accurately accomplish a task every time, the robot is guaranteed to do so, assuming the tolerances are input correctly. If the robot is inherently very inaccurate, then this guarantee may be infrequent, but it will be a guarantee nonetheless. Note, then, that when Baxter performs actions that with enough accuracy sometimes but not every time, we will at the moment assess that to mean that Baxter is not accurate enough. Essentially, we currently employ a binary system of 100% accurate or otherwise not accurate enough. This is to prevent false positives – where Baxter falsely deduces that it accurate enough. It can be argued that this method is highly conservative, and future work should attempt to relax the strictness of this constraint.

5.5 Additional Considerations

Now that we have successful simulations, we can also verify our system on more complicated trajectories with more data. In fact, regarding the GMM, more data is better for learning, as the results can be more generalized – similar to how more random samples of a population improves the scope of that experiment.

It is also vital that we extrapolate our work to more data points so that other individuals who want to replicate it in the future will have more references and analyses to look back on. Given that society is irrefutably progressing towards an era of automation, our work has high stakes and significant outcomes. After all, since the limitation of resources is always of concern, any progress at enhancing the potential of cheaper products is certainly a great stride.

6 CONCLUDING REFLECTIONS

(Author: Su)

In comparison to where our capstone team began, we certainly have more clearly defined goals with appropriately modularized portions that were systematically tackled. While it is true that not all features in the original plan were implemented (e.g. haptic guidance), the fundamental motivation of our project, which was to research the possibilities of improving the commercial value of a low-tier robot, was successfully addressed in our research. From a managerial standpoint, a major takeaway is that project management absolutely helped structure our path in achieving our results. By setting goals and milestones right from the start, we were always able to track the progress of our work based on what we had initially proposed. As such, we were able to adapt and get ourselves back on schedule when we noticed that we were not hitting our milestones.

Additionally, project management ensured that our team maintained consistent documentation, allowing us and others to clearly monitor the progress that our team has been making. Moreover though, project management helped ensure that this level of documentation did not significantly impede the research process, by having the project manager remove a large portion of the paperwork responsibilities for the remaining team members. Otherwise, time that would have been spent by those team members on paperwork would have greatly detracted from much of the technical work that they accomplished later on.

Following from that point, if others wish to pick up where we left off, they should retrieve the code that we archived on Github as well as read through the steps that we documented in setting up and running those files. We are incredibly fortunate in the sense that much of our research is software-based, making the transfer of information more convenient through digital means.

All in all, it is evident that this capstone project has come a long way since its inception. We as a team are grateful for all that we have learned, and we anticipate exponentially greater interest in this field as society advances to the future.

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