Target-Conditioned Shape-Based Object Search Using Tactile Sensing

Fardifa Fathmiul Alam **Tanzina Taher Ifty**
Department of Electrical and Computer Engineering
George Mason University
falam20@gmu.edu tifty@gmu.edu

1 Abstract

Object search in robotic manipulation is often limited by the reliability of vision, especially in cluttered, occluded, or visually degraded environments. Tactile sensing offers a compelling alternative by directly capturing local surface geometry through physical contact. In this work, we present a target-conditioned tactile object search framework that enables a robot to identify a desired object from a set of four shape categories—sphere, cube, cylinder, and cone using touch alone. Given a target object's tactile information, the robot sequentially explores the available objects using a simulated tactile sensing pad and decides whether the currently touched object matches the target. We formulate this as a reinforcement learning problem in which the agent learns when to continue probing an object, when to discard it, and when to stop upon detecting the correct match. Our system operates without any visual observations and uses 2D pressure-map tactile images generated from contact forces, which are processed by a ConvNeXt-Tiny classifier to provide shape predictions. Experiments in a simulated multi-object environment show that the classifier achieves strong performance and supports effective baseline search behavior, while a PPO-based policy improves exploration on ambiguous ones but struggles to stop early when confidence is high. Overall, the framework provides a first step toward learned, tactile-only object search in visually challenging environments.

Keywords: Tactile Sensing, Active Tactile Exploration, Reinforcement learning

2 Introduction

Robotic manipulation commonly depends on vision for object recognition [2], but visual perception can degrade significantly in cluttered, occluded, or low-light environments [4, 16]. In operational domains such as warehouses [1], disaster response [22], and medical settings [13], objects frequently overlap, lighting conditions vary unpredictably, and reliable visual cues cannot always be maintained. Tactile sensing offers a robust complementary modality in these situations: contact-based feedback is invariant to illumination, directly reflects local surface geometry, and provides discriminative information well suited for identifying object shape [30, 12]. As a result, tactile perception plays a critical role in manipulation scenarios where vision alone is insufficient for dependable object identification.

This project examines a tactile-based approach to *target-conditioned object search* [36, 5, 19, 11]. Given multiple objects and a desired shape (e.g., cube), the robot must physically probe each candidate and decide whether to continue exploring, reject it, or confirm it as the target. Unlike standard tactile classification [18, 7, 17], this setting requires learning not only *what* is being touched but also *how* and *when* to probe. Efficient search emerges from balancing two competing demands: collecting enough tactile evidence when uncertain, while minimizing unnecessary interactions once confident [14, 31].

Although prior work in tactile perception has demonstrated shape recognition, most of these advances focus on single isolated objects [36, 5, 19, 11, 14, 31]. Far less attention has been given to *multi-object*

38th Conference on Neural Information Processing Systems (NeurIPS 2024).

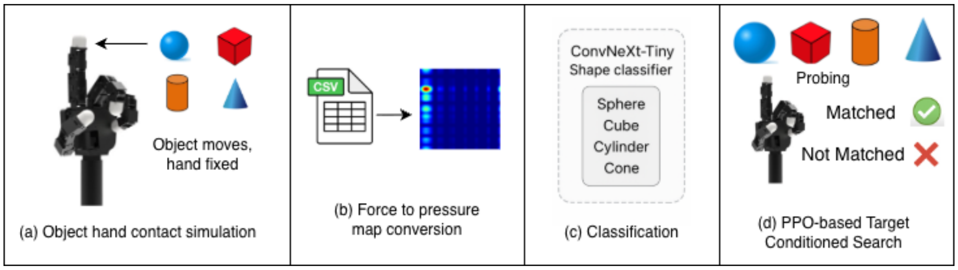


Figure 1: Overview of the complete system.

active tactile search—the problem of sequentially exploring multiple objects and comparing tactile observations to a goal representation. This is a critical capability in realistic tasks such as selecting tools from a cluttered container, recovering items in visually degraded environments, or verifying component identity during manipulation.

We develop an end-to-end simulation framework in MuJoCo [32] for studying active tactile search. Contact interactions are converted into 2D pressure-map tactile images using force-based rendering, enabling ConvNeXt-Tiny [34] to perform shape recognition. On top of this perceptual backbone, we compare a simple deterministic probing strategy with a reinforcement learning policy trained via PPO [29] to learn when to probe, reject, or confirm a candidate in a multi-object search setting.

Contributions: This work has the following contributions:

- A MuJoCo-based tactile simulation pipeline for generating controlled contact interactions across multiple object shapes using a fixed tactile sensing pad.
- A method for transforming force-based contacts into Gelsight inspired 2D pressure-map tactile images, enabling CNN-based shape recognition directly from simulated touch.
- A tactile classifier based on ConvNeXt-Tiny that achieves 81% accuracy and provides feature embeddings for downstream decision-making.
- A PPO-based, target-conditioned reinforcement learning framework for active tactile exploration and multi-object search.

Together, these components form a unified framework for studying touch-based object identification. Beyond demonstrating that tactile sensing and RL can be combined for multi-object search, our results show a clear pattern: the quality of tactile perception strongly shapes how well any search policy can perform, and learned policies behave differently from fixed ones - sometimes helping in difficult cases but often exploring more than necessary in easy ones. These insights point to a simple conclusion: improving tactile representations and giving the policy better ways to judge when to stop would likely lead to much stronger active tactile search performance.

3 Related Works

Robotic object search has **traditionally relied on visual perception** to detect, localize, and recognize objects in a scene. Akbaş et al. [2] demonstrated that active, foveated vision can improve detection efficiency by directing high-resolution attention toward likely regions of interest. In addition to attention mechanisms, other vision-based approaches have focused explicitly on using global or boundary-based shape descriptors to identify and segment objects within an image [33]. These methods leverage holistic shape information to match or discriminate objects visually, highlighting the effectiveness of vision-driven object search when visibility conditions are controlled.

However, achieving robust object search with vision alone becomes challenging in realistic environments. Prior work has noted that even advanced vision pipelines degrade under occlusion, clutter, and poor lighting, leading to unreliable detection and reduced precision [8]. In contrast, **tactile sensing** offers rich, direct feedback through physical contact, enabling robots to recover local surface geometry and contact structure even when visual cues are unavailable. This makes tactile exploration particularly useful in manipulation settings where line-of-sight cannot be maintained [35]. Beyond compensating for visual limitations, tactile sensing has also been widely explored for general object characterization. Early works used tactile signals to reconstruct 3D object shape [3], detect fine surface features such as ridges and bumps through sliding exploration [20], and estimate material properties like hardness or softness using piezo-electric vibration sensors [21]. Force-sensitive fingers have been employed to maintain compliant contact during manipulation [6], while other methods use tactile feedback to estimate the pose of objects with known shapes [23]. Additional studies classify objects by accumulating geometric contact features over time, including approaches that categorize objects into simple primitives such as boxes, spheres, and cylinders [26], as well as whisker-based tactile classification methods [27].

Several studies have explored how tactile sensing can be used for **shape perception** and active haptic exploration. Some methods treat tactile sensing as a source of geometric information, reconstructing local or global object shape through sequential contact observations or multi-finger exploration strategies [9]. Other approaches formulate haptic exploration as an information-gathering process, where the robot purposefully scans an object's surface and interprets tactile readings as images to support object identification [24]. Complementary methods use gradient-based analysis of tactile images to classify edged and edgeless objects and reconstruct 3D topology from touch [10]. Tactile-only identification frameworks based on bag-of-words models have also been proposed, where multiple grasps are used to build feature vocabularies for discriminating among objects [28]. While these works demonstrate the discriminative potential of tactile information, they focus on single-object recognition and do not enable target-conditioned search or sequential decision-making across multiple candidate objects.

Reinforcement learning has increasingly been used to exploit tactile and force feedback for adaptive, contact-rich robot behaviors. Tactile information has been shown to substantially improve sample efficiency and manipulation performance in dexterous in-hand tasks, demonstrating the benefits of integrating touch into learned control policies [37]. Force- and haptic-aware RL strategies have also been proposed to enhance safety, robustness, and sim-to-real transfer in dynamic manipulation settings; for example, force-based policies achieve more stable and efficient pushing behaviors under uncertainty [15]. RL has further been applied to active sensing, where an agent controls a tactile or range sensor to iteratively acquire informative measurements for object classification or pose estimation [25]. Taken together, prior work shows that tactile sensing paired with reinforcement learning can enable richer interaction and more informed decision making in contact-rich tasks.

Although tactile sensing has been widely studied for perception, recognition, and manipulation, none of these efforts address the problem of target-conditioned object search. Most existing systems focus on reconstructing shape, identifying one object at a time, or improving local exploration, but they do not compare tactile observations to a target object while searching through several candidates. Consequently, the task of deciding whether the object under exploration matches a given target using only tactile feedback remains largely unexplored.

4 Problem Formulation

We consider a setting where a robot must identify a target object from a set of candidates using only tactile information. Several objects with different shapes (cube, sphere, cylinder, cube) are placed. At the beginning of each episode, the robot is given a target label $g \in \{\text{cube}, \text{sphere}, \text{cylinder}\}$. The goal is to determine which physical object matches this target shape by interacting with them one at a time.

Tactile Observations. At each step, the robot makes contact with the current object and receives tactile feedback in the form of 128×128 2D pressure-map tactile RGB images generated from simulated contact forces. These tactile images are processed by a trained convolutional classifier f_θ, which outputs a predicted shape label $\hat{y}_t$ and a probability distribution $\mathbf{p}_t \in \mathbb{R}^4$ over the four object classes. . Together, these outputs summarize the current contact and serve as the perceptual input for guiding the robot's next action.

Decision Process. We model the task as a sequential decision-making problem. During interaction with an object, the robot must decide whether to:

- **continue probing** to gather additional tactile information,

- **reject** the current object and move on to the next candidate, or
- **confirm** that the current object matches the target shape.

Reward Function. The objective is to correctly identify the target object while minimizing the number of actions taken. To capture this trade-off, we define a reward structure that encourages accurate decisions and penalizes unnecessary probing. When the robot issues a `CONFIRM` action, it receives a reward of $+1$ if the current object matches the target and -1 otherwise. Similarly, a `REJECT` action yields $+1$ when the object is not the target and -1 when the robot incorrectly rejects the true target. For all probing actions, a small step penalty $-\lambda$ is applied to discourage overly long interactions. This formulation encourages the policy to gather sufficient evidence when uncertain, while still promoting efficient search behavior.

5 Methodology

Our approach follows a two-stage pipeline: (1) a tactile perception module that transforms simulated contact into GelSight-style tactile images and extracts shape features, and (2) an active search module that will eventually use these features to guide decision-making during multi-object exploration.

5.1 Simulation Environment

We simulate tactile interactions in MuJoCo using a Franka Emika Panda arm with an attached Allegro Hand. Although the full robot model is present, our experiments use a fixed tactile pad mounted in front of the hand instead of articulated finger motions. This simplifies control while preserving realistic contact geometry. Four geometric objects (sphere, cube, cylinder, cone) are placed in the workspace, and MuJoCo provides per-step contact forces and object poses for tactile rendering.

5.2 Object Placement

Robot and sensor pad: The robot uses a single rigid "finger" structure to hold the tactile sensing pad. The finger is modeled as two connected box segments—a base (0.02 × 0.02 × 0.05) and a smaller finger tip (0.02 × 0.02 × 0.02)—ending in a rectangular tactile pad mounted at the tip. The pad itself is a compact box-shaped sensor element (0.007 × 0.015 × 0.015) positioned at the front of the finger and oriented along the X-axis, allowing incoming objects to make direct, planar contact with its surface.

Different shaped objects: During training, each object is placed in its own dedicated scene. All objects are positioned in the air within the X–Z plane at the same height (Z = 0.07), aligned with the height of the tactile pad. In the testing phase, all four objects (sphere, cube, cylinder, cone) are loaded into a single scene, but only one object is active at a time. The remaining objects are kept in a designated parking area outside the sensing region. After the robot finishes exploring the current object, that object is moved to the parking position and the next candidate becomes active. This setup enables controlled, sequential exploration while ensuring consistent object height relative to the tactile pad.

5.3 Contact Dynamics

During training, each object is explored in an isolated scene following a repeated approach–contact–withdraw cycle. At the beginning of each cycle, the object is placed at a fixed starting position and translated along the X-axis toward the stationary tactile sensor pad. As the object moves forward, the simulation monitors the contact force; once the force exceeds a small threshold or the object reaches the predefined contact position, the forward motion stops and the system briefly pauses to allow stable force readings. The object then retracts to its initial position, after which it undergoes a random rotation. Rotations are applied around all three axes, enabling force data collection from a wide variety of orientations and contact geometries. This forward–pause–backward–rotate sequence repeats until a sufficient number of tactile samples are collected.

In the exploration phase, the same contact dynamics are used, but all objects are present in a single scene. Only one object is active at any time: it follows the same forward approach to the pad, produces a contact force profile, and is evaluated by the learned policy. The policy determines whether to

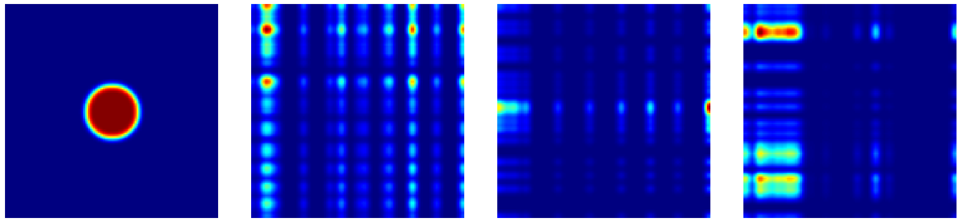


Figure 2: Example 2D pressure-map tactile images for each object shape. Spheres produce a symmetric circular contact pattern, cylinders show repeated vertical ridge-like activations, cubes exhibit sharper edge-driven responses, and cones generate asymmetric gradients due to their sloped surfaces.

continue probing the object, classify it as the target, or reject it. Once a decision is made, the current object is moved to the parking area, and the next object becomes active for exploration. This ensures consistent, controlled tactile interactions while enabling sequential multi-object evaluation.

5.4 Contact Force/Depth Data Collection

For each approach–contact cycle, the simulator records the tactile force generated as the object presses against the fixed sensor pad. At every timestep, the system logs a structured data entry containing the current simulation time, the object's Cartesian position, the measured contact force, and the current motion phase (forward, pause, backward, or rotation). These samples are stored sequentially as a CSV file for each object, forming a clear time-series representation of how force evolves with contact depth and surface geometry. Multiple cycles with randomized object orientations produce a diverse tactile dataset for all four shapes. For downstream learning, each force–depth sequence is subsequently converted into a 2D pressure map representation, which serves as the input observation for the reinforcement learning policy.

5.5 Tactile Image Generation

Although the Allegro Hand is modeled, MuJoCo does not provide GelSight-style deformation fields. Instead, we use the fingertip's 3-axis force vector to produce a structured 2D tactile representation. Each force reading is mapped onto a 128×128 pressure grid, where intensity encodes force magnitude. When the contact point moves, the pressure is placed at the normalized (x, y) location; for stationary contacts, a smooth circular patch is rendered with radius proportional to force. The map is then Gaussian-smoothed, normalized, and colored using a perceptual colormap, yielding a pseudo–GelSight RGB image suitable for CNN-based classification.

The final output is a 128×128 RGB image used for both classification and RL state encoding.

5.6 Dataset Construction

We generate a dataset by repeatedly probing each object and converting force–depth segments into images using a sliding-window approach. Each image is labeled with the corresponding shape class. The final dataset contains approximately 700 images per class (2800 total), organized into class-specific folders.

5.7 Shape Classification Model

We use a ConvNeXt-Tiny backbone, initialized with ImageNet-1K pretrained weights, to classify 128×128 pseudo-GelSight tactile images into four shape categories: cone, cube, cylinder, and sphere. The final layer is replaced to output class logits for these categories.

Each tactile image is processed to produce: (1) a 768-dimensional latent feature vector $\mathbf{f}$, (2) a softmax probability distribution $\mathbf{p} \in \mathbb{R}^4$, and (3) the predicted class label $\hat{y}$. The latent features provide a compact representation of contact geometry for downstream components.

The model is trained with supervised learning using the AdamW optimizer (learning rate 1×10^{-4}, weight decay 1×10^{-4}) and a weighted cross-entropy loss. We apply light data augmentation (small rotations and flips) and a cosine-annealing schedule over 30 epochs to improve robustness to contact variation.

5.8 Active Search with Reinforcement Learning

The second stage uses reinforcement learning (RL) to decide *how* to probe and *when* to stop. Instead of following a fixed exploration sequence, an RL agent learns to choose informative poses, reject non-targets quickly, and confirm the correct object when sufficiently confident.

We treat active tactile exploration as a finite-horizon decision process. For each target shape $y^\star \in \{\text{cone}, \text{cube}, \text{cylinder}, \text{sphere}\}$, we train a separate PPO policy $\pi_\theta^{(y^\star)}$ that interacts with one object at a time and must decide whether it matches the target.

State representation. At each step, the policy observes:

$$s_t = [\, \mathbf{p}_t,\ \mathbf{e}(a_{t-1}),\ t/T_{\max} \,],$$

where:

- $\mathbf{p}_t \in \mathbb{R}^4$: classifier probability distribution over the four shapes,
- $\mathbf{e}(a_{t-1})$: one-hot encoding of the previous action,
- $t/T_{\max}$: normalized timestep.

Action space. The agent chooses from:

$$\mathcal{A} = \{\text{POSE}_0, \ldots, \text{POSE}_5,\ \text{CONFIRM},\ \text{REJECT}\},$$

where the six POSE actions correspond to predefined tactile exploration motions. CONFIRM and REJECT terminate the episode with a decision.

Reward design. Rewards promote accurate and efficient decisions:

$$r_t = \begin{cases} +1 & \text{if CONFIRM and } y = y^\star, \\ -1 & \text{if CONFIRM and } y \neq y^\star, \\ +1 & \text{if REJECT and } y \neq y^\star, \\ -1 & \text{if REJECT and } y = y^\star, \\ -\lambda & \text{for POSE actions.} \end{cases}$$

Here, $\lambda > 0$ penalizes long trajectories and β provides a small shaping reward based on how the classifier's belief changes from one step to the next.

Training. We train one PPO agent using simulated episodes where the environment randomly presents either a matching object (positive episode) or a distractor (negative episode). The policy and value networks are shallow MLPs with two hidden layers. At test time, a fixed target class is chosen and the trained policy is run sequentially on four unknown objects. The agent probes each object until CONFIRM or REJECT, and we record success rate and number of probes per trial.

6 Experiments

6.1 Simulation Setup

Experiments are conducted in a MuJoCo simulation of a Franka Panda arm equipped with an Allegro Hand, where tactile feedback is produced using a fixed rectangular sensor pad. Four rigid objects (sphere, cube, cylinder, cone) are mounted on linear guides that translate each object into the sensor for controlled contact. The environment provides six predefined exploration poses around each object. During contact, MuJoCo force signals are converted into 128×128 pseudo-GelSight RGB images, which are classified by a ConvNeXt-Tiny model to obtain shape probabilities. A Bayesian belief tracker updates the posterior after each touch. For multi-object search, all four objects are present and visited in randomized order. A target shape is specified at the start of each episode, and results are averaged across repeated trials with shuffled object arrangements.

Table 1: Classification results for the tactile classifier.

Class	Prec	Rec	F1	Support
Cone	0.77	0.79	0.78	144
Cube	0.77	0.80	0.78	144
Cylinder	0.71	0.67	0.69	141
Sphere	1.00	1.00	1.00	131

Table 2: Success rate of multi-object search.

Shape	Manual	PPO
Sphere	1.00	0.46
Cube	1.00	0.13
Cylinder	0.05	0.15
Cone	0.08	0.20

6.2 Classifier Training Experiments

Classifier experiments are conducted in Google Colab on an NVIDIA L4 GPU (CUDA 12.4). The full tactile dataset contains 2,797 images across four shape classes. We use an 80/20 split, resulting in 2,237 training images and 560 validation images. The ConvNeXt-Tiny classifier is trained for 30 epochs using the AdamW optimizer and hyperparameters described in Section 5.7.

6.3 Active RL Experiments

We evaluate whether a PPO-based policy can improve multi-object tactile search relative to a fixed, hand-designed exploration strategy. All RL experiments use the same MuJoCo environment, pseudo-GelSight generator, and classifier used in the manual pipeline.

PPO training: For each target shape, we train a separate PPO policy that learns how to probe a single object and decide when to confirm or reject it. The agent receives the classifier's current shape probabilities along with simple action-history cues, and chooses among six exploration poses or a terminal decision. Rewards encourage correct decisions and penalize unnecessary probing. Policies are trained for a fixed number of simulated episodes, while the tactile classifier and image-generation pipeline remain unchanged throughout training.

Manual exploration baseline: To provide a non-learning comparison, we implement a deterministic baseline that follows a fixed sequence of exploration poses. After each contact, the classifier output is checked against two thresholds: if the target class probability exceeds a high threshold for two consecutive frames, the baseline issues CONFIRM; if the probability falls below a low threshold, it issues REJECT. Otherwise, it continues probing until a maximum number of contacts is reached. This baseline approximates a simple, confidence-driven strategy.

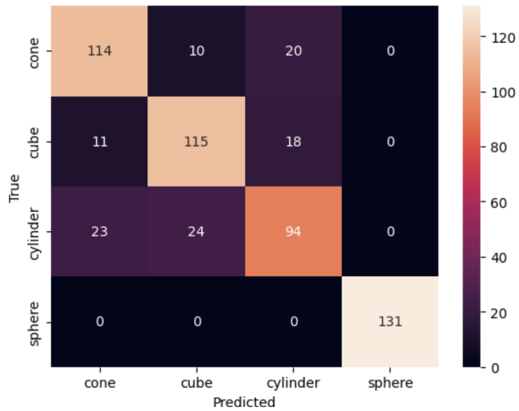
Multi-object evaluation. At test time, each PPO agent is evaluated in a four-object search scenario. In each episode, the four shapes appear in a random order. For each object in turn, the agent interacts using the same online pseudo-GelSight generator and updates its belief after every contact. The episode terminates when the agent issues a CONFIRM or after all objects have been rejected.

We compare PPO and the manual baseline using two primary metrics: (i) success rate, defined as the fraction of episodes in which the correct object is identified, and (ii) the number of tactile contacts per episode.

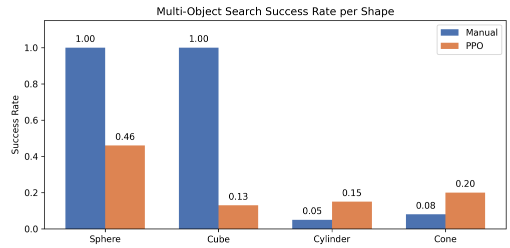
7 Results and Discussion

7.1 Classification Results

The classifier achieves an overall validation accuracy of 81% across four shape categories (Table 1). Spheres are recognized perfectly due to their highly symmetric pressure profiles, and cubes and cones show similarly strong performance. Cylinders, however, remain challenging (F1 $= 0.69$), as their limited local surface curvature often produces contact patterns that resemble cubes or cones. These perceptual ambiguities directly propagate into the downstream search task, limiting how confidently either policy can identify such objects.



(a) Confusion matrix for the tactile classifier.



(b) Manual vs. PPO success rates for multi-object search.

Figure 3: (a) Classification performance and (b) downstream search accuracy across object categories.

7.2 Multi-Object Search Results

We evaluate both the fixed-rule manual policy and the PPO-trained policy in a four-object search task. Table 2 and Figure 3(b) report success rates over 100 trials per target shape.

Both policies use the same classifier, yet they behave differently because of how they explore and when they choose to stop. The manual policy performs exceptionally well on spheres and cubes (100% success), as its fixed probing sequence reliably produces clean tactile observations for these shapes. In practice, it often becomes confident after only one or two contacts and stops early, avoiding unnecessary exploration. However, the same rigidity hurts performance on cylinders and cones: without viewpoint diversity, the classifier receives insufficient evidence to distinguish them from cubes, leading to low accuracy on these shapes.

The PPO policy shows a contrasting pattern. It performs slightly better than the manual baseline on the harder shapes (cylinder and cone), indicating that learned exploratory motions can extract additional information when the default sequence is insufficient. However, PPO performs substantially worse on spheres and cubes. Step-by-step rollouts show that PPO often reaches high confidence early—just like the manual policy—but continues probing in an attempt to avoid premature decisions. These additional contacts sometimes produce inconsistent or off-angle tactile patterns that reduce classifier confidence and occasionally flip an initially correct belief. Thus, PPO trades reliability on easy cases for modest gains on ambiguous ones.

Overall, the search results reflect a tight coupling between perception and control: when the classifier is highly reliable (sphere, cube), a simple rule-based policy outperforms reinforcement learning, while RL provides limited benefits for perceptually ambiguous objects. Improving tactile image realism, increasing pose diversity, or incorporating confidence-aware stopping rules may yield greater gains than further adjustments to the policy itself.

7.3 Limitations and Future Work

This project faced several limitations. First, because MuJoCo does not support GelSight-style tactile simulation, we relied on approximate force–heatmap images. These lacked the fine-grained surface deformation patterns of real tactile sensors, reducing the classifier's ability to distinguish visually similar shapes. Second, although the Allegro Hand model was available, we could not implement full dexterous manipulation; instead, the system used a single fixed sensor pad, limiting the diversity of exploratory motions available to both the manual and learned policies. Third, PPO performance was constrained by both its exploration strategy and the perceptual signal it depended on. The policy frequently continued probing even after the classifier produced strong evidence, leading to confidence drift and avoidable errors on shapes the classifier already recognized well. At the same time, the classifier itself struggled to separate similar shapes due to the simplified tactile representation, meaning PPO had little opportunity to improve in these ambiguous cases.

Since downstream decision-making cannot exceed the reliability of the underlying perception, richer tactile inputs (e.g., deformation fields) or a jointly trained tactile encoder would likely provide more discriminative signals and better support learning.

Future work could incorporate realistic tactile rendering, coordinated finger-level control, and uncertainty-aware stopping rules. In addition, feeding richer tactile observations to PPO or jointly training the classifier and policy may allow the agent to exploit confident predictions early while avoiding unnecessary exploration. Together, these steps could substantially improve both recognition accuracy and active search performance.

8 Conclusion

This work introduces a novel formulation of target-conditioned multi-object tactile search, a problem that has received little explicit attention in prior literature. By combining simulated tactile sensing, learned shape classification, and reinforcement learning for action selection, we demonstrate the feasibility of performing object search using touch alone. Even though overall search accuracy remains limited, the system reveals important insights: tactile classifiers strongly shape downstream decision quality, adaptive exploration can meaningfully assist in ambiguous cases, and calibrated stopping behavior is critical for real-world deployment. These findings establish a foundation for future research on active tactile perception and offer promising directions toward more capable, touch-driven robotic manipulation systems.

References

[1] Adnan Aijaz and Mahesh Sooriyabandara. The tactile internet for industries: A review. *Proceedings of the IEEE*, 107(2):414–435, 2018.

[2] Emre Akbas and Miguel P Eckstein. Object detection through search with a foveated visual system. *PLoS computational biology*, 13(10):e1005743, 2017.

[3] Peter K Allen. Integrating vision and touch for object recognition tasks. *The International Journal of Robotics Research*, 7(6):15–33, 1988.

[4] Qiang Bai, Shaobo Li, Jing Yang, Qisong Song, Zhiang Li, and Xingxing Zhang. Object detection recognition and robot grasping based on machine learning: A survey. *IEEE Access*, 8:181855–181879, 2020.

[5] Michael Danielczuk, Andrey Kurenkov, Ashwin Balakrishna, Matthew Matl, David Wang, Roberto Martín-Martín, Animesh Garg, Silvio Savarese, and Ken Goldberg. Mechanical search: Multi-step retrieval of a target object occluded by clutter. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 1614–1621. IEEE, 2019.

[6] Zoe Doulgeri and Yiannis Karayiannidis. Force position control for a robot finger with a soft tip and kinematic uncertainties. *Robotics and Autonomous Systems*, 55(4):328–336, 2007.

[7] D Gonzalez-Aguirre, Julian Hoch, Sebastian Röhl, Tamim Asfour, Eduardo Bayro-Corrochano, and Rüdiger Dillmann. Towards shape-based visual object categorization for humanoid robots. In *2011 IEEE International Conference on Robotics and Automation*, pages 5226–5232. IEEE, 2011.

[8] Mohsen Kaboli, Kunpeng Yao, Di Feng, and Gordon Cheng. Tactile-based active object discrimination and target object search in an unknown workspace. *Autonomous Robots*, 43(1):123–152, 2019.

[9] Farshad Khadivar, Kunpeng Yao, Xiao Gao, and Aude Billard. Online active and dynamic object shape exploration with a multi-fingered robotic hand. *Robotics and Autonomous Systems*, 166:104461, 2023.

[10] Anwesha Khasnobish, Garima Singh, Arindam Jati, Amit Konar, and DN Tibarewala. Object-shape recognition and 3d reconstruction from tactile sensor images. *Medical & biological engineering & computing*, 52(4):353–362, 2014.

[11] Andrey Kurenkov, Joseph Taglic, Rohun Kulkarni, Marcus Dominguez-Kuhne, Animesh Garg, Roberto Martín-Martín, and Silvio Savarese. Visuomotor mechanical search: Learning to retrieve target objects in clutter. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 8408–8414. IEEE, 2020.

[12] Mark H Lee. Tactile sensing: new directions, new challenges. *The International journal of robotics research*, 19(7):636–643, 2000.

[13] Su-Lin Lee, Mirna Lerotic, Valentina Vitiello, Stamatia Giannarou, Ka-Wai Kwok, Marco Visentini-Scarzanella, and Guang-Zhong Yang. From medical images to minimally invasive intervention: computer assistance for robotic surgery. *Computerized Medical Imaging and Graphics*, 34(1):33–45, 2010.

[14] Nathan F Lepora, Kirsty Aquilina, and Luke Cramphorn. Exploratory tactile servoing with active touch. *IEEE Robotics and Automation Letters*, 2(2):1156–1163, 2017.

[15] Nan Lin, Linrui Zhang, Yuxuan Chen, Yujun Zhu, Ruoxi Chen, Peichen Wu, and Xiaoping Chen. Reinforcement learning for robotic safe control with force sensing. In *2019 WRC Symposium on Advanced Robotics and Automation (WRC SARA)*, pages 148–153. IEEE, 2019.

[16] Huaping Liu, Yupei Wu, Fuchun Sun, and Di Guo. Recent progress on tactile object recognition. *International Journal of Advanced Robotic Systems*, 14(4):1729881417717056, 2017.

[17] Huitan Mao, Jing Xiao, Mabel M Zhang, and Kostas Daniilidis. Shape-based object classification and recognition through continuum manipulation. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 456–463. IEEE, 2017.

[18] Hiroyuki Nakamoto, Fumio Kojima, and Futoshi Kobayashi. *Shape classification using tactile information in rotation manipulation by universal robot hand*. INTECH Open Access Publisher, 2010.

[19] Changjoo Nam, Jinhwi Lee, Younggil Cho, Jeongho Lee, Dong Hwan Kim, and ChangHwan Kim. Planning for target retrieval using a robotic manipulator in cluttered and occluded environments. *arXiv preprint arXiv:1907.03956*, 2019.

[20] Allison M Okamura and Mark R Cutkosky. Haptic exploration of fine surface features. In *Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No. 99CH36288C)*, volume 4, pages 2930–2936. IEEE, 1999.

[21] Sadao Omata, Yoshinobu Murayama, and Christos E Constantinou. Real time robotic tactile sensor system for the determination of the physical properties of biomaterials. *Sensors and Actuators A: Physical*, 112(2-3):278–285, 2004.

[22] Shinsuk Park, Yoojin Oh, and Daehie Hong. Disaster response and recovery from the perspective of robotics. *International Journal of Precision Engineering and Manufacturing*, 18(10):1475–1482, 2017.

[23] Anna Petrovskaya, Oussama Khatib, Sebastian Thrun, and Andrew Y Ng. Bayesian estimation for autonomous object manipulation based on tactile sensors. In *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, pages 707–714. IEEE, 2006.

[24] Zachary Pezzementi, Erion Plaku, Caitlin Reyda, and Gregory D. Hager. Tactile-object recognition from appearance information. *IEEE Transactions on Robotics*, 27(3):473–487, 2011.

[25] Kevin Riou, Kaiwen Dong, Kevin Subrin, and Patrick Le Callet. Reinforcement learning based tactile sensing for active point cloud acquisition, recognition and localization. *IEEE Journal of Selected Topics in Signal Processing*, 2024.

[26] R Andrew Russell. Object recognition by a'smart'tactile sensor. In *Proceedings of the Australian Conference on Robotics and Automation*, pages 93–8, 2000.

[27] R Andrew Russell and Jaury Adi Wijaya. Object location and recognition using whisker sensors. In *Australasian Conference on Robotics and Automation*, pages 761–768. Aust. Robot. Autom. Assoc Sydney, 2003.

[28] Alexander Schneider, Jürgen Sturm, Cyrill Stachniss, Marco Reisert, Hans Burkhardt, and Wolfram Burgard. Object identification with tactile sensors using bag-of-features. In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 243–248. IEEE, 2009.

[29] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

[30] Lucia Seminara, Paolo Gastaldo, Simon J Watt, Kenneth F Valyear, Fernando Zuher, and Fulvio Mastrogiovanni. Active haptic perception in robots: a review. *Frontiers in neurorobotics*, 13:53, 2019.

[31] Amir-Hossein Shahidzadeh, Seong Jong Yoo, Pavan Mantripragada, Chahat Deep Singh, Cornelia Fermüller, and Yiannis Aloimonos. Actexplore: Active tactile exploration on unknown objects. In *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pages 3411–3418. IEEE, 2024.

[32] Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In *2012 IEEE/RSJ international conference on intelligent robots and systems*, pages 5026–5033. IEEE, 2012.

[33] Alexander Toshev, Ben Taskar, and Kostas Daniilidis. Shape-based object detection via boundary structure segmentation. *International journal of computer vision*, 99(2):123–146, 2012.

[34] Sanghyun Woo, Shoubhik Debnath, Ronghang Hu, Xinlei Chen, Zhuang Liu, In So Kweon, and Saining Xie. Convnext v2: Co-designing and scaling convnets with masked autoencoders. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 16133–16142, 2023.

[35] Wenzhen Yuan, Siyuan Dong, and Edward H Adelson. Gelsight: High-resolution robot tactile sensors for estimating geometry and force. *Sensors*, 17(12):2762, 2017.

[36] Sheng Zhong, Nima Fazeli, and Dmitry Berenson. Soft tracking using contacts for cluttered objects to perform blind object retrieval. *IEEE Robotics and Automation Letters*, 7(2):3507–3514, 2022.

[37] Yanmin Zhou, Yiyang Jin, Ping Lu, Shuo Jiang, Zhipeng Wang, and Bin He. T-td3: A reinforcement learning framework for stable grasping of deformable objects using tactile prior. *IEEE Transactions on Automation Science and Engineering*, 2024.