Multi-Fingered End-Effector Grasp Reflex Modeling for One-Shot Tactile Servoing in Tool Manipulation Tasks

Emily Sheetz[1,2], Misha Savchenko[2], Emma Zemler[2],
Abbas Presswala[2], Andrew Crouch[2], Shaun Azimi[2], and Benjamin Kuipers[1]

***Abstract*— Autonomous tool manipulation tasks are challenging for robots because they must reason over the tool's object affordances, how to grasp the tool so it may be used, how the tool will interact with other objects in the environment, and how to perform the complex tool affordances to complete the manipulation task. Focusing on tool grasping presents further challenges, specifically generalization to novel tools and modeling the problem in an explainable way suitable for safety-critical task domains, such as robots operating autonomously to perform repair tasks in NASA lunar habitats. In this work, we focus on grasping tools in an explainable way that can be generalized to novel tools. We present a logistic regression based *grasp reflex model*, which maps continuous end-effector sensor data to a set of discrete symbolic states. An adjustment policy uses these symbolic states to compute the appropriate gradient to change the end-effector pose and increase the probability of a secure tool grasp. Once the tool grasp is sufficiently secure, the robot proceeds with the rest of the manipulation task. We test our *grasp reflex model* on 6 novel tools, and find that the model achieves one-shot generalization by successfully using tactile servoing to secure grasps from one example of a secure grasp state. The robot's ability to learn to grasp tools in an explainable way that achieves one-shot generalization to novel tools demonstrates the power of our *grasp reflex model* in allowing robots to achieve autonomous tool manipulation tasks.**

I. INTRODUCTION

As robots become more capable and take on more tasks, autonomous tool manipulation will be an important task for robots to accomplish. Not only do we want robots to be able to use tools, but we want robots to be able to generalize their knowledge and apply their learned behaviors to a wide variety of tools without significant retraining. Tool manipulation is of particular interest for robotics since it requires understanding of the tool's object affordances [14], grasping the tool intentionally so it may be used in the subsequent manipulation task, reasoning over object-centric interactions [2], [15] between the tool and other objects, and executing complex tool-use behaviors through composition [33] and sequencing [7] of lower-level actions. In this work, we focus on learning to grasp tools in a way that generalizes to novel tools.

Autonomously grasping tools presents a number of challenges. Data-driven approaches show significant promise, but neural network based algorithms reduce the explainability of the learned model. While these algorithms have proven to generalize well to novel tools, inexplicable black box algorithms cannot be trusted in safety-critical task domains [29], [30]. The challenge we aim to address in this work is how to use a data-driven approach to learn to grasp tools using a *simple explainable model* that *generalizes to grasping novel tools* not present in the training data.

The authors are with the [1]University of Michigan and [2]NASA Johnson Space Center.

Disclaimer: Trade names and trademarks are used in this report for identification only. Their usage does not constitute an official endorsement, either expressed or implied, by the National Aeronautics and Space Administration (NASA).

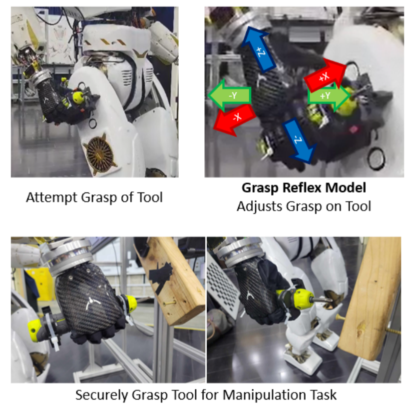


Fig. 1: A robot using a *grasp reflex model* to iteratively adjust its grasp until a secure grasp is achieved.

We take inspiration from a human grasp reflex by allowing the robot to adjust its grasp. As seen in Figure 1, the robot will attempt a grasp on the tool, validate the grasp using sensor data, and adjust the grasp as needed until the tool is securely grasped. By allowing for adjustments to the grasp, we simplify the learned model to map from sensory input to a small set of discrete states that can be adjusted to improve the grasp quality. This approach of adjusting the grasp to increase the probability of a secure grasp is tool-agnostic, and can generalize to unseen tools.

In this paper, we present a logistic regression based ***grasp reflex model*** for multi-fingered end-effectors. Our *grasp reflex model* maps from multi-fingered end-effector sensor data to a set of discrete symbolic states. We use a policy that adjusts the grasp according to the detected symbolic state in order to increase the probability of a secure power grasp. Once the robot is reasonably confident the grasp around the tool is secure, it proceeds with the rest of the tool manipulation task. In constructing our *grasp reflex model*, logistic regression analysis identified statistically significant interactions between tool-agnostic model variables. We test the generalization of our model on a set of 6 novel tools, and find that our *grasp reflex model* achieves one-shot tactile servoing on these tools with a success rate of about 0.73. This success rate indicates that the *grasp reflex model* accurately captures grasping relationships for tools similar to the tool used for training, but may not sufficiently secure grasps on tools that are significantly different in size, shape, or weight from the training tool. Our work in multi-fingered end-effector grasp reflex modeling for one-shot tactile servoing demonstrates the power of training a simple explainable *grasp reflex model* that generalizes to novel tools and furthers robots' capabilities of autonomously performing tool manipulation tasks.

II. RELATED WORK

A. Grasping in Object Manipulation Tasks

Robot grasping aims to restrain and manipulate objects, and comes with unique challenges of controlling an end-effector while achieving contacts with and applying forces to objects [5]. Many works have explored solving the problem of robot grasping. Approaches to grasping are analytic (geometric) or data-driven (empirical); model-based (which often involves pose estimation of known objects) or model-free (which aims for generalized grasps on novel objects) [19]; and discriminative (probabilistically ranking grasp candidates) [38], generative (generating grasp candidates) [41], or hybrid (combining modeling and learning techniques) [25]. Robot grasping can be performed autonomously, with real-time teleoperation from a human operator, or with autonomous assistance to the operator [20]. Grasping is highly dependent on the robot hardware, as gripper designs support different grasp configurations and affect how the robot will interact with objects [6], [10], [11], [1].

Grasping for tool manipulation tasks presents several unique challenges. Tool manipulation tasks require manipulation-oriented grasps [40], in which tools are grasped for use in further manipulation tasks [12]. Tool grasp requirements constrain grasping tasks such that finding optimal grasps can be formulated as a search problem [40]. We take inspiration from searching for grasps [40] by testing and verifying successful tool grasps with sensory feedback [17].

B. Tactile Servoing

Because we expect the robot to try tool grasps and verify the grasp based on sensor data, we considered *tactile servoing* methods. A counterpart to visual servoing, tactile servoing uses data from tactile or contact sensors to control a robot [24]. Tactile servoing is essential for autonomous dexterous manipulation and in-hand manipulation. Since tactile servoing methods utilize the abundant sensory signals from arrays of tactile contact sensors to estimate contacts and forces between end-effectors and objects, these approaches typically rely on multi-fingered robot hands as opposed to grippers in order to provide more sensory information [18].

Many works explore the variety of control tasks that can be achieved through tactile servoing [39], [23]. Visual and tactile servoing can often work together, with vision information improving tactile servoing methods and tactile information improving visual servoing methods [8]. For example, exploratory tactile servoing or active touch can be applied to identifying object shapes through active perception [21]. Combining visual and tactile feedback has also been explored for tool grasping and manipulation tasks [17].

Since tactile servoing methods typically rely on large amounts of data from tactile sensor arrays, many works utilize data-driven machine learning approaches. Several works utilize algorithms such as convolutional neural networks [45], deep learning neural networks [22], or offline neural network based learning [42]. While these algorithms have proven effective, these black box models reduce explainability, which can be problematic for safety-critical problem domains [29], [30]. In this work, we take inspiration from data-driven learning from demonstration approaches [42] but aim to process our sensor data using a more explainable model for use in safety-critical applications.

C. Human-Inspired Grasp Reflex

The human grasp reflex has been well studied in developmental psychology. In newborn humans, the palmar reflex is an involuntary response in which babies close their fingers around an object when the palm is touched. This reflex disappears at a young age when babies are able to voluntarily use their hands and grasp objects [13], [27].

Since tactile servoing often relies on multi-fingered robot end-effectors, many works turn to biologically-inspired and human-inspired multi-fingered grasps. To mimic the vast amount of sensory information provided by human hands, some works outfit robot hands with large arrays of tactile contact sensors [28]. Many works explore training robot end-effectors to mimic human grasp reflexes to assist people who use prosthetic hands [37] and aid people in recovering from paralysis through robotic rehabilitation [31].

Several works take biological inspiration for the algorithms themselves. For example, one work takes inspiration from human grasps and assumes uniform contact between all fingers and the object is required for a secure grasp [26] rather than exploring the true model of the robot grasp. Tomovic *et al.* [44] attempt to geometrically model the object being grasped using a number of geometric primitives in order to simplify a human-inspired generalized grasp. Deckers *et al.* [9] demonstrate that robots can learn to grasp objects based on proprioceptive information from a gripper using reinforcement learning. Another work models a grasp reflex using biological neuron models [3] as opposed to the artificial neuron models in neural networks. Tieck *et al.* [43] propose a biologically-inspired spiking neural network, which achieves one-shot learning on sphere, cylinder, and pinch grasp primitives. While these works demonstrate the power of biologically-inspired algorithms, we aim to explore simpler more explainable algorithms for a human-inspired robotic grasp reflex.

Rather than imitating biological systems, *artificial reflex control (ARC)* aims to create an analogous approach [4], resulting in a simpler more explainable reflex model. ARCs analyze sensory data to learn patterns of response. ARCs emphasize the importance of responding to sensory information, and map sensory patterns to appropriate joint states to create the reflex behavior [4]. He *et al.* [16] apply ARCs to demonstrate an open/close gripper reflex that responds to pressure, similar to a human baby's pressure-based grasp reflex. We take inspiration from ARC principles and aim to apply ARCs to more complex tool manipulation tasks. We also aim to learn the mapping function from sensory inputs to joint states to reduce knowledge engineering and hand-written rules required in past ARC implementations [4].

III. METHODS

A. Problem Formulation

To perform tool manipulation tasks, the robot must first securely grasp the tool. We aim to model a grasp reflex that guides the robot's fingered end-effector to achieve a secure grasp. Due to uncertain nondeterministic robot motion, we expect the robot to attempt a grasp, detect the state of the fingered end-effector relative to the tool, and adjust the relative poses and configurations until the grasp is secure.

The end-effector state at time t is represented by the end-effector pose $\mathbf{x}_t \in SE(3)$ and the end-effector joint configuration $\mathbf{q}_t \in C$ for configuration space C. We assume we have a set of actions $A = \{a_1, \cdots, a_n\}$ such that each action represents a translational or rotational control adjustment along one of the end-effector basis directions. At time t, we aim to express the continuous end-effector state $\mathbf{x}_t, \mathbf{q}_t$ as a discrete symbolic state s_t. The symbolic states $s_i \in S$ are defined as the prerequisite states for the actions $a_i \in A$, such that each symbolic state represents a disjoint region of the continuous state space, indicating the appropriate grasp adjustment action. Once the symbolic state s_t is identified, the robot can adjust its grasp on the tool using the policy $\pi : S \rightarrow A$, where $\pi(s_i) = a_i$ for all $1 \leq i \leq n$. After making a sequence of adjustment actions $a_1, \cdots, a_t$, the robot will have secured a grasp on the tool when the predicted probability of a secure grasp in the current state is above probability threshold p^*. The robot has achieved a secure grasp at time t when $\hat{P}(s_t = s_{\text{secure\_grasp}}) > p^*$.

B. Problem Statement

The goal of our work is to model the unknown function f that maps end-effector information $\mathbf{x}_t, \mathbf{q}_t$ and a reference secure grasp configuration $\mathbf{q}^* \in C$ for the tool being grasped to one of the symbolic states $s_i \in S$ with known adjustment actions $a_i \in A$. In particular, we need to learn the function $f : SE(3) \times C \times C \rightarrow \mathbb{R}^n$, which maps end-effector state information and a reference secure grasp configuration to the *probability predictions* for each symbolic state. Let

$$f(\mathbf{x}_t, \mathbf{q}_t, \mathbf{q}^*) = \mathbf{v}_t = \begin{bmatrix} v_{t,1} \\ \vdots \\ v_{t,n} \end{bmatrix} = \begin{bmatrix} \hat{P}_t(s_1) \\ \vdots \\ \hat{P}_t(s_n) \end{bmatrix} \quad (1)$$

where the elements of output vector $\mathbf{v}_t$ give probability predictions for symbolic states $s_1, \cdots, s_n$. The model f classifies end-effector state information at time t into symbolic states as

$$s_t = \arg\max(\mathbf{v}_t) = \underset{1 \leq j \leq n}{\arg\max}(v_{t,j}) \quad (2)$$

which selects the state with the greatest predicted probability. This state classification s_t is fed into the policy to determine the adjustment action $a_t = \pi(s_t)$. The grasp is secured when the model f predicts the probability for state $s_{\text{secure\_grasp}}$ is above probability threshold p^*. Let $s_j = s_{\text{secure\_grasp}}$ for some $1 \leq j \leq n$ and $v_{t,j}$ be the predicted probability of state s_j at time t, as seen in Equation 1. The robot's grasp is secure at time t when $v_{t,j} = \hat{P}_t(s_j) = \hat{P}_t(s_{\text{secure\_grasp}}) > p^*$.

C. Grasp Reflex Model

We propose a *grasp reflex model*, which models function $\mathbf{v}_t = f(\mathbf{x}_t, \mathbf{q}_t, \mathbf{q}^*)$ in Equation 1 as a *logistic regression model*. For some reference tool, a reference secure grasp joint configuration $\mathbf{q}^*$ should be recorded, either with assistance from a human operator or learned from experience. The n basis adjustment actions and corresponding symbolic states will be defined for the robot's fingered end-effector. The definitions used for our implementation are described in Section IV-A. To train the *grasp reflex model*, data must be collected demonstrating examples of each of the n symbolic states, possibly hand labeled through teleoperation of the robot. For each example, end-effector pose and configuration information should be recorded for the best modeling.

Performing a logistic regression analysis on all collected variables as well as interactions between variables will identify which proprioceptive sensor data is most relevant to identifying the symbolic states for the fingered end-effector. Once statistically significant variables are identified, the final *grasp reflex model* can be trained and validated.

Note that validation accuracy of the *grasp reflex model* will quantitatively evaluate the model's accuracy in predicting the symbolic states according to the hand labeled training data, and will only give a small indication of the performance. Full evaluation is determined when the *grasp reflex model* is deployed on the robot and used to direct the robot to secure grasps on different tools, as described in Section IV-C.

IV. EXPERIMENTS AND RESULTS

We aimed to model the grasp reflex for a PSYONIC Ability Hand [34], [35] mounted on NASA Johnson Space Center's Valkyrie robot [36]. The PSYONIC hand has 6 joints: one for each of the 4 fingers and 2 in the thumb (roll and pitch). We wanted Valkyrie to carry tools onboard, so Valkyrie was outfitted with a tool holster on its right hip. Since the tool holster is rigidly attached to the robot's hip, it was added to the robot model, described in the Unified Robot Description Format (URDF) [32]. The holster's pose was used as the initial guess for all autonomous grasp attempts, but the actual pose of the tool is not known. Due to uncertainty and nondeterminism in the robot motion, the robot needs to use tactile servoing to adjust its grasp from this initial guess. Figure 2 shows our experimental setup.

Fig. 2: NASA Johnson Space Center's Valkyrie robot (left) with the PSYONIC Ability Hand mounted (center) and a tool holster on the right hip (right).

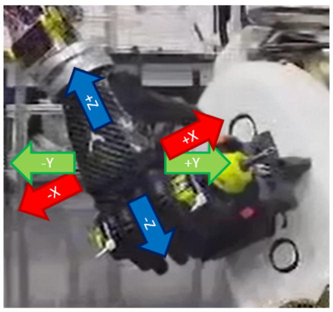


Fig. 3: The action space is defined by small translational offsets along each of the end-effector x, y, z basis directions.

A. Action and State Space Definitions

1) Basis Adjustment Actions: The fingers of the PSYONIC hand are strong enough that small rotational offsets did not affect the success of the grasp. If the hand's rotation varied slightly from the rotation of the tool, the fingers pulled the hand's rotation into alignment with the tool when it attempted a grasp. For this reason, we considered only positive and negative translational offsets along the end-effector x, y, z basis directions for our action space, as seen in Figure 3. Each translational offset corresponds to an adjustment δ of the end-effector pose $\mathbf{x}_t$ along one of the basis directions. For our implementation, we used $\delta = 0.03$ meters along the basis directions. We found that this offset resulted in small enough adjustments as to not overshoot a secure grasp, which could lead to a local minimum when searching for a secure grasp.

2) Symbolic States: Each action in the action space corresponds to a symbolic state that will be identified based on our *grasp reflex model* prediction as in Equation 2. These symbolic states indicate the pose of the end-effector relative to the tool being grasped. We refer to these symbolic states using intuitive colloquial terms, for example "too far" or "too high". We also found it useful to denote different secure states, for example when the thumb is securely grasping the tool, when 2 or more fingers are securely grasping the tool, etc. The symbolic states do not provide any criteria for grasp security, however we gathered training data for different variations of secure grasps. Note that the colloquial labeling of and differentiation between these symbolic states is ultimately up to the discretion of the operators based on the particular fingered end-effector and robot hardware in use. The only requirement for our method is that there are n symbolic states corresponding to adjustments that can be made by the n basis actions.

Fig. 4: Set of tools used for experiments, including the reference drill (top) used for training. The novel tool instances (bottom) from left to right: compressed air can, selfie stick, screwdriver, level, gyroscopic drill, paint scraper.

3) Grasp Adjustment Policy: Based on the action and state space definitions provided above, we define the following policy (visualized in Figure 3) for adjusting the PSYONIC hand's pose $\mathbf{x}_t$ relative to the tool in state s_t:

$$a_t = \pi(s_t) = \begin{cases} \mathbf{x}_t & s_t = s_{\text{no\_contact}} \\ \mathbf{x}_t + \delta[1,0,0] & s_t = s_{\text{too\_backward}} \\ \mathbf{x}_t - \delta[1,0,0] & s_t = s_{\text{too\_forward}} \\ \mathbf{x}_t + \delta[0,1,0] & s_t = s_{\text{too\_far}} \\ \mathbf{x}_t - \delta[0,1,0] & s_t = s_{\text{too\_close}} \\ \mathbf{x}_t + \delta[0,0,1] & s_t = s_{\text{too\_low}} \\ \mathbf{x}_t - \delta[0,0,1] & s_t = s_{\text{too\_high}} \\ \mathbf{x}_t & s_t = s_{\text{secure\_grasp}} \end{cases} \quad (3)$$

Note that state $s_{\text{secure\_grasp}}$ covers all of the different secure states mentioned in Section IV-A.2. Also note that state $s_{\text{no\_contact}}$ cannot be adjusted. However, it is important to include this state in the *grasp reflex model* to identify when not enough information is available to adjust the grasp.

B. Trained Grasp Reflex Model

We selected a drill as the reference tool to train our *grasp reflex model*, as seen in Figure 4. This tool was selected because it is symmetrical, relatively easy for the PSYONIC hand to grasp, and not too heavy. By placing the tool in the robot's hand, we acquired a reference joint configuration $\mathbf{q}^*_{\text{drill}}$ for a secured grasp around this drill.

For each symbolic state in the state space, we teleoperated the robot to 10 examples of that state. At each of these states, we recorded 10 data points in order to characterize sensor noise. This gave us 100 data points per symbolic state to train our *grasp reflex model*. For each data point, we recorded data on the commanded and actual end-effector poses, commanded and actual joint states, and distances of each joint from the reference secured joint configuration. This data was split into training and validation sets for the construction of our *grasp reflex model*.

We performed a logistic regression analysis to identify relevant variables and to explore interactions between variables. This analysis identified the following variables as statistically significant (with p-value $p < 0.01$ for each variable's effect on the predicted state):

- Interaction between (multiplication of) the index and pinky distances between reference secure configuration and current configuration
- Interaction between (multiplication of) the middle and pinky distances between reference secure configuration and current configuration

Our final trained *grasp reflex model* $\hat{f}$ is the logistic regression approximation of Equation 1. Let $d_j = \|q_j^* - q_j\|$ be the distance between the reference secure and current configuration for end-effector joint j. Based on our logistic regression analysis, the final form for our learned *grasp reflex model* $\hat{f}$ is $\hat{f}(\mathbf{x}_t, \mathbf{q}_t, \mathbf{q}^*) = \frac{1}{1+e^{-\mathbf{u}_t}}$ where:

$$\mathbf{u}_t = \mathbf{c}_0 + \mathbf{c}_1(d_{\text{index}} \cdot d_{\text{pinky}}) + \mathbf{c}_2(d_{\text{middle}} \cdot d_{\text{pinky}}) \quad (4)$$

with learned model coefficients $\mathbf{c}_0, \mathbf{c}_1, \mathbf{c}_2$. Interestingly, the statistically significant variables indicate that not all fingers are required for the end-effector to securely grasp the tool, indicating redundancy in our fingered end-effector. The logistic regression analysis also indicated that the model is statistically significant with p-value $p << 0.001$. This indicates that we reject the null hypothesis, and there is a significant relationship between the identified variables and the symbolic grasp states. When validating the accuracy of this model against the validation data, the *grasp reflex model* achieved about 89% accuracy in identifying the symbolic grasp states.

C. Generalization to Novel Tool Instances

To test the *grasp reflex model*'s ability to secure tool grasps in real-world tool manipulation tasks, we deployed our final trained model $\hat{f}$ on the Valkyrie robot. We wanted to test the *grasp reflex model*'s ability to secure grasps on both the drill used for initial model training, as well as novel tools. We considered a set of 6 novel tools, as seen in Figure 4.

For each tool k, we placed the tool in the robot's hand and acquired a single reference joint configuration $\mathbf{q}_k^*$ for a secure grasp around the tool. Note that this single reference secure configuration for each tool means we are asking our trained *grasp reflex model* $\hat{f}$ to perform *one-shot tactile servoing* on novel tools. To secure a grasp on tool k at time t, the robot used our *grasp reflex model* $\hat{f}$, current end-effector state $\mathbf{x}_t, \mathbf{q}_t$, and reference secure joint configuration $\mathbf{q}_k^*$ to predict the symbolic state $s_t = \arg\max(\hat{f}(\mathbf{x}_t, \mathbf{q}_t, \mathbf{q}_k^*))$. This state was then fed to the policy function π (Equation 3) to find the action $a_t = \pi(s_t)$ that would allow the robot to adjust its grasp on the tool and increase the model's predicted probability of a secure grasp. The robot would continue adjusting its grasp based on the *grasp reflex model*'s predictions indefinitely until the grasp was sufficiently secure. When the *grasp reflex model* predicted that the current state was secure $\hat{P}_t(s_{\text{secure\_grasp}}) > p^*$, the robot would pull the tool from the tool holster and continue with the tool manipulation task. We used an intentionally low probability threshold $p^* = 0.10$ for detecting secure grasps to stress test the *grasp reflex model*'s ability to accurately detect states in the context of tool manipulation tasks.

For each tool, we performed 6 trials, with each trial beginning with a different initial guess on the grasp (noise was added to the tool holster pose to alter this initial guess). For each trial, we recorded whether the grasp resulted in a secure *in-hand grasp* and a secure *manipulation grasp*. Here, we consider in-hand grasps secure if the robot successfully pulled the tool from the holster without dropping it to the ground. We consider manipulation grasps secure if a human operator could not pull the tool from the robot's hand without backdriving the PSYONIC finger joints. The resulting grasp success rates for each individual tool as well as the cumulative grasp success rates are shown in Table I. Examples of one-shot tactile servoing instances for each of the 6 novel tools can be seen in Figure 5.

D. Practical Interpretation of Grasp Reflex Model

The set of 6 novel tools was selected to stress test how well the *grasp reflex model* generalizes to novel tools. The novel tools were selected because they differed from the reference drill in size, graspable surface area, symmetry, weight, and/or weight distribution. In testing these tools, we found hardware limitations of the specific end-effector we modeled. In particular, the compressed air can and selfie stick seemed to mark the upper and lower limits, respectively, of how big around an object could be for the PSYONIC to securely grasp. Even with help from a human operator, it was difficult to obtain the reference secure joint configurations $\mathbf{q}^*_{\text{air\_can}}$ and $\mathbf{q}^*_{\text{selfie\_stick}}$. Due to the hardware limitations, these objects are likely not practical for the end-effector to reliably manipulate in tool manipulation tasks. For this reason, Table I notes both the total cumulative in-hand and manipulation success rates for all 7 tools as well as the total *practical* cumulative in-hand and manipulation success rates for the 5 practical tools.

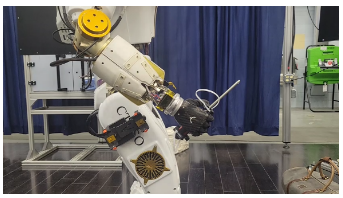
Even when considering the impractical tools, the *grasp reflex model* achieves manipulation grasps with a success rate of 0.60, indicating that the *grasp reflex model* effectively models the symbolic grasp states for the end-effector and generalizes to novel tools, achieving secure grasps more often than not. However, when we consider only the tools that can be *practically* manipulated given the end-effector hardware, the *grasp reflex model* achieves a higher manipulation grasp success rate of 0.73. Furthermore, since our definition of manipulation grasp is much more constrained than our definition of in-hand grasp, we expect manipulation grasps to be generally more difficult to achieve. Regardless of whether we consider the practical tools or all tools, the *grasp reflex model* achieves in-hand grasps with a success rate of over 0.97. This indicates that depending on how secure a grasp is required, our *grasp reflex model* achieves secure grasps with high fidelity without hand-tuned parameters or re-tuned parameters for generalization to different tools.

V. DISCUSSION AND CONCLUSION

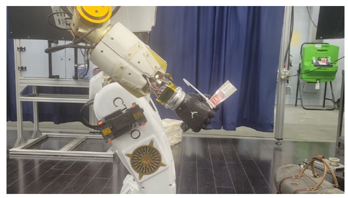
The robot's ability to successfully grasp novel tools with one-shot tactile servoing demonstrates the modeling and

Tool	Practical for End-Effector	In-Hand Grasp Success Rate	Manipulation Grasp Success Rate
Drill	Yes	1.00	1.00
Screwdriver	Yes	1.00	0.83
Paint Scraper	Yes	1.00	0.67
Level	Yes	0.83	0.67
Gyroscopic Drill	Yes	1.00	0.50
Selfie Stick	**No**	1.00	0.33
Compressed Air Can	**No**	1.00	0.17
TOTAL	**-**	**0.98**	**0.60**
PRACTICAL TOTAL	**-**	**0.97**	**0.73**

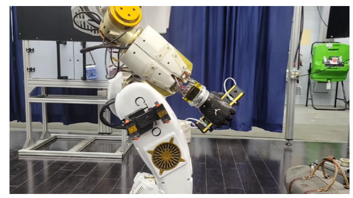
TABLE I: Results across 42 tool manipulation trials, with 6 trials per tool. We consider in-hand grasps secure if the robot did not drop the tool, and manipulation grasps secure if a human operator could not pull the tool from the robot's hand. The drill performs the best, since this tool was used to train the grasp reflex model. Other tools are more challenging since they differ from the drill in terms of size (paint scraper), graspable surface area (level), and/or weight distribution (front-heavy gyroscopic drill). Note that the selfie stick and compressed air can are not practical for the given end-effector, as they represent the lower and upper limits, respectively, of what can reasonably be grasped by the PSYONIC hand.



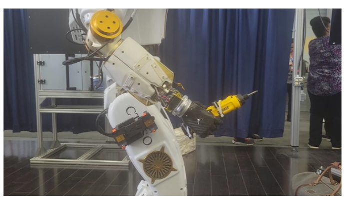
(a) Screwdriver: **SUCCESS**



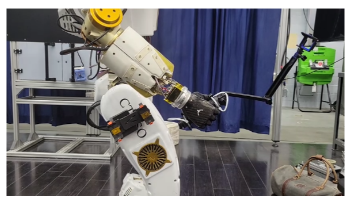
(b) Paint Scraper: FAILED



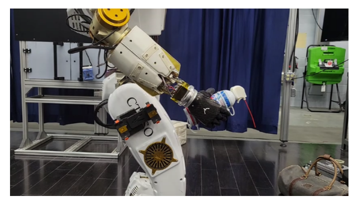
(c) Level: FAILED



(d) Gyroscopic Drill: **SUCCESS**



(e) Selfie Stick: **SUCCESS**



(f) Compressed Air Can: **SUCCESS**

Fig. 5: Random trials of the *grasp reflex model* for one-shot tactile servoing on novel tools. Note that in all trials, in-hand grasps were achieved, but manipulation grasps may or may not have been achieved.

generalization capabilities of our proposed ***grasp reflex model***. Because our *grasp reflex model* is trained from a logistic regression model, it is not a black box (such as a neural network), and therefore could be flight certified for NASA space applications, where safety is critical and model explainability is required. We demonstrate the power of grasp reflex modeling to allow robots to grasp tools and achieve one-shot generalization on novel tools without relearning or re-tuning the *grasp reflex model* parameters.

Future work includes extending to a larger action space, specifically rotational adjustments. Training the *grasp reflex model* over a set of representative tools (rather than just a single reference tool) could improve grasp success rates by modeling a distribution over challenging features such as tool size and weight distribution. This grasp reflex modeling approach could be generalized to different types of tool grasps—such as precision grasps—rather than just the single overhand power grasp modeled in this work. The robot could learn from experience about each object it grasps, such as learning the reference close configuration for each tool or learning from failure cases to improve performance. Finally, we found that stress testing the *grasp reflex model* exposed hardware limitations of the end-effector, and further modeling and stress testing could improve our understanding of the practical capabilities of a given end-effector.

In this work, we proposed a ***grasp reflex model*** that classified end-effector state information into meaningful symbolic states. By taking adjustment actions from these symbolic states, the robot achieved secure tool grasps. Furthermore, our *grasp reflex model* effectively modeled the relationship between end-effector joint data and these adjustable symbolic states, allowing the robot to achieve *one-shot tactile servoing* to secure grasps on novel tool instances. Our work in grasp reflex modeling demonstrates the robot's ability to autonomously perform tool manipulation tasks with one-shot generalization to novel tools.

ACKNOWLEDGMENTS

This work was supported in part by NASA Space Technology Graduate Research Opportunity (NSTGRO) grant 80NSSC20K1200. We would like to thank the members of the NASA Johnson Space Center Dexterous Robotics Team.

REFERENCES

[1] V. Babin and C. Gosselin, "Mechanisms for Robotic Grasping and Manipulation," *Annual Review of Control, Robotics, and Autonomous Systems*, 2021.

[2] D. H. Ballard, "Task Frames in Robot Manipulation," *Association for the Advancement of Artificial Intelligence (AAAI)*, 1984.

[3] C. Bauer, G. Milighetti, W. Yan, and R. Mikut, "Human-Like Reflexes for Robotic Manipulation using Leaky Integrate-and-Fire Neurons," *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2010.

[4] G. A. Bekey and R. Tomovic, "Robot Control by Reflex Actions," *IEEE International Conference on Robotics and Automation (ICRA)*, 1986.

[5] A. Bicchi and V. Kumar, "Robotic Grasping and Contact: A Review," *IEEE International Conference on Robotics and Automation (ICRA)*, 2000.

[6] N. Boubekri and P. Chakraborty, "Robotic Grasping: Gripper Designs, Control Methods and Grasp Configurations - A Review of Research," *Integrated Manufacturing Systems*, 2002.

[7] R. R. Burridge, A. A. Rizzi, and D. E. Koditschek, "Sequential Composition of Dynamically Dexterous Robot Behaviors," *International Journal of Robotics Research*, 1999.

[8] A. N. Chaudhury, T. Man, W. Yuan, and C. G. Atkeson, "Using Collocated Vision and Tactile Sensors for Visual Servoing and Localization," *IEEE Robotics and Automation Letters (RA-L)*, 2022.

[9] P. Deckers, A. M. Dollar, and R. D. Howe, "Guiding Grasping with Proprioception and Markov Models," *Workshop on Robot Manipulation: Sensing and Adapting to the Real World, Robotics: Science and Systems (RSS) Conference*, 2007.

[10] A. M. Dollar and R. D. Howe, "Towards Grasping in Unstructured Environments: Optimization of Grasper Compliance and Configuration," *IEEE International Conference on Intelligent Robots and Systems (IROS)*, 2003.

[11] A. M. Dollar, "Design Principles for Robust Grasping in Unstructured Environments," Ph.D. Thesis, Harvard University, 2006.

[12] K. Fang, Y. Zhu, A. Garg, A. Kurenkov, V. Mehta, L. Fei-Fei, and S. Savarese, "Learning Task-Oriented Grasping for Tool Manipulation from Simulated Self-Supervision," *The International Journal of Robotics Research*, 2020.

[13] Y. Futagi, Y. Toribe, and Y. Suzuki, "The Grasp Reflex and Moro Reflex in Infants: Hierarchy of Primitive Reflex Responses," *International Journal of Pediatrics*, 2012.

[14] J. J. Gibson, "The Theory of Affordances," in *Perceiving, Acting, and Knowing: Towards an Ecological Psychology*, volume 1, pp. 67-82, Erlbaum, 1977.

[15] S. Hart, S. Dinh, and K. Hambuchen, "The Affordance Template ROS Package for Robot Task Programming," *IEEE International Conference on Robotics and Automation (ICRA)*, 2015.

[16] K. He, Y. Liu, M. Wang, G. Chen, Y. Jiang, J. Yu, C. Wan, D. Qi, M. Xiao, W. R. Leow, H. Yang, M. Antonietti, and X. Chen, "An Artificial Somatic Reflex Arc," *Advanced Materials*, 2020.

[17] H. Hoffmann, Z. Chen, D. Earl, D. Mitchell, B. Salemi, and J. Sinapov, "Adaptive Robotic Tool Use under Variable Grasps," *Robotics and Autonomous Systems*, 2014.

[18] Z. Kappassov, J.-A. Corrales, and V. Perdereau, "Tactile Sensing in Dexterous Robot Hands," *Robotics and Autonomous Systems*, 2015.

[19] K. Kleeberger, R. Bormann, W. Kraus, and M. F. Huber, "A Survey on Learning-Based Robotic Grasping," *Current Robotics Reports*, 2020.

[20] A. E. Leeper, K. Hsiao, M. Ciocarlie, L. Takayama, and D. Gossow, "Strategies for Human-in-the-Loop Robotic Grasping," *ACM/IEEE international Conference on Human-Robot Interaction*, 2012.

[21] N. F. Lepora, K. Aquilina, and L. Cramphorn, "Exploratory Tactile Servoing with Active Touch," *IEEE Robotics and Automation Letters (RA-L)*, 2017.

[22] N. F. Lepora and J. Lloyd, "Pose-Based Tactile Servoing: Controlled Soft Touch using Deep Learning," *IEEE Robotics and Automation Magazine*, 2021.

[23] Q. Li, C. Schürmann, R. Haschke, and H. J. Ritter, "A Control Framework for Tactile Servoing," *Robotics: Science and Systems (RSS)*, 2013.

[24] Q. Li and N. Lepora, "Tactile Servoing Tutorial," *Tutorial at IROS 2022*, 2022. [Online]. Available: https://sites.google.com/view/tactile-servoing

[25] M. Liarokapis and A. M. Dollar, "Combining Analytical Modeling and Learning to Simplify Dexterous Manipulation with Adaptive Robot Hands," *IEEE Transactions on Automation Science and Engineering*, 2018.

[26] E. Luberto, Y. Wu, G. Santaera, M. Gabiccini, and A. Bicchi, "Enhancing Adaptive Grasping Through a Simple Sensor-Based Reflex Mechanism," *IEEE Robotics and Automation Letters (RA-L)*, 2017.

[27] M. V. Marques-de-Moraes, J. Dionisio, U. Tan, and E. Tudella, "Palmar Grasp Reflex in Human Newborns," *Pediatrics & Therapeutics*, 2017.

[28] T. Mouri, H. Kawasaki, and S. Ito, "Unknown Object Grasping Strategy Imitating Human Grasping Reflex for Anthropomorphic Robot Hand," *Journal of Advanced Mechanical Design, Systems, and Manufacturing*, 2007.

[29] National Aeronautics and Space Administration, "NASA Safety Culture Handbook," NASA Technical Standards System, 2015. [Online]. Available: https://standards.nasa.gov/sites/default/files/standards/NASA/Baseline/1/nasa-hdbk-870924_with_change_1.pdf

[30] National Aeronautics and Space Administration, "NASA Risk Management Handbook," NASA Technical Reports Server, 2011. [Online]. Available: https://ntrs.nasa.gov/api/citations/20120000033/downloads/20120000033.pdf

[31] S. Okajima, F. S. Alnajjar, H. Yamasaki, M. Itkonen, Á. C. García, Y. Hasegawa, and S. Shimoda, "Grasp-Training Robot to Activate Neural Control Loop for Reflex and Experimental Verification," *IEEE International Conference on Robotics and Automation (ICRA)*, 2018.

[32] Open Robotics, "XML Robot Description Format (URDF)," ROS.org, 2023. [Online]. Available: https://wiki.ros.org/urdf/XML/model

[33] R. Platt, A. H. Fagg, and R. A. Grupen, "Manipulation Gaits: Sequences of Grasp Control Tasks," *IEEE International Conference on Robotics and Automation (ICRA)*, 2004.

[34] PSYONIC, "The World's First Touch-Sensing Bionic Hand," PSYONIC, 2024. [Online]. Available: https://www.psyonic.io/

[35] PSYONIC, "Meet the Ability Hand," PSYONIC, 2024. [Online]. Available: https://www.psyonic.io/ability-hand

[36] N. A. Radford, P. Strawser, K. Hambuchen, J. S. Mehling, W. K. Verdeyen, A. S. Donnan, J. Holley, J. Sanchez, V. Nguyen, L. Bridgwater, R. Berka, R. Ambrose, M. M. Markee, and N. J. Fraser-Chanpong, "Valkyrie: NASA's First Bipedal Humanoid Robot," *Journal of Field Robotics*, 2015.

[37] Z. Ray and E. D. Engeberg, "Human-Inspired Reflex to Autonomously Prevent Slip of Grasped Objects Rotated with a Prosthetic Hand," *Journal of Healthcare Engineering*, 2018.

[38] A. Saxena, J. Driemeyer, J. Kearns, and A. Ng, "Robotic Grasping of Novel Objects," *Advances in Neural Information Processing Systems*, 2006.

[39] P. Sikka, H. Zhang, and S. Sutphen, "Tactile Servo: Control of Touch-Driven Robot Motion," *Experimental Robotics III*, 2005.

[40] Y. Sun, Y. Lin, and Y. Huang, "Robotic Grasping for Instrument Manipulations," *IEEE International Conference on Ubiquitous Robots and Ambient Intelligence (URAI)*, 2016.

[41] M. Sundermeyer, A. Mousavian, R. Triebel, and D. Fox, "Contact-GraspNet: Efficient 6-DOF Grasp Generation in Cluttered Scenes," *IEEE International Conference on Robotics and Automation (ICRA)*, 2021.

[42] G. Sutanto, N. Ratliff, B. Sundaralingam, Y. Chebotar, Z. Su, A. Handa, and D. Fox, "Learning Latent Space Dynamics for Tactile Servoing," *IEEE International Conference on Robotics and Automation (ICRA)* 2019.

[43] J. C. V. Tieck, K. Secker, J. Kaiser, A. Roennau, and R. Dillmann, "Soft-Grasping with an Anthropomorphic Robotic Hand using Spiking Neurons," *IEEE Robotics and Automation Letters (RA-L)*, 2020.

[44] R. Tomovic, G. A. Bekey, and W. J. Karplus, "A Strategy for Grasp Synthesis with Multifingered Robot Hands," *IEEE International Conference on Robotics and Automation (ICRA)*, 1987.

[45] C.-T. Wen, S. Arai, J. Kinugawa, and K. Kosuge, "Tactile Servoing Based Pressure Distribution Control of a Manipulator using a Convolutional Neural Network," *IEEE Access*, 2021.