

AGGRO: Autonomous Gatherer with Guided Retrieval Operations

by

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To Professor Choi and my fellow researchers in the Choice Robotics Lab, there is no easy way to express the importance of you all having faith in my work. I greatly appreciate your consistent proof of character, resilience, and camaraderie in the pursuit of great knowledge. I also must thank each and every one of the people close to me, who I hope know full well their meaning to me and my gratitude.

ABSTRACT

This thesis presents AGGRO: The Autonomous Gatherer with Guided Retrieval Operations, an innovative robotic system designed to enhance object manipulation in cluttered environments. Building on the foundations of Deep Q-Learning (DQL) and advanced reinforcement learning techniques, AGGRO integrates machine learning, robotics hardware, and sophisticated algorithms to address the "Grasping the Invisible" problem at scale. The system employs a combination of primitive synergies to achieve efficient and precise manipulation of occluded objects. Through comprehensive real-world testing and simulation, the thesis explores various *exploration* policies, dynamic clutter generation, and the impact of structured clutter scenarios on system performance. The results demonstrate a three-policy approach to efficiently reveal targets, fully uncover them, and finally singulate to grasp.

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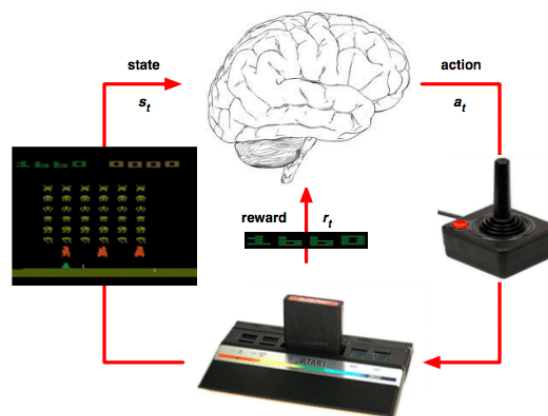
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CHAPTER ONE: BACKGROUND

Machine Learning and Video Games

The journey of machine learning in video games has paved the way for significant advancements in artificial intelligence (AI) and robotics. Atari video games, with their simplistic yet challenging environments, provided an ideal testbed for developing and testing reinforcement learning algorithms, particularly Deep Q-Learning (DQL). The discrete input action space in these games, consisting of basic controls like up, down, left, right, A, B, and start, allowed researchers to model and learn optimal policies for decision-making.



[FIGURE 1: ATARI VIDEO GAME WITH DQL LEARNING ALGORITHM]

In these environments, the state space is represented by the pixel data from the game screen, which is processed by convolutional neural networks (CNNs) to extract relevant

features. The state-action pairs, combinations of game states and possible actions, form the basis of the DQL algorithm. This algorithm uses these pairs to learn which actions lead to higher rewards by updating a Q-value function, which estimates the expected future rewards of taking certain actions in given states. Rewards, defined based on game outcomes such as points scored or levels completed, guide the learning process, helping the algorithm to maximize cumulative rewards over time.

The success of DQL in Atari games demonstrated the potential of deep reinforcement learning and set the stage for its application in more complex domains. This method's effectiveness in learning and adapting to various game scenarios provided a strong foundation for further advancements in AI.

Robotics and Deep Q-Learning

Building on the foundations laid by machine learning in video games, Deep Q-Learning has been effectively transferred to the field of robotics. This transfer has enabled robots to learn complex tasks through interaction with their environment. In robotic navigation, for instance, DQL trains robots to find optimal paths to destinations while avoiding obstacles, much like navigating through a maze or a dynamic environment. The ability to learn from experiences and improve over time is crucial for autonomous navigation systems.



[FIGURE 2: EXAMPLE OF ROBOTIC NAVIGATION USING DQL]

In robotic manipulation tasks, DQL helps robots learn to grasp and move objects. The robots receive feedback based on the success of their actions, refining their strategies for handling objects in various scenarios. This capability is particularly valuable in assembly lines or warehouse automation, where precise and reliable object handling is essential.

Examples from video games, such as Mario Kart and Super Mario World, where DQL agents are trained to complete levels, find rewards, and navigate complex terrains, serve as analogs for real-world robotic tasks. These examples illustrate how DQL can be used to train autonomous vehicles to navigate city streets or robotic arms to assemble products.

Beyond video games and robotics, DQL has achieved significant milestones in other fields. Notable examples include AlphaGo, which defeated world champion Go players, and AlphaFold, which made groundbreaking advances in protein structure prediction.

These achievements underscore the versatility and potential of deep reinforcement learning in solving complex, high-dimensional problems with long-term dependencies.

Intelligent Coordination & Primitive Synergy

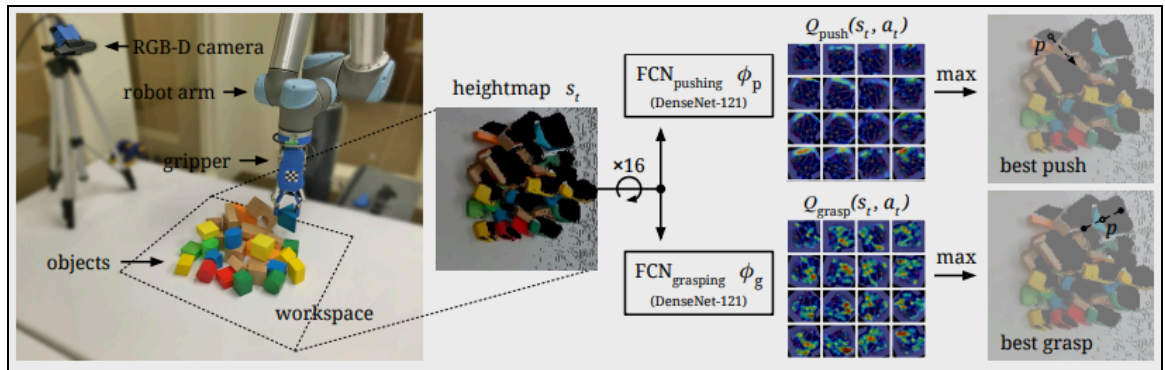
Intelligent coordination is critical in robotic systems. It involves the seamless integration of basic robotic actions, or primitives, to achieve high-level goals. This process includes task decomposition, which breaks down complex tasks into simpler sub-tasks that can be handled by primitive actions. Coordination algorithms like behavior trees and hybrid automata are used to manage the execution of these primitives in a coordinated manner. In multi-robot systems, intelligent coordination ensures that multiple robots work together effectively to complete collaborative tasks, such as moving large objects or conducting search and rescue missions. [15]

Primitive synergy refers to the effective combination of these basic robotic actions to perform complex tasks. These primitives can include actions such as move forward, turn, grasp, and release, which serve as building blocks for more sophisticated behaviors. By combining these primitives, robots can execute complex tasks. For example, a sequence of move and grasp actions enables a robot to pick up an object from the ground. Learning these primitives efficiently involves techniques like imitation learning, where robots mimic human demonstrations to acquire the necessary skills.

By combining intelligent coordination with primitive synergy, robots can achieve sophisticated and efficient task execution, enabling them to handle a wide range of complex activities autonomously.

Visual Push and Grasp (VPG)

The Visual Push and Grasp (VPG) technique, developed by Princeton University, represents a significant advancement in robotic manipulation. VPG combines visual perception with pushing and grasping actions to enable robots to manipulate objects in cluttered environments.



[FIGURE 3: VPG TECHNIQUE WITH RGB-D AND AFFORDANCE MAP]

VPG utilizes depth cameras to capture 3D information about the environment. This depth data provides critical insights into the spatial arrangement of objects, helping the robot to plan its actions more effectively. The depth information is projected onto a 2D plane, creating an affordance map that highlights the most promising areas for pushing and grasping actions. [18]

Deep Q-Learning is employed to train the robot to make optimal decisions based on the affordance map. The robot learns to maximize cumulative rewards by executing sequences of pushing and grasping actions that clear the clutter and successfully grasp the target object. Two neural networks, PushNet and GraspNet, are trained to predict the best locations and directions for pushing and grasping actions, respectively. These networks are trained using reinforcement learning, where the robot receives rewards based on the success of its actions.

The integration of depth information, projection, and DQL in the VPG technique enables robots to interact with cluttered environments effectively, showcasing the power of combining visual perception with reinforcement learning for robotic manipulation.

Multi-View Change Observation-Based Approach (MV-COBA)

The Multi-View Change Observation-Based Approach (MV-COBA) enhances robotic capabilities by using multiple viewpoints to improve the accuracy of visual inference. By capturing images from different angles, MV-COBA provides a more comprehensive understanding of the environment, helping in better detecting objects and understanding their spatial relationships.

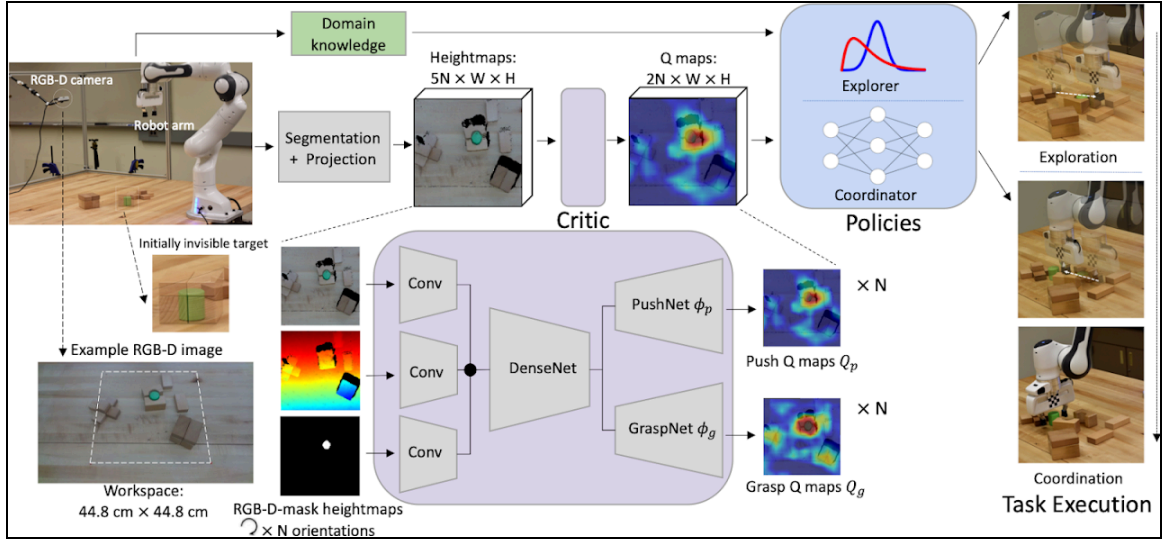
The additional viewpoints allow for more accurate inference in terms of object detection and placement, resulting in more precise predictions for pushing and grasping actions. This approach is particularly useful in cluttered environments where objects might be partially hidden from a single viewpoint.

The enhanced object detection accuracy provided by MV-COBA improves the robot's ability to plan and execute actions, reducing the likelihood of errors. The approach also helps in identifying the best points of interaction for manipulating objects, leading to more effective and efficient robotic systems. [9]

Grasping the Invisible (GTI)

Standing as the seminal work of this thesis, Grasping the Invisible provides insight into the powers of emergent behavior when primitive synergies are given a task-driven reward pathway. Building on the VPG approach, and, the concept of Grasping the Invisible, introduced by the University of Minnesota's CHOICE Robotics Lab, addresses the challenge of manipulating objects that are partially or fully occluded. This method enhances the robot's ability to handle cluttered environments by incorporating a target mask, which indicates the location of the target object within the workspace.

The target mask serves as a third input metric for the neural networks, helping the robot to prioritize actions that are more likely to partially uncover and grasp the target object. This addition improves the efficiency of the manipulation process, making it more targeted and effective.



[FIGURE 4: GTI AND AFFORDANCE MAP TARGET MASKS]

This synergy between actions allows the robot to clear obstacles and singulate the target, even when it is not immediately visible. The Grasping the Invisible method is particularly useful in scenarios where the target is a specific shape or color, such as locating a red block hidden among other objects. The robot uses the target mask to focus its efforts on uncovering and grasping the target efficiently. [15]

This pivotal method and its applications will be covered in much more depth in a later chapter.

Transporter Networks and Advanced Planning

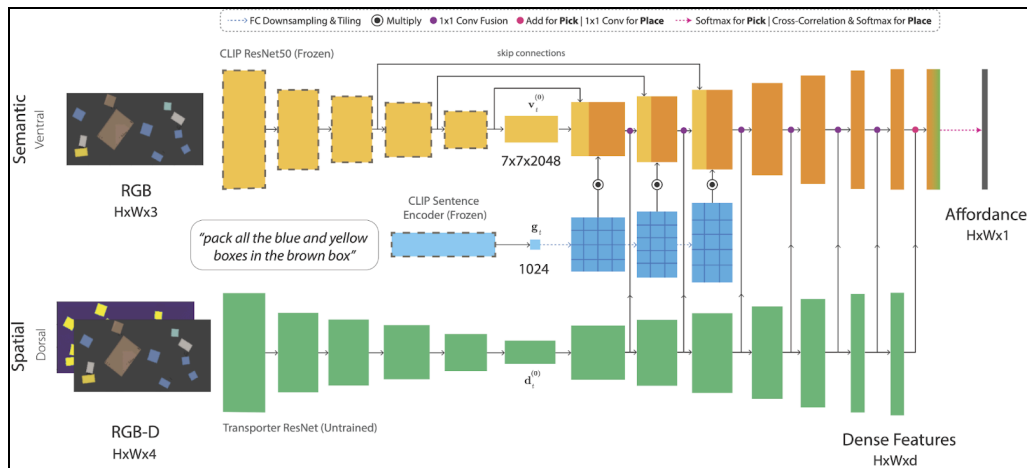
Transporter networks represent a significant leap in robotic manipulation, focusing on learning spatial transformations to manipulate objects. These networks understand the

geometric and spatial relationships between objects and their environments, allowing robots to perform complex tasks with precision.

Transporter networks typically consist of encoder-decoder structures, where the encoder processes the input data to capture spatial information, and the decoder generates the desired transformations. These networks are used in various robotic tasks, such as sorting, assembly, and packing, where precise manipulation of objects is required.

CLIP-based Transporter (CLIPort)

CLIPort integrates the capabilities of the CLIP (Contrastive Language-Image Pre-Training) model with transporter networks to enhance robotic manipulation. CLIP is a powerful model developed by OpenAI that aligns images with their corresponding textual descriptions, enabling it to understand and generate rich representations of visual and linguistic data.



[FIGURE 5: CLIP PIPELINE]

CLIPort leverages the representation power of CLIP to enhance the spatial and geometric understanding required for transporter networks. The model can understand commands given in natural language and execute corresponding manipulation tasks, such as "place the red block on the green block." This ability to comprehend the spatial arrangement and orientation of objects allows for intelligent and precise manipulation. [12]

CLIPort's integration with language models and advanced planning techniques makes it highly effective for organizing objects in a workspace based on both visual and linguistic cues. This development points towards a future where robots can understand and act upon high-level instructions, making them more practical and versatile in real-world applications.

Image-driven Object Searching and Grasping (IOSG)

Image-driven Object Searching and Grasping (IOSG) is an innovative approach that enables robots to retrieve specific objects from cluttered scenes using a reference image. Developed by the Choice Robotics Lab at the University of Minnesota, IOSG eliminates the need for extensive manual annotations by employing a Target Similarity Network. This network generates a probability map to infer the target object's location, guiding the robot to identify and grasp objects without prior knowledge. The hierarchical policy framework comprises high-level and low-level policies: the high-level policy predicts whether to explore or coordinate, while the low-level policies, explorer and coordinator, execute these tasks. The explorer searches for the target when occluded, and the coordinator performs targeted pushing and grasping actions to retrieve the object.

The IOSG pipeline starts with the robot receiving a reference image of the target object. The Target Similarity Network processes this image along with object segments in the environment to produce a similarity projection map. The high-level policy uses this map to determine the appropriate subtask, and the deep Q-Network predicts Q maps for pushing and grasping actions. Trained with full self-supervision in simulation, IOSG has demonstrated high success rates in both simulated and real-world applications. This work, which is also a direct continuation of the Grasping the Invisible Problem, shows how another direction of attacking the problem allows for greater possibilities, particularly in addressing segmentation abilities and other critical elements related to visual processing. [16]

Conclusion

The journey of machine learning from video games to robotics demonstrates the transformative power of Deep Q-Learning (DQL) and other advanced AI techniques. Initially, DQL proved its efficacy in Atari games, where it learned optimal decision-making by interpreting pixel data and maximizing rewards. This success laid the groundwork for applying similar principles in robotics, where DQL has enabled robots to navigate environments and manipulate objects with precision.

Key techniques like Visual Push and Grasp (VPG) and the Multi-View Change Observation-Based Approach (MV-COBA) have significantly enhanced robotic capabilities, allowing robots to effectively handle cluttered environments. The concept of Grasping the Invisible (GTI) further improves manipulation efficiency by using target

masks to deal with occluded objects, demonstrating the synergy between intelligent coordination and primitive actions.

Transporter networks and advanced models like CLIPort integrate spatial understanding and linguistic commands, enabling precise and versatile manipulations. Meanwhile, the Image-driven Object Searching and Grasping (IOSG) framework takes a different approach by allowing robots to retrieve specific objects from cluttered scenes using reference images, enhancing their accuracy and efficiency.

Overall, these advancements underscore the versatility and potential of deep reinforcement learning. The techniques discussed illustrate significant milestones and pave the way for future innovations in AI and robotics, leading to more intelligent, adaptable, and autonomous systems capable of tackling increasingly complex tasks. This chapter sets the stage for further exploration of advanced methodologies and their practical applications in robotic manipulation and coordination.

CHAPTER TWO: ROBOTIC HARDWARE

In the quest to enhance autonomous systems, the development of robust robotic hardware is crucial. This chapter delves into the intricate details of hardware development, exploring the integration of technologies across computing, physical design, and visual systems. AGGRO: The Autonomous Gatherer with Guided Retrieval Operation, represents a significant step in robotic manipulation and environmental perception. We

leverage open-source, easy-to-repair, and scalable robotics hardware that can accomplish identical task sets to those of 7 DOF arms at a fraction of the engineering burden.

Computing Requirements and NVIDIA Architecture

High-Performance Computing in Robotics

Robotic systems, especially those designed for complex tasks such as visual perception, motion planning, and real-time decision-making, require substantial computational power. AGGRO's computational backbone relies on NVIDIA's CUDA architecture, specifically utilizing the NVIDIA 1080Ti GPUs. These GPUs are crucial for executing complex neural network models, enabling AGGRO to process large datasets efficiently and make real-time decisions.

Future Scalability and AI Integration

The computational framework provided by NVIDIA GPUs not only supports current tasks but also lays the groundwork for future scalability. As AI algorithms become more sophisticated, the need for robust computational infrastructure will grow. AGGRO's reliance on NVIDIA architecture ensures that it can adapt to these advancements, maintaining its relevance and efficiency in evolving scenarios.

FarmBot Genesis and Open Source Hardware Integration

The Versatile Platform

The FarmBot Genesis V1.6 serves as AGGRO's foundational hardware platform, offering a scalable Cartesian workspace premise for agricultural applications. Its modular design allows for easy customization, making it a versatile tool for various research and operational needs.

Key Components and Integration

Equipped with custom integration boards, AGGRO achieves robust control and communication capabilities. The FarmDuino manages power distribution, motor control and failsafe, while the Raspberry Pi runs the FarmBot OS, handling host computer communication, scheduling, and task execution. This integration ensures seamless operation and facilitates real-time data collection and processing, essential for autonomous agricultural tasks.

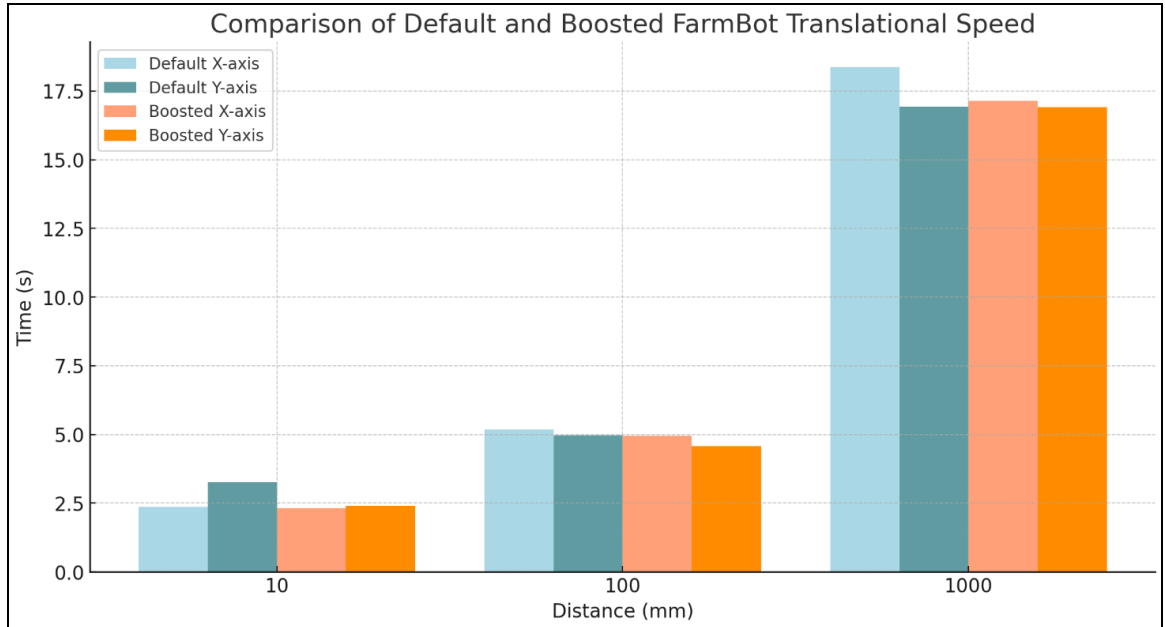
Open-Source Principles and Collaboration

By embracing open-source hardware, AGGRO not only reduces development costs but also fosters a collaborative innovation environment. Researchers and developers can customize and enhance the system, driving continuous improvement and adaptation to specific challenges. This approach democratizes access to advanced robotic technologies, enabling broader adoption and innovation in the field.

Hardware Validation and Power Restrictions

AGGRO has been validated to perform effectively within the same force requirements as traditional 7-degree-of-freedom (7DOF) robotic arms and the FarmBot Genesis, making it a cost-effective solution for precision farming and small-scale automation. Traditional robotic arms, such as the KUKA LBR IIWA 14 R820, Universal Robots UR10, and Franka Emika Panda, exert pushing forces ranging from approximately 60 N to 200 N, while the FarmBot Genesis, powered by NEMA 17 stepper motors, can handle pushing tasks requiring up to 45-50 N.

The validation of FarmBot's speed, as demonstrated in the performance benchmarking graph, indicates that the FarmBot can operate efficiently under both default and boosted settings. This is crucial when considering the feasibility of running hundreds to thousands of experiments. While seminal works may focus on iterations, human patience is a critical factor in controlled experiments. The ability of the robotic farming robot to perform real-time tasks efficiently ensures that it can handle extensive experimentation without causing undue delays, making it a practical tool for large-scale agricultural research and development.



[FIGURE 6: PERFORMANCE BENCHMARKING OF FARMBOT SPEED]

This benchmarking demonstrates AGGRO's speed, force, and reliability in real-world applications, ensuring it meets the research standards at a fraction of the overhead. However, it is important to note that the robotic hardware used in FarmBot is at the extreme low end of all possible object manipulation machines. Originally designed for surveying agricultural operations, it should be kept in mind for experimentation that operating the FarmBot in intelligent pipelines as mentioned earlier will likely push it to its maximum output.

Enhancing Operational Efficiency

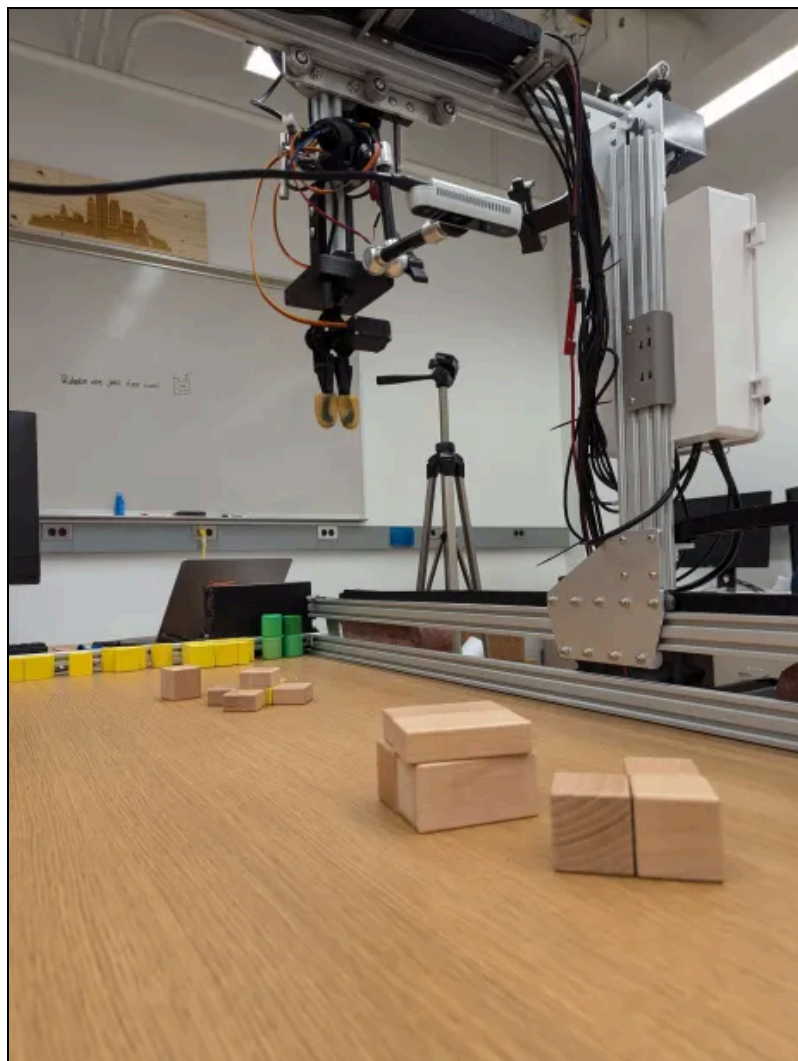
Optimizing speed and torque characteristics is vital for AGGRO's efficiency in task execution. Whether it's precise harvesting maneuvers or delicate soil management tasks,

AGGRO's robust hardware ensures high reliability and adaptability in varying operational conditions. This efficiency directly translates to improved productivity and reduced operational costs in agricultural practices.

Visual Integration with Intel RealSense:

AGGRO enhances its environmental perception capabilities through the integration of Intel RealSense RGB-D cameras. In robotics research, the Intel RealSense camera is ubiquitously utilized due to its high-resolution depth and RGB imaging, which are crucial for accurate spatial mapping and object recognition. However, traditionally, projection maps are used alongside the Intel RealSense to create height maps, which can often be prone to high areas of invalid data and calibration issues, affecting the ability to accurately infer the X, Y, Z location based on the IR and color camera inference data.

In the AGGRO robotic system, we have innovated beyond these limitations by mounting the RealSense camera directly on the physical end effector of the device, adopting a wrist-mount architecture. This new configuration eliminates the need for real-world projection height maps, which, while effective in simulation, often fail in real-world applications. In the real world, these projection height maps suffer from poor quality and frequent disruptions; any nudge to the IR camera necessitates recalibration, leading to data loss and the need for reproduction.



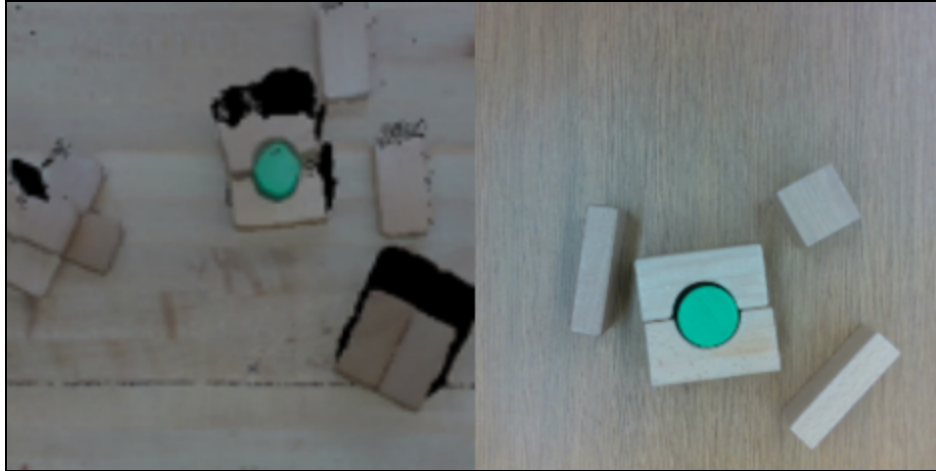
[FIGURE 7: WRIST-MOUNTED CAMERA CONFIGURATION ON AGGRO]

The advanced perception capabilities of AGGRO are significantly enhanced by this robust design. The mounting and top-down perspective not only minimize occlusions and shadows but also ensure a more stable and reliable visual data capture system. This allows AGGRO to maintain high precision in navigation and manipulation tasks, making it a powerful tool for real-world applications where traditional methods fall short.

Additionally, this setup transforms the coordinate systems used in our pipeline from absolute encoding to relative encoding of position. The benefit of this approach lies in the ability to always determine the absolute position of the end effector within the global workspace. From that absolute position, we can compute the vector to the camera's position, which is wrist-mounted. This allows us to understand our relative location by utilizing the projected positions seen by the IR camera.

Improving Visual Data Quality

By adopting a top-down view, AGGRO achieves higher fidelity heightmaps and depth calculations. This perspective ensures consistent image capture, essential for effective decision-making and task execution. One key advantage of this approach is the reduction of occlusion-related shadows—areas where data is unavailable due to objects blocking the infrared (IR) dot projection. In the "grasping the invisible" problem, items scattered randomly can create significant shadowed areas in the visual field, hindering accurate perception. The integration of advanced classification models further enhances AGGRO's ability to identify and interact with objects, improving operational precision and efficiency. By reducing these shadowed areas, we not only avoid the need for frequent recalibration of the visual integration system before each test, but also improve the acuity of our visual data, resulting in more valid values across color height maps, depth height maps, and target height maps.



[FIGURE 8: VISUAL DATA QUALITY WITH TRADITIONAL VS. ORTHO]

Practical Applications

In practical terms, this visual integration allows AGGRO to perform complex tasks such as targeted object searching and manipulation with high accuracy. Advanced visual systems enable AGGRO to navigate cluttered environments, identify targets, and execute precise actions, significantly enhancing its effectiveness in applications like generalist warehousing, disaster recovery, and other complex operational environments. [16]

End Effector and Physical Interface Design

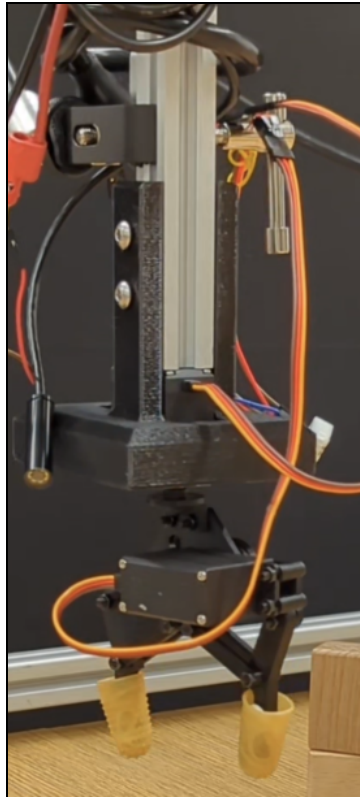
Custom-Designed Grippers

Central to AGGRO's physical interaction capabilities are its custom-designed grippers and end effectors. These components are developed using CAD software and 3D printing technologies, allowing for iterative refinement and optimization. The grippers are

designed to handle diverse tasks, from precise object manipulation to robust soil sampling.

Material Science Considerations

Materials like PETG and PLA are rigorously tested for performance under varying conditions. PETG offers durability and flexibility, while PLA provides ease of printing and strength. These materials are chosen based on their ability to withstand stress and maintain performance over extended periods, ensuring reliability in agricultural environments.



[FIGURE 9: 3D PRINTED CUSTOM GRIPPER]

Gripper Design Evolution

As previously demonstrated through hardware validation, the carrying capacity and force exerted by our FarmBot hardware are at their maximum threshold. This necessitates the use of less heavy robotic hardware to enhance grasping and lifting capabilities while also enabling more powerful sliding motions. These improvements increase the normal force when applying forces for pushing.

Initially, our design featured a PETG-printed 3D parallel gripper, created by an undergraduate student for a senior design project. Despite its theoretical promise, the design proved too heavy for magnetic mounting on the UTM (Universal Tool Mount) of the FarmBot, making it impractical for fine-grained pushing actions. Furthermore, the servo encountered control issues, such as frequent twitching, unrelated to power stability. These issues can stem from interference in control signals, mechanical binding, or inadequate servo specifications.

With these challenges in mind, we explored articulated jaw designs. We tested two versions: one made of PLA and another of PETG. The PLA design failed due to its flimsiness and inability to maintain structural integrity during articulation. Subsequently, we adopted a design from an online repository and modified it to attach to the FarmBot's z-axis, incorporating additional gripping types.

Our naive approach began with using rubber bands to enhance grip strength for better push and grasp actions. This evolved into using a thimble commonly used in sewing, and finally, employing a mold or casting technique to fill the thimble with hot glue. This was

then attached to the fingers or end effectors of our final black articulated PETG gripper, which proved to be effective and reliable in our final implementation.

Power Management and Reliability

Addressing power constraints is a critical aspect of AGGRO's design. The system integrates sophisticated power management solutions to stabilize voltage and current flow during intensive operations. Voltage sag, often caused by high current draw from servo motors, is mitigated through dedicated power supply units. These intelligent power management solutions ensure consistent performance and minimize operational downtime, which is crucial for continuous autonomous operations in agricultural settings. By stabilizing power delivery, the operational stability of the grippers is enhanced, allowing them to perform reliably during critical tasks and maintaining consistent performance across different agricultural applications.

Through faults in power management, grippers could enter forbidden states, causing their gears to tear out and resulting in numerous reprints. The robust power management system is designed to prevent such faults, thereby protecting the integrity of the grippers and ensuring their longevity and reliability.

Conclusion

AGGRO represents a significant milestone in robotic hardware development, amalgamating cutting-edge technologies to advance autonomous agricultural systems. By leveraging the FarmBot Genesis V1.6 platform, NVIDIA CUDA architecture, Intel

RealSense visual integration, and custom-designed end effectors, AGGRO achieves scalability, efficiency, and adaptability. This integrative approach not only stabilizes power delivery and enhances operational stability but also addresses the critical challenges of power management and gripper reliability.

One of AGGRO's key strengths is its ability to achieve performance benchmarks of traditional robotic systems at a reduced burden, making advanced robotic technologies more accessible and feasible for broader application in agricultural settings. Its modular and open-source design further enhances scalability, allowing for continuous improvements and adaptations. Future development will focus on enhancing hardware capabilities, expanding application domains, and integrating ML-driven algorithms for optimized decision-making and autonomy, ensuring AGGRO's efficiency and effectiveness in real-world applications.

CHAPTER THREE: RE-GRASPING THE INVISIBLE

Grasping the Invisible (GTI) is a complex and challenging task involving the manipulation of objects that are partially or fully occluded within a cluttered environment. This chapter delves into the methodologies developed in previous work, provides adequate critique, and explores advancements in the AGGRO system that can push development further. This exploration represents a deep investigation into the fundamental philosophy of machine learning, the integration of robotics hardware, and the sophisticated algorithms that combine to create a functional robotic system. By

thoroughly examining each aspect of the GTI pipeline we aim to identify and address key faults and issues. We will showcase the performance of these elements in real-world settings, providing insights that will inform our future chapters, where we advance these themes and further develop the pipeline

Enhancing Data Accuracy and Practicality

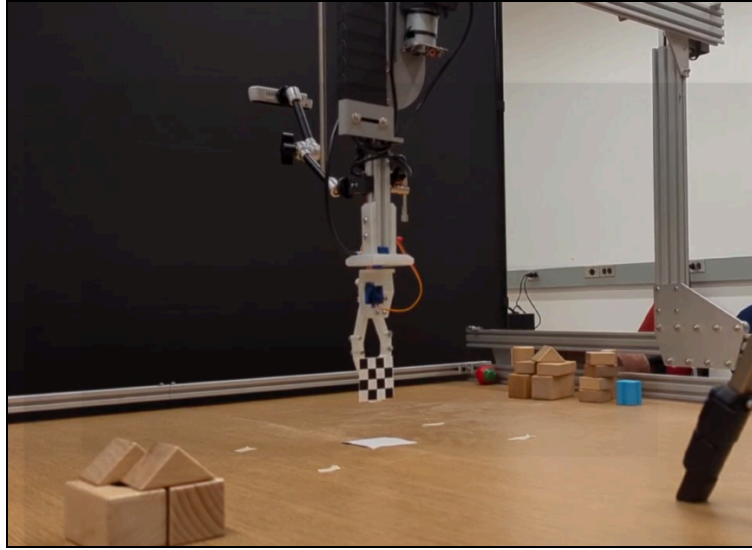
Accurate visual performance is crucial for the success of machine learning models. Enhancing the acuity and resolution of visual inputs to neural networks can significantly improve their effectiveness. This principle is fundamental: poor data input results in poor data output. This holds true for basic regression models and the most advanced deep Q-learning models alike.

Data Integrity and System Robustness

One significant motivation for switching to an overhead camera was the frequent inaccuracies encountered with a camera mounted on a tripod looking at the workspace. Such setups were susceptible to data amalgamations, leading to positional inaccuracies of several centimeters whenever the state of the environment changed. By using an overhead camera, not only was acuity increased and invalid data points decreased, but the need for constant recalibration was also eliminated.

This improvement allows the system to repeatedly collect data without requiring any form of recalibration, opening the possibility for online training. Previously, online training was not feasible due to the difficulty of maintaining calibration across different

domains in real-world training scenarios. The enhanced stability and accuracy provided by the overhead camera setup lay the groundwork for powerful real-world online training in future research. However, it should be noted that online training is not within the scope of this current work but is identified as an interesting avenue for progressive research.

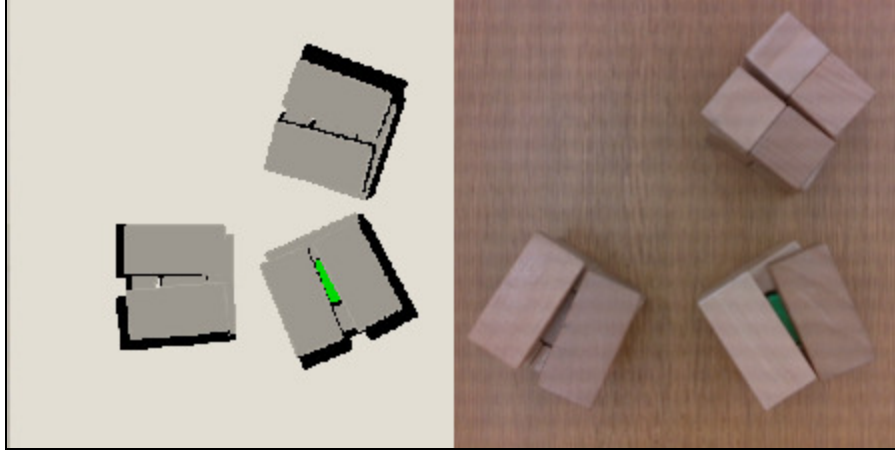


[FIGURE 10: TYPICAL EXTRINSIC CALIBRATION PROCESS]

Real-World Integration and Challenges

In real-world simulations and tasks, the overhead top-down camera significantly improved data quality. The reduction in invalid data points and enhanced visibility of objects allowed the system to detect and manipulate items more effectively in cluttered settings. However, this also introduced new challenges, such as focusing issues. Ensuring adequate cropping and upscaling was essential when processing the original 720p RGBD color and depth information, which was cropped down to a 224 by 224 scheme and then upscaled again. This method, different from the original methods explored in the GTI₂₆

VPG pipelines, involved the projection and deprojection of UV to XYZ coordinates, which proved to be effective.



[FIGURE 11: CONSISTENT GEOMETRY ACROSS ENVIRONMENTS]

Maintaining a stable visual baseline was also critical to ensure consistent data input. Any fluctuations in the baseline could result in inconsistencies that affect the performance of the neural networks. Ensuring geometric consistency is paramount; the objects viewed in the training set are essentially numerical representations of the visual field. It is crucial that these numbers are accurately represented. Exploring different training paradigms at varying distances from the target clutter could potentially enhance the system's learning capabilities. By incorporating variation in distance, the system could learn to discern whether it is close to or far from the objects, thereby leveraging these perspectives for improved robotic manipulation.

The quality of visual data directly impacts the performance of machine learning models. Ensuring high-quality data input is essential for achieving accurate and reliable outputs. This was particularly evident in efforts to recreate real-world results on the Franka Emika Panda robotic arm. Despite these challenges, the optimized visual performance and the use of a scalable, orthogonally mounted camera resulted in adequate real-world performance.

By addressing both the quality of visual data and the practical aspects of its integration, the robot's ability to perform complex tasks has been enhanced, thereby advancing the field of robotic manipulation and machine learning integration. Moreover, the benefits of real-world online training become increasingly powerful as the accuracy and reliability of systems improve.

Segmentation Approaches

Segmentation is a critical process in robotic perception, enabling the identification and separation of different objects within a scene. Various segmentation techniques were employed, each with distinct performance characteristics and real-world applicability.

Lightweight RefineNet

In the GTI pipeline, a lightweight RefineNet was initially used to generate segmented masks of target objects. While effective in simulations and controlled environments, its performance degraded in real-world tests due to lighting variations and occlusions. The primary issue was that in real-world environments, the colors and patterns observed

caused the semantic segmenter to label objects that were not desired targets but fell into the same color categories as the targets (e.g., red, orange, yellow, green, indigo, purple). This mislabeling was a direct result of the pipeline's design and highlighted the need for a more advanced scheme.

Despite these challenges, lightweight RefineNet has shown successes, particularly in less complex environments. Its limitations in high occlusion contexts were a significant focus in the broader research corpus. For example, Image-driven Object Searching and Grasping (IOSG) employs a Target Similarity Network to tackle these high occlusion issues, guiding robots to identify and grasp objects using a reference image. While this method addresses some of the key segmentation challenges, the current research chose not to focus on this approach. Instead, the work relied on the intuitions derived from target segmentation masks to continue developing the grasping framework.

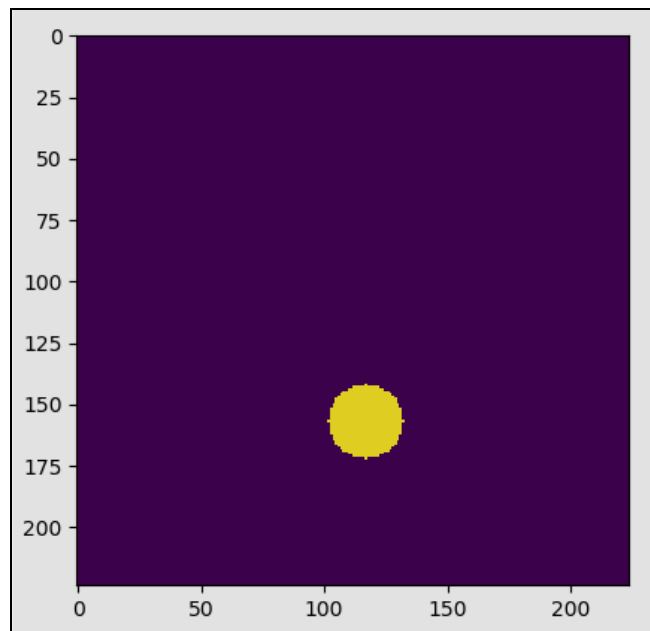
YOLO (You Only Look Once)

YOLO, a renowned object detection algorithm, was considered for integration with segmentation tasks. Although promising for object detection, its complexity and computational requirements posed challenges. While not covered in the current research context, YOLO's potential becomes evident as the diversity of objects to be segmented increases. Future progression may benefit from YOLO's capabilities, especially when dealing with a wider range of objects such as people, animals, or specific household items. Its ability to detect and segment various objects could provide more comprehensive object recognition capabilities in more diverse applications. Future work

could explore using YOLO on top of existing segmentation models to enhance performance in more complex scenarios.

K-Means Segmentation

K-Means segmentation emerged as a simple and effective approach. By grouping pixels based on color similarity, it provided a straightforward and efficient method for generating masks. K-Means segmentation proved to be highly effective for the specific task of generating an accurate mask of the target. Its ability to perform this task efficiently makes it the most practical choice for the current pipeline. The method's effectiveness is particularly evident in reducing the incidence of false positives, such as misidentifying random objects as target objects based on color similarity.



[FIGURE 12: K MEANS TARGET MAP]

Comparative Analysis

In real-world tests, lightweight RefineNet performed well in controlled environments but struggled with variability. The most significant issue was its tendency to mislabel objects due to similar colors and patterns, which was problematic when identifying specific target objects. However, its successes in simpler environments indicate potential with further development. The broader research corpus, such as the work done in IOSG, provides complementary approaches addressing high occlusion problems. However, this research opted to focus on the practical advantages of K-Means segmentation. K-Means offered a balanced solution, providing adequate accuracy and speed, particularly effective in generating target masks with high precision and reducing false positives. This simplicity, speed, and practical use in the pipeline underscore its suitability for efficiently uncovering ambiguous targets.

Grasping the Invisible: Comprehensive Framework and Implementation

The "Grasping the Invisible" (GTI) problem addresses the challenge of manipulating objects that are partially or fully occluded within a cluttered environment. This section delves into methodologies from previous PhD work and current advancements in AGGRO-robotics, focusing on exploration, coordination, singulation, and grasping.

The primary goal is to manipulate the environment to make the target object accessible for grasping. The GTI pipeline involves data collection, processing through DenseNet to

produce PushNet and GraspNet heat maps, and selecting the optimal pixel location for pushing or grasping actions.

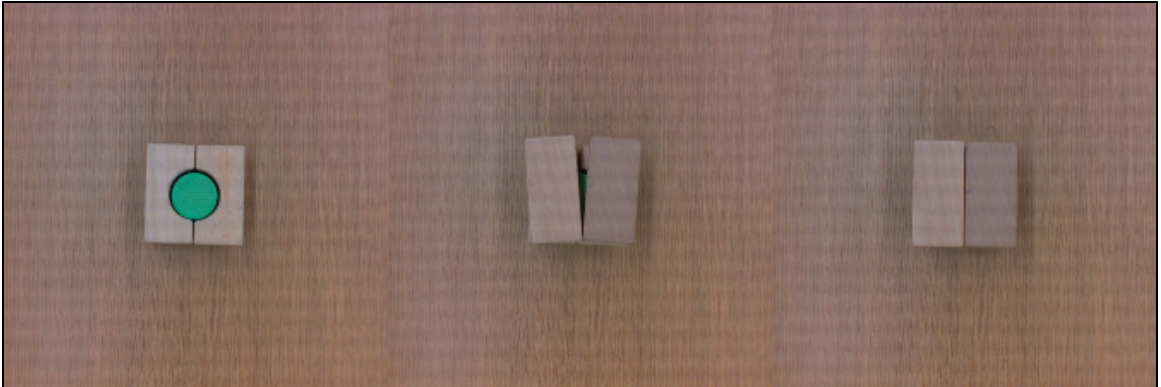
The pipeline operates in two stages: exploration and coordination. In the exploration stage, only push actions are performed to reveal the target object, driven by probabilistic maps to avoid redundant exploration. Once the target becomes visible, the system transitions to the coordination stage, deciding between push and grasp actions. Due to the high failure rate of grasp attempts in cluttered environments, the system often defaults to push actions, leading to emergent behavior where 90% to 95% of actions are pushes.

The reward structure shapes the system's behavior. For push actions, rewards are given for increasing the margin around the target and moving across the target to improve visibility. For grasp actions, rewards are given for successful grasps, or if aligned with the target mass. The system employs DeepQ learning and replay training to refine its policy, revisiting past successes to accelerate learning.

Delta analysis between scenes, focusing on changes in height maps, feeds into the reward structure to measure the marginal occupation index, determining the target's accessibility. This facilitates behaviors like revealing and singulation.

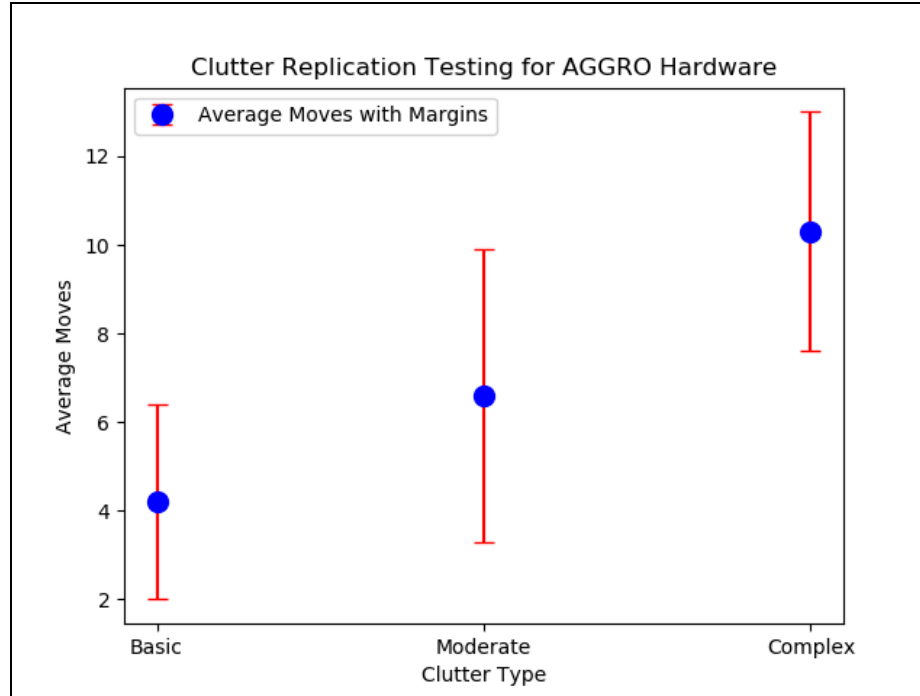
Despite having a simpler four-degree-of-freedom Cartesian configuration compared to the seven-degree-of-freedom Franca Emika robot arm, AGGRO effectively replicates the GTI pipeline's actions. Utilizing simpler segmentation models, it achieves comparable performance, proving the hardware's robustness.

To validate robustness, clutter scenarios similar to those in GTI testing environments were recreated, ranging from basic to complex. The system's ability to handle varying levels of occlusion and complexity ensures it can effectively "grasp the invisible."



[FIGURE 13: BASIC, MODERATE, AND COMPLEX CLUTTER TYPES]

The GTI pipeline, with its structured approach, advanced learning mechanisms, and robust reward structure, provides a comprehensive framework for grasping occluded objects. By integrating DeepQ learning, replay training paradigms, and delta analysis, the system ensures efficient exploration and coordination, leading to emergent behaviors that enhance target accessibility and successful grasps. The AGGRO-robotic platform demonstrates the feasibility and effectiveness of these principles in real-world applications, paving the way for further advancements in robotic manipulation in cluttered environments.



[FIGURE 14: GTI PIPELINE RESULTS REAL-WORLD SCENARIOS]

Subsequent chapters will explore how these principles and critiques are used to build a more advanced robotic system, enhancing AGGRO's capabilities and advancing robotic manipulation in complex environments.

Conclusion

The "Grasping the Invisible" (GTI) challenge embodies the intersection of advanced machine learning techniques and sophisticated robotic hardware to address the complex task of manipulating occluded objects within cluttered environments. Through critical examination of existing methodologies and the integration of novel approaches in the

AGGRO system, significant advancements have been achieved in enhancing data accuracy, system robustness, and practical applicability.

The transition to an overhead camera setup has markedly improved data quality and system stability, facilitating the potential for real-world online training. The exploration of various segmentation approaches, including lightweight RefineNet, YOLO, and K-Means segmentation, has provided valuable insights into their respective advantages and limitations, ultimately leading to the adoption of K-Means for its efficiency and practicality.

The comprehensive GTI framework, encompassing exploration and coordination stages, has demonstrated robust performance in handling occlusion and complexity, driven by an effective reward structure and advanced learning mechanisms such as DeepQ learning and replay training. The emergent behaviors observed in the AGGRO-robotic platform validate the feasibility of these principles, showcasing the system's capability to manipulate occluded objects successfully.

This chapter lays a solid foundation for further advancements in robotic manipulation, setting the stage for subsequent chapters to build upon these principles, refine the AGGRO system, and push the boundaries of what is possible in complex, real-world environments. The integration of these methodologies promises to enhance the efficiency and effectiveness of robotic systems, paving the way for future innovations in the field.

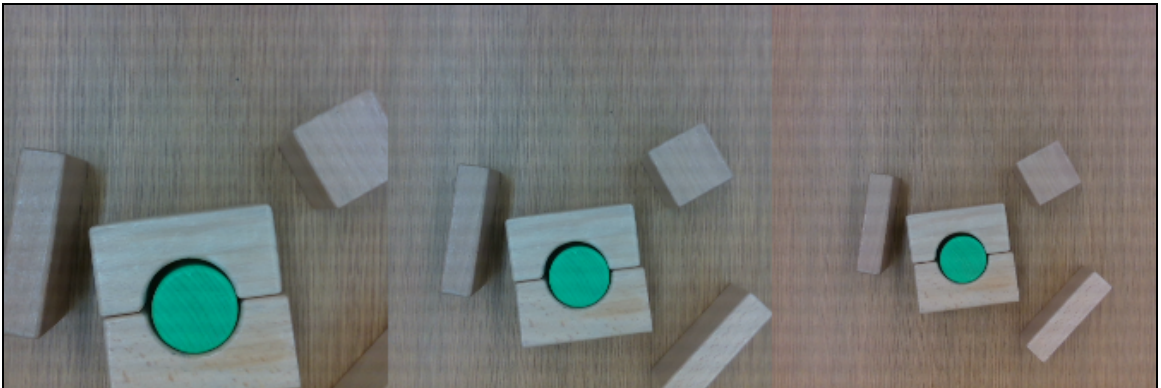
CHAPTER FOUR: EXPLORTATION

Advancing robotic exploration and manipulation capabilities hinges on overcoming the Sim-to-Real gap. This chapter delves into a comprehensive approach of reverse engineering and enhancing the Grasping the Invisible (GTI) pipeline, moving seamlessly between real-world applications and simulated environments using the AGGRO robotic system. The primary problem addressed is expanding the GTI pipeline through the affordances gained via the AGGRO system. Our orthogonal cameras, scalable system, and desire for efficient exploration and discovery of target objects hidden under clutter drive this endeavor. Identifying the areas where the real-world AGGRO robotic searching system falls short in adequately exploring its environment with efficient pushes highlights the need for advancements. These gaps serve as the impetus for improvements made through the AGGRO system.

Real-World Testing

The journey began with real-world testing of the GTI pipeline using the AGGRO robotic system, leveraging existing robotic hardware and software infrastructure. This phase involved executing real-world experiments based on prior emulations in simulation. Initial tests revealed substantial insights but also inherent limitations, such as segmentation inaccuracies, robustness challenges, and suboptimal task performance under real-world conditions.

When trying to recreate the pipeline exactly, it became evident that focus and distance from the object were critical. Ensuring accurate data input is paramount, as suboptimal data leads to poor performance in machine learning. The goal was to maximize the behavior of the AGGRO robotic system to emulate the previous behavior observed in both simulation and prior real-world experiments from the GTI framework. This effort was crucial in identifying and addressing the specific areas where the AGGRO system fell short in exploring its environment with efficient pushes. Validation of the AGGRO system against previous testing showed its capability to perform similar tasks; however, new challenges emerged under real-world conditions. These observations helped in refining the system to better handle the complexities of real-world environments.



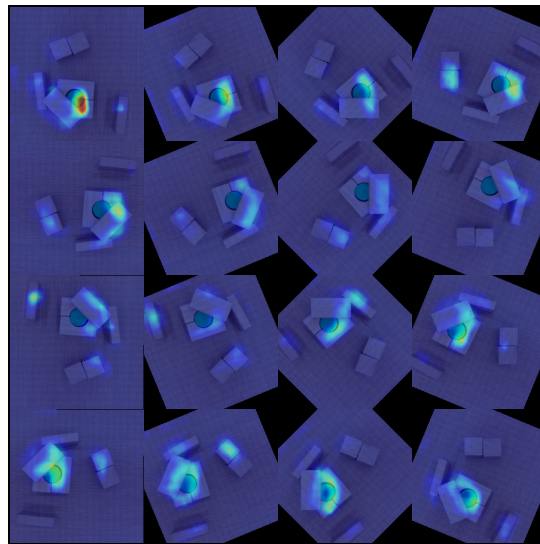
[FIGURE 15: STAND-OFF DISTANCE 20 cm, 120 cm, 220 cm]

Challenges Observed

When scaling the AGGRO system from a single workspace, as used in previous GTI work, to a two-by-two array of four unique sets of clutter, several challenges were identified. The primary challenge was enabling the robot to efficiently explore its

environment without knowing if the partially visible object is the actual target. This aspect is fundamental to the thesis. In large-scale environments, such as a ten meter by ten meter workspace, it is crucial to be certain that the target object being pursued is the correct one. This necessity motivates the objective of uncovering the complete target object more reliably.

By fully uncovering objects, the system can make better decisions about coordination. This approach ensures the GTI pipeline can operate on a fully uncovered mask, rather than spending turns on tasks it is not specifically geared for, like singulating once it has already seen the full expanse of its covering. While uncovering objects is an emergent behavior in the GTI pipeline, the goal is to make it a purposefully trained behavior, thereby enhancing its exploration and uncovering phases.



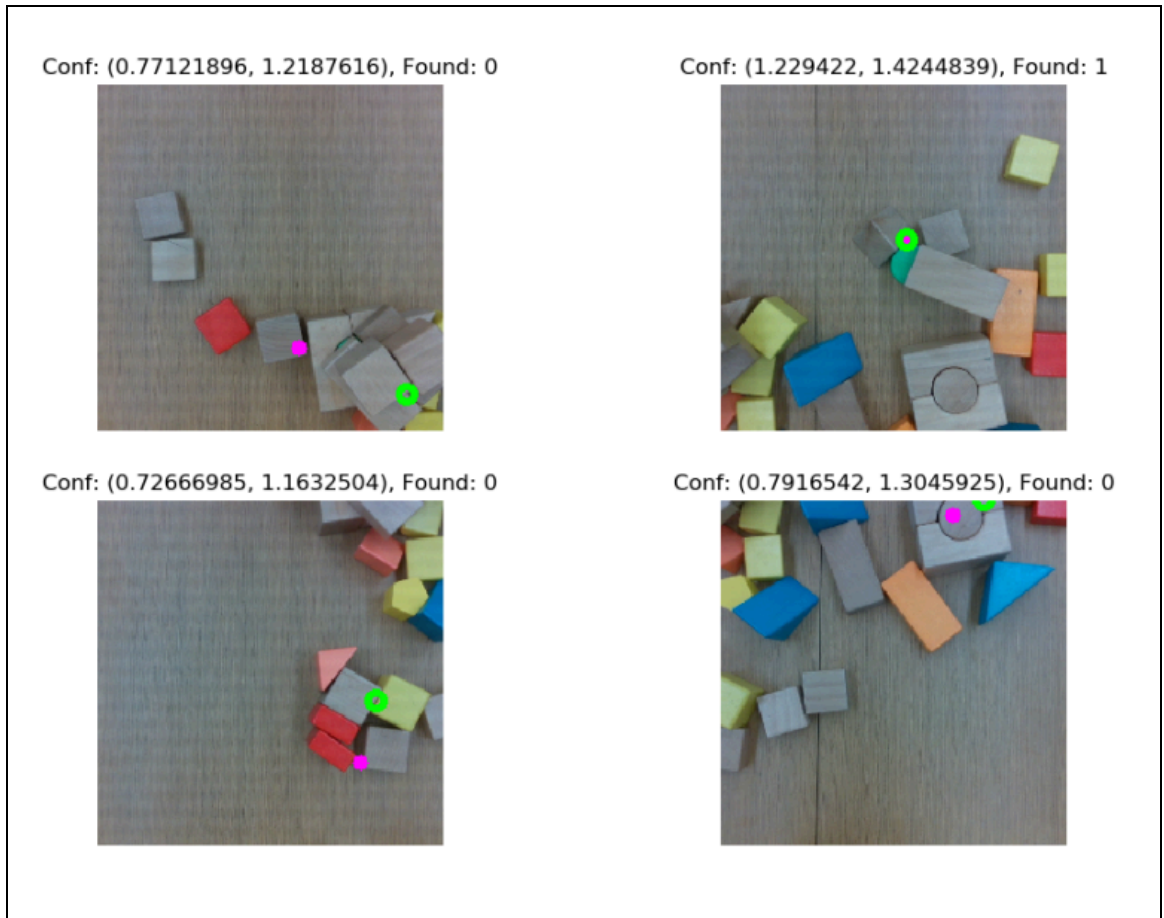
[FIGURE 16: Q-MAP FOR ORGANIC GTI PIPELINE IN REAL-WORLD]

The emergent behaviors previously observed in grasping points within constrained scenarios highlighted the importance of margin occupation. This metric helps infer whether pushes are effective or if grasping can be performed correctly. By fully uncovering the objects, the system facilitates better coordination and decision-making, aligning with the trained behavior of the GTI pipeline. At scale, it is essential to integrate higher-resolution inference and finer-grain decision-making into the reward functions at different stages throughout the pipeline to ensure robust performance.

When scaling a robotic workspace system to perform searching actions for a fully occluded object, it is vital to confirm that the identified target is indeed the target of interest. The GTI pipeline's original design might misinterpret a single pixel of a segmented target mask as a complete target, leading it to check margin occupation indices prematurely. This misinterpretation can result in erroneous grasp attempts, as the system may incorrectly assess its margin occupation due to partial visibility. The proposed approach argues for a new policy that focuses on further uncovering the object at this critical stage, regardless of the situation. This ensures that the system doesn't rely on potentially misleading emergent behaviors but instead uses purposefully trained behaviors to accurately identify and grasp targets.

In simulation, the behavior of scaling was recreated by using a single workspace, similar to how an orthogonal camera operates, while instantiating and saving multiple workspaces in memory. This allowed examination of different height maps and QMaps to infer better pushing locations. The affordance maps across each section of the two-by-two

array of explored areas were normalized, enabling comparison of maximum affordance values. The highest affordance value from one scene could be compared against others to determine the best pushing location. This naive approach aimed to improve exploration performance without training new policies. Although some successes were found, consistent performance was lacking, leading to further testing being deferred.



[FIGURE 17: NAIVE SCALABLE HEURISTIC]

By combining the understanding of scaling issues with the challenges observed, the focus shifts towards refining exploration policies to provide the GTI pipeline with

comprehensive data, enabling it to perform optimally in large-scale environments. This approach addresses the fundamental issues of ensuring accurate target identification and effective object manipulation.

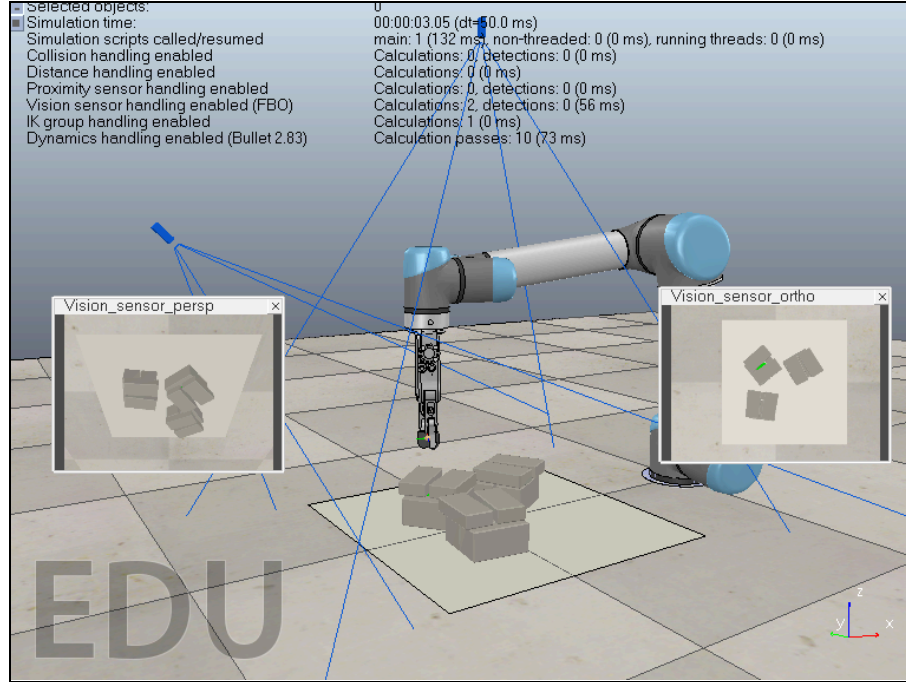
REAL2SIM

Refining exploration policies is a critical next objective to address scaling issues and enhance the AGGRO system's performance in dynamic environments. The new training paradigm aims to replicate real-world complexities within a simulated environment, allowing the system to learn and adapt to various scenarios before deployment. This is essential because the previous GTI pipeline was not trained on any form of real stylized clutter. Instead, it was trained on scenarios where random blocks were dropped into the scene, and the target object was nearby other objects. The GTI pipeline followed its reward structure to perform simulation actions but lacked exposure to structured clutter scenarios that reflect real-world complexities.

Creating structured clutter scenarios involves using blocks from previous GTI pipeline testing sets but now incorporating a programmatically and automatically implemented stylized clutter population technique. Inside the workspace, stylized clutter can be spawned in with random rotations and positions on a grid, ensuring that they do not overlap. Each piece of stylized clutter is uniquely rotated and placed within the scene. This clutter includes square prism configurations where the green cylinder is held between two bridge-like blocks and covered with two flat rectangular prisms. This specific clutter setup is a classic example from previous GTI work, chosen for its

prominence in initial testing and validation. While acknowledging the potential for overfitting to this stylized clutter, it was selected as the initial experiment to extend the idea of uncovering and advancing the exploration capabilities of the GTI pipeline at scale.

Dynamic clutter generation refers to spawning and despawning clutter in random locations and rotations, similar to the random object placement in the original GTI pipeline. This approach creates an infinite set of randomly rotated and uniquely dynamic clutter for the agents to explore and interact with. The implementation involved using existing data arrays to input configuration files in code, specifying the positions and rotations of the clutter as well as their mesh files. To accelerate the typically tedious process of extracting specific locations of target clutter in testing sets, AI assistants were utilized. These assistants not only helped understand the stylized clutter but also populated it automatically. This approach, while initially using a grid structure, opens promising directions for creating more unique and dynamically populated environments for the training paradigm.



[FIGURE 18: DYNAMIC CLUTTER POPULATION SCHEME]

By implementing these steps, the goal is to develop a robust training paradigm that enables the AGGRO system to handle complex environments effectively. This approach involves both creating unique policies and exploring the possibility of fine-tuning existing policies to expand the potential of the GTI pipeline at different stages of the “Grasping the Invisible” problem. It ensures that the system is well-prepared for real-world applications by leveraging simulation to its full potential.

Motivations and Initial Policy Development

Developing multiple policies for the AGGRO system focuses on maximizing the efficacy of the push net. Given that the grasp net is not necessary for any of the stages of exploration or uncovering, it has been omitted from the training structure. The primary

interest lies in enhancing the push net's effectiveness across the most difficult scenarios for the original GTI pipeline.

The reward structures in the GTI pipeline were originally based on metrics like push effectiveness, margin increase, and proper target motion. However, these metrics cannot be accurately inferred if the target mask is unavailable. Therefore, new policies are required in approaching these training paradigms. A key aspect of this new approach involves defining policies for different stages of occlusion. Specifically, there needs to be a policy for stages of full occlusion, where the target object is completely hidden, and another for stages of extreme occlusion, where only a few pixels of the target mask are visible.

Starting with the more familiar scenario of extreme occlusion, the following initial policies are based on the existence of the target mask. These policies aim to utilize the affordances of the target mask to guide the uncovering process.

Baseline Policy

The first baseline policy for this new work aims to increase the efficacy of the push net policy. This baseline uses the target mask sum as a reward indicator. There is a direct linear relationship between the reward provided and the percentage of the target uncovered between each turn. For instance, if a push action increases the uncovered pixels from 40 to 80, it is considered a 100% reward. This system aims to promote

continuous growth, encouraging the system to uncover more of the target object from any initial stage.

Penalty Policy

Building on the baseline policy, the penalty policy introduces punitive elements. Instead of rewarding zero for negative motions and only rewarding positive actions, this policy rewards zero for negative motions but gives a small reward for maintaining stasis or making progress. This approach aims to guide the system towards making positive moves while discouraging ineffective or negative actions.

Strict Policy

The strict policy focuses on rewarding the system only for significant uncovering actions. This policy rewards actions that achieve substantial increases in the target mask sum, such as achieving 10 times the original uncovered pixels or more. The hypothesis is that this policy will foster the development of expert-level uncovering strategies with minimal other destruction. This policy emphasizes precision and significant progress, aiming for the most focused and effective uncovering actions.

Even though this might seem trivial with a simple target like a cylinder, mastering this behavior can yield significant benefits when dealing with more complex targets or wider areas where simple singulation is not sufficient to uncover the target object.

Across these three policies—the baseline, penalty, and strict policies—the goal is to observe their impact on behavior when run across thousands of training iterations and

hundreds of testing iterations. By comparing these approaches, insights can be gained into the most effective strategies for improving the push net's performance in various scenarios.

Next, building upon these principles, the focus shifts to developing new policies that address the challenge of full occlusion, where the target object is completely hidden. These policies will leverage the foundational understanding gained from the initial policies to create robust strategies for uncovering targets in scenarios with no visible target mask.

Policies for Full Occlusion

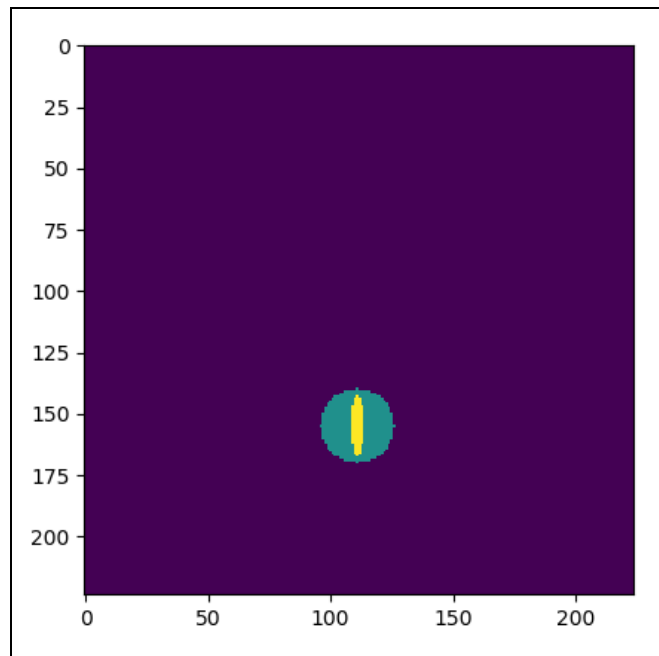
The new policies for full occlusion still utilize the existing frameworks, including stylized clutter and random initialization. However, these policies introduce the concept of pseudo-target masks. When full occlusion occurs, a pseudo-target mask is applied to simulate a guided retrieval operation. This involves placing a pseudo-target mask over the target area, even if the target is not visibly present.

The objective is to train policies to recognize that if there is a high probability of a target being under a cluttered area, the system should learn the best techniques to uncover and peek to verify the target's presence. If the target is not found after several attempts, or if the policy deems further attempts unproductive, it should move on. The pseudo-target mask will be represented as a 0.5 value on an 8-bit scale, where the actual target mask would have a full value of 1 on the 8-bit scale, referring to 128 and 255, respectively.

This allows the system to learn to recognize and respond to partial visibility cues and potential target locations as it trains over thousands of iterations. The goal is to train the system to use these cues to effectively search large areas without committing to a full GTI pipeline process for a non-confident target classification.

Pseudo Policy

The pseudo policy builds on the baseline principle and uses the pseudo-target mask. The reward structure maintains the same linear relationship with the uncovering percentage. The presence of the pseudo mask, placed on the target height map in simulation, guides the system to uncover the target by rewarding legitimate uncovering actions while still providing the visual context of potential target locations.



[FIGURE 19: PSEUDO-TARGET HEIGHTMAP]

Fine-Tuned Policy on GTI Pipeline

The next policy involves fine-tuning the GTI pipeline. This policy uses the baseline principle but incorporates the established singulation policy from the GTI pre-training. The fine-tuned policy leverages the neural fingerprint ingrained during the GTI pre-training phase, aiming to develop a more controlled and less destructive singulation policy. This policy focuses on uncovering the target object efficiently while minimizing damage to the surrounding clutter.

Pseudo + Fine-Tuned Policy on GTI Pipeline

The final policy is a combination of the pseudo policy and the fine-tuned GTI pipeline. This hybrid approach uses the pseudo-target mask alongside the fine-tuned GTI pre-training. The objective is to combine the benefits of guided retrieval provided by the pseudo mask with the controlled uncovering capabilities of the fine-tuned GTI policy. This policy aims to enhance the system's ability to uncover targets efficiently while maintaining a focus on precision and minimal destruction.

These new policies will be tested alongside the baseline policies to evaluate their effectiveness. By comparing these approaches, insights can be gained into the most efficient strategies for uncovering targets in fully occluded scenarios. This process includes an ablation study to assess the impact of the pseudo-target mask and fine-tuning on the system's performance.

Conclusion

This chapter has outlined the comprehensive approach taken to enhance the AGGRO system's capabilities in addressing the Sim-to-Real gap. Beginning with real-world testing, the limitations and challenges of the GTI pipeline were identified, leading to the development of refined exploration policies. By leveraging both structured clutter scenarios and dynamic clutter generation, a robust training paradigm was established. The introduction of multiple policies, including baseline, penalty, strict, and new pseudo-target mask policies, highlights the innovative strategies employed to improve the system's performance.

The next chapter will evaluate these policies through extensive testing and analysis. The results and discussions will provide insights into the effectiveness of the proposed policies, determine their impact on the system's ability to uncover and identify targets in complex environments, and guide future advancements in robotic exploration and manipulation.

CHAPTER FIVE: PERFORMANCE & DISCUSSION

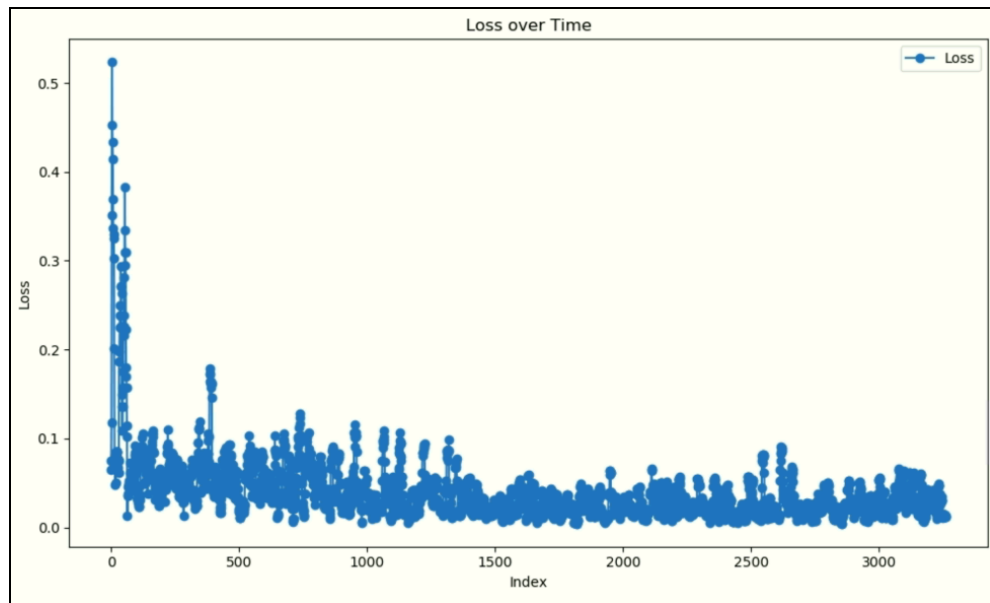
This chapter evaluates the training and performance of the various policies developed for the AGGRO system. Each policy underwent 3,000 iterations of training. The focus will be on understanding the convergence patterns, learning rates, and behavioral adaptations

exhibited by the policies. Additionally, the effectiveness of the trained models will be assessed using dynamically generated and stylized clutter scenarios.

Training Evaluation

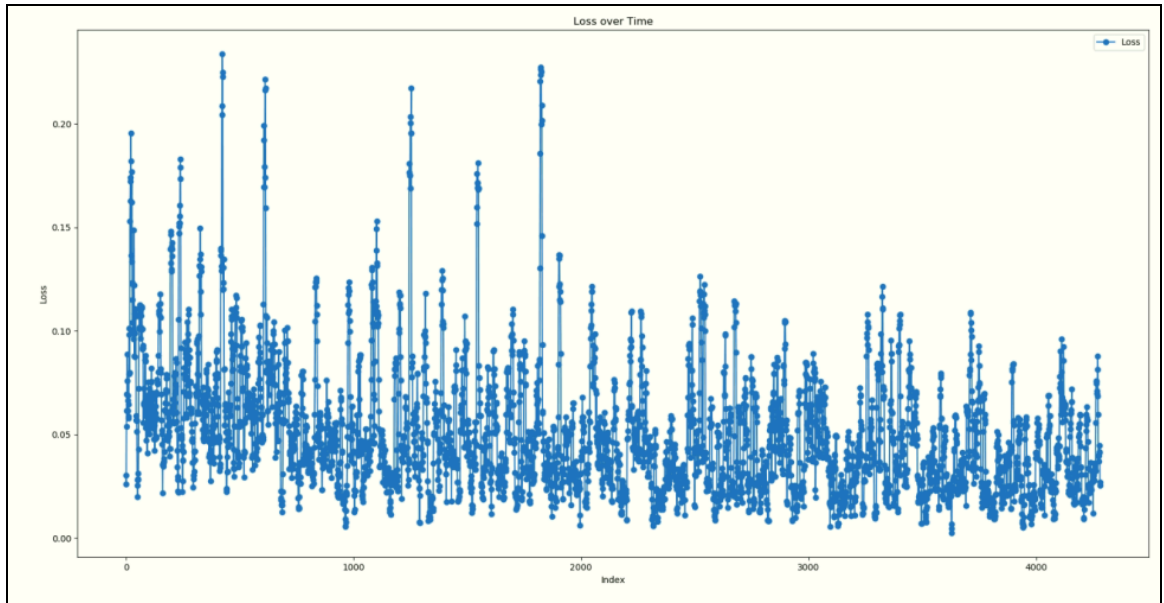
Convergence Patterns

All six policies—baseline, penalty, strict, pseudo, fine-tuned GTI, and pseudo plus fine-tuned GTI—showed signs of convergence within the 3,000 training iterations. Some policies converged more effectively than others. The baseline policy exhibited the fastest and most stable convergence, suggesting its predictive ability was highly consistent.



[FIGURE 20: BASELINE POLICY TRAINING SESSION]

Conversely, the GTI fine-tune, GTI plus pseudo, and penalty policies showed larger oscillations, indicating periods of strong learning followed by adjustments. Despite these fluctuations, all policies converged to within a margin of error between 0.15 and 0.25.



[FIGURE 21: GTI FINE-TUNE + PSEUDO POLICY TRAINING SESSION]

Learning Rates and Behavioral Adaptations

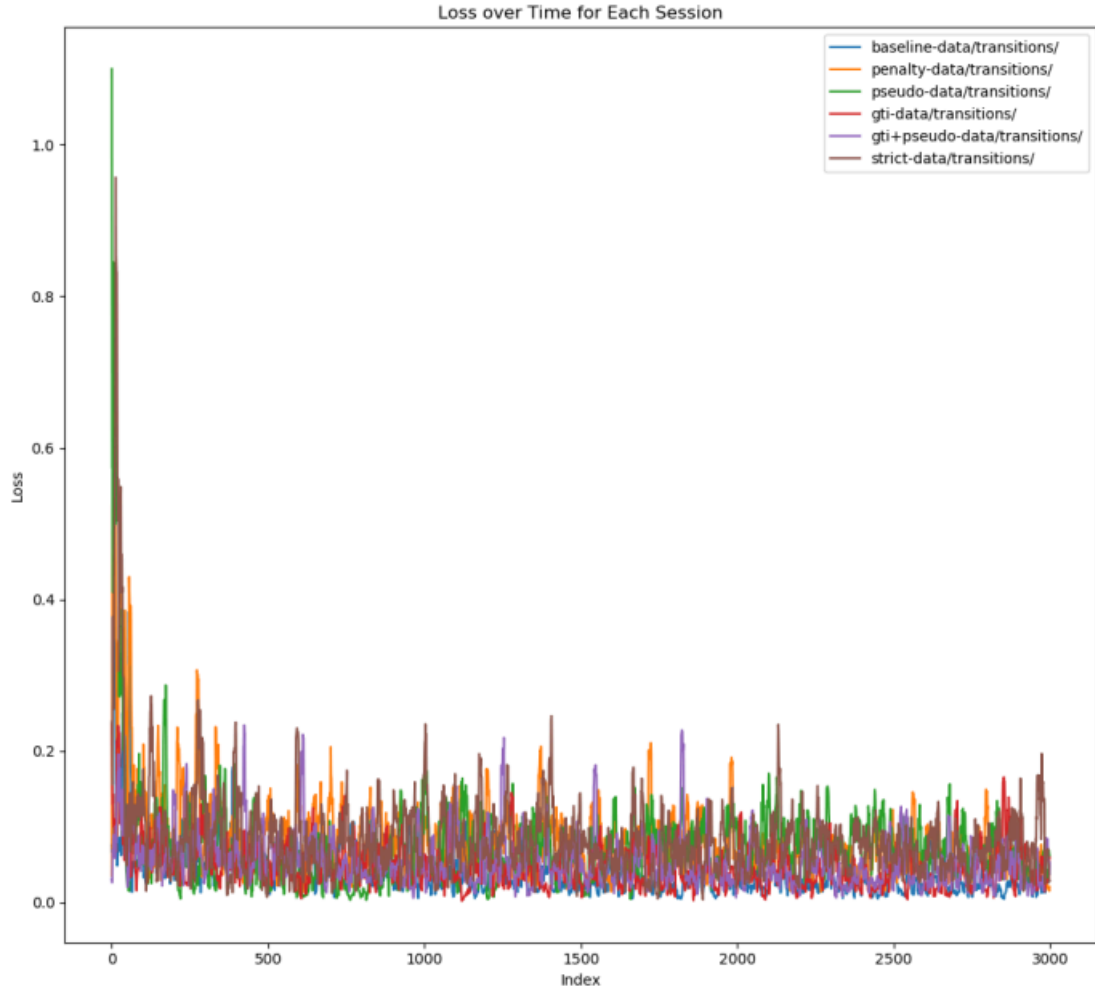
The baseline policy demonstrated the most stable learning rate, maintaining consistency throughout the training period. The GTI fine-tune plus pseudo policy exhibited the most significant oscillations, reflecting its intensive learning and adaptation phases.

Distinct behavioral patterns emerged during training for each policy. The baseline, pseudo, and GTI plus pseudo policies frequently succeeded in the fundamental task of uncovering the target, aligning well with the expected operation. In contrast, the penalty

and GTI fine-tune policies, along with the strict policy, struggled to perform as effectively.

Accuracy of Training

Analyzing the training graphs revealed that most policies exhibited significant improvements in behavior around the 1,500 to 2,000 iteration mark. This indicated a substantial learning phase during this period. However, when the stylized clutter was distributed in a particularly chaotic form, all models struggled with pattern recognition, leading to poorer performance. This behavior was expected, as the destruction of stylized patterns reduced the system's intuitive capabilities.



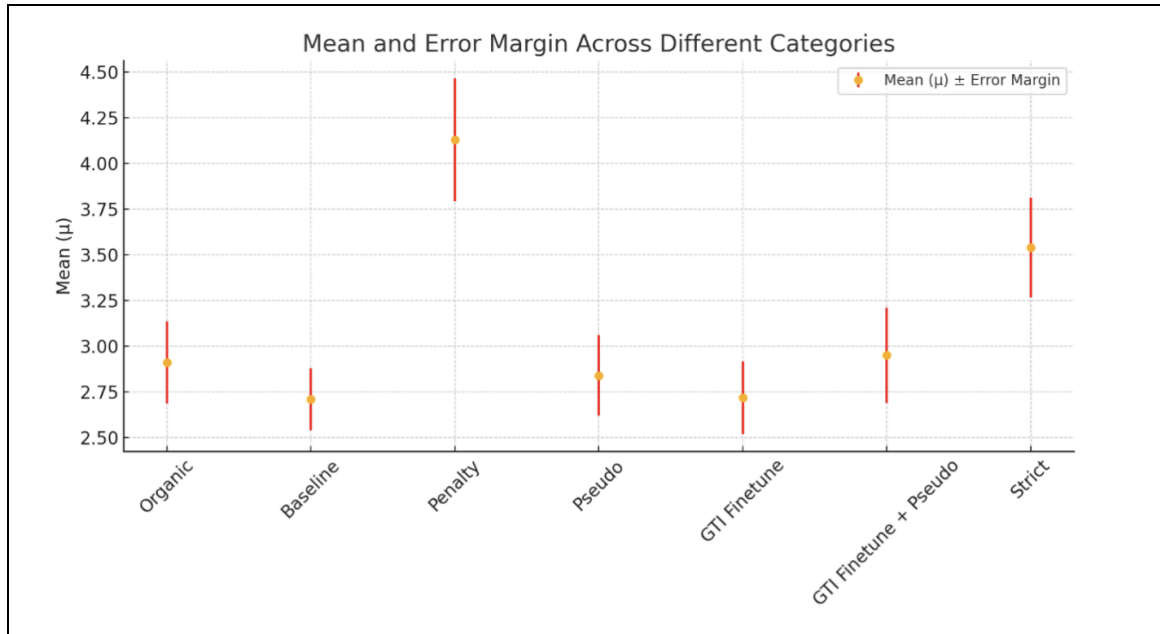
[FIGURE 22: MULTI-POLICY LOSS DATA]

Performance Evaluation

Testing and Validation

The trained models were evaluated using dynamically generated and stylized clutter scenarios. This setup provided a robust testing ground to assess the effectiveness of each

policy. The evaluation involved running 100 iterations for each policy and measuring the efficiency in fully uncovering the target object.

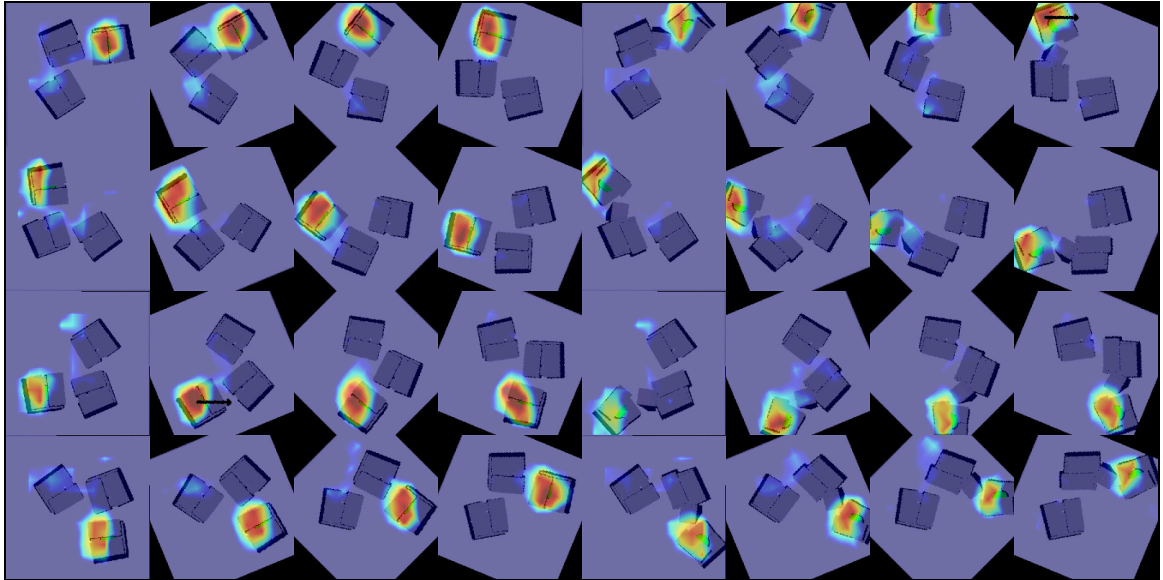


[FIGURE 23: UNCOVERING PERFORMANCE ACROSS POLICIES]

In terms of uncovering efficiency, the baseline policy achieved the highest performance, demonstrating the best uncovering efficiency. The pseudo policy followed as the second-best performer. The GTI fine-tune plus pseudo policy came next, showing good performance but with higher variability. The fine-tuned GTI policy ranked fourth. The strict policy showed moderate efficiency. The penalty policy had the lowest performance among the tested policies. The original GTI pipeline's performance fell between the pseudo and GTI fine-tune plus pseudo policies.

The baseline policy demonstrated the greatest adaptability to different levels of occlusion and clutter complexity. The pseudo policy also showed strong adaptability, particularly in

non-destructive uncovering scenarios. The GTI fine-tune policies retained some destructive tendencies from their pre-trained behaviors, affecting their adaptability negatively.



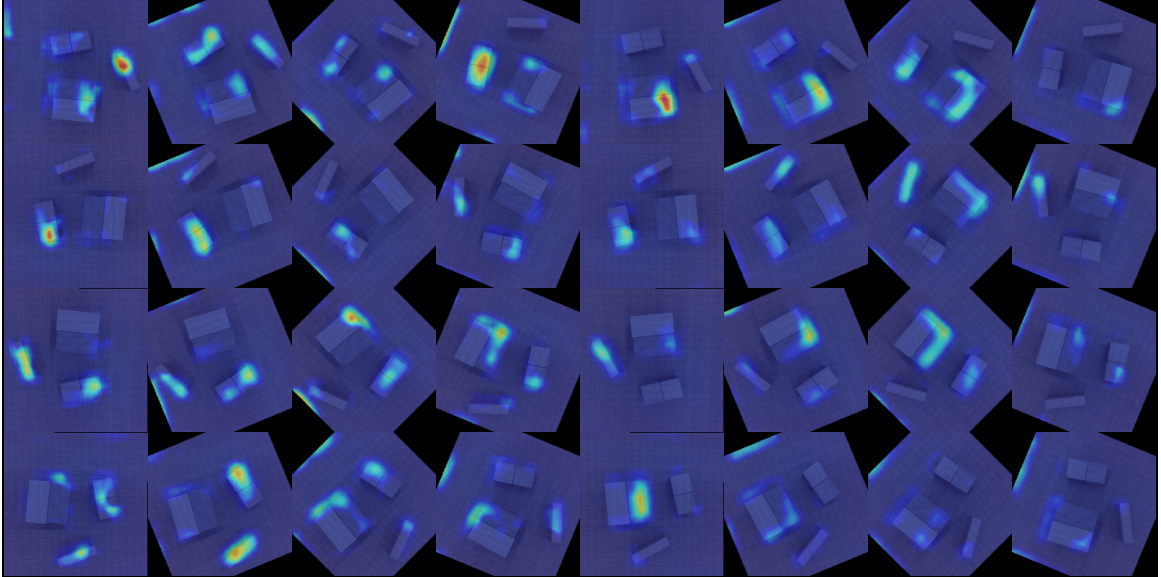
[FIGURE 24: BASELINE POLICY Q-MAPS IN VARIED CLUTTER]

Both the baseline and pseudo policies provided excellent precision in uncovering the target object without causing excessive disruption to the surrounding clutter. The GTI fine-tune policies, while effective in reducing the number of iterations needed to complete the task, exhibited more destructive behavior, which is less desirable for non-destructive uncovering objectives.

Feasibility Real-World Validation

Minimal real-world testing was completed using the fully occluded or defined winner of policies in the fully occluded setting, namely the pseudo policy, and the winner of the

extreme occlusion policy, which is the baseline. This testing aimed to validate the performance of these policies in actual scenarios.



[FIGURE 25: FULL OCCLUSION Q-MAPS (ORGANIC GTI / PSEUDO)]

When implementing guided retrieval in fully occluded scenes or expected scenes where targets are not visible, a pseudo-target mask must be manually placed over the clutter.

This approach indicates the need for further research and development to optimize guided retrieval operations using trained policies.

Insights and Inferences

Training Success

The baseline and pseudo policies successfully learned effective behaviors, as indicated by their stable learning rates and consistent performance during testing. These policies

demonstrated strong uncovering capabilities and adaptability, making them ideal for scenarios requiring precise and efficient target uncovering.

Performance Metrics

Based on the performance evaluations, the baseline policy emerged as the most effective in real-world-like scenarios, closely followed by the pseudo policy. The fine-tuned GTI policies, while effective in certain aspects, showed more destructive tendencies, making them less ideal for non-destructive uncovering tasks.

Policy Comparisons

Comparing the different policies revealed distinct strengths and weaknesses. The baseline policy demonstrated the best overall performance, stable learning, and precise uncovering. The pseudo policy exhibited strong non-destructive uncovering capabilities, leveraging guided retrieval effectively. The fine-tuned GTI policies were effective in reducing iterations but showed more destructive tendencies. The strict and penalty policies struggled with consistency and efficiency, showing less desirable performance characteristics.

Conclusion

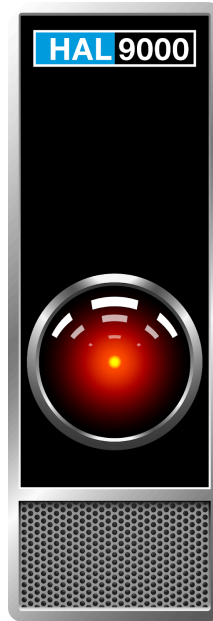
This chapter has outlined the comprehensive approach taken to enhance the AGGRO system's capabilities in addressing the Sim-to-Real gap. Beginning with real-world testing, the limitations and challenges of the GTI pipeline were identified, leading to the development of refined exploration policies. By leveraging both structured clutter

scenarios and dynamic clutter generation, a robust training paradigm was established.

The introduction of multiple policies, including baseline, penalty, strict, and new pseudo-target mask policies, highlights the innovative strategies employed to improve the system's performance.

Minimal real-world testing confirmed the potential of these policies, particularly the pseudo and baseline policies, in guided retrieval operations. Moving forward, the methodology for the AGGRO 9000 system involves a multi-step process. Initially, a two-by-two array of fully occluded clutter is deployed to scan all areas and collect height maps. Guided retrieval operations then use a pseudo mask to infer the best pushing actions with the pseudo policy. If the target is partially uncovered, the baseline policy is employed to fully uncover the target. Finally, the original GTI pipeline is relied upon for singulation once the target is fully uncovered.

This approach integrates the three key policies—pseudo, baseline, and GTI organic—summarizing the 9,000 iterations of training and the resulting AGGRO-9000 system's capabilities.



[FIGURE 26: HAL-9000 / 2001: A Space Odyssey]

The next chapter will focus on future insights and directions. It will discuss the implications of this work, compare it to prominent commercial and enterprise applications, and explore potential advancements in robotic exploration and manipulation. The goal is to provide a broader context for the contributions made by this research and to identify pathways for future development.

CHAPTER SIX: FUTURE DIRECTION

The advancements in AI and robotics have set high expectations for the capabilities of autonomous systems. As we move forward, it is crucial to establish realistic and achievable goals that guide future research and development. This section discusses the

potential trajectories and the integration of new technologies to enhance robotic systems' efficiency, reliability, and applicability in real-world scenarios.

Transformers and Their Applications to Robotic Manipulation

Transformers have revolutionized various fields of AI, particularly in natural language processing. Their ability to handle long-range dependencies and process sequential data makes them a promising candidate for robotic manipulation tasks. In the context of AGGRO, transformers could be utilized to improve the decision-making process by analyzing sequences of actions and their outcomes, leading to more coherent and effective manipulation strategies.

Within our lab, transformer architectures have been integrated into the encoding and decoding schemes for the Grasping the Invisible pipelines and similar works. This approach aligns with broader trends in robotics, where transformers are being incorporated into large language models and other advanced architectures. For instance, technologies like CLIP have shown the potential for robust object recognition and interaction, which can be translated into transporter networks and synergistic primitive machines. Future research should explore the adaptation of transformer architectures to enhance the understanding and execution of complex robotic tasks, leveraging modern AI affordances.

Incorporating RFusion for Enhanced Target Localization

RFusion, which combines RF and visual data for precise localization, presents a significant opportunity to enhance the AGGRO framework. This technology can be particularly valuable in disaster recovery scenarios, where locating and rescuing trapped individuals is critical. By attaching RFID tags to individuals, the system can initially use RF signals to estimate the target's location, which can then be refined using the visual system guided by a pseudo target mask.



[FIGURE 27: RFUSION IN GRASPING CONTEXTS]

In practical applications, RFusion can be employed in various scenarios. For a home robotics assistant, RF signals from tagged items can help the robot locate and interact

with specific objects. In a warehouse, RF tags on inventory items can assist in efficiently locating and retrieving goods. In large-scale disaster scenarios, RF tags on victims can aid in their precise localization and rescue. In all these cases, RF signals can provide an initial estimate of the target location, similar to how a pseudo mask is used in fully occluded scenarios. This initial localization can be refined through visual data, employing the pseudo, baseline, and GTI organic policies to uncover and interact with the target effectively.

Thermal Imaging for Improved Detection

Thermal imaging can be a powerful addition to the AGGRO framework, especially in disaster recovery. Thermal cameras can detect heat signatures, which are crucial for identifying living beings in cluttered environments. Integrating thermal data with existing RGB and depth information can enhance the system's ability to locate and identify targets, even under challenging conditions.



[FIGURE 28: TYPICAL APPLICATION OF THERMAL IMAGING]

To integrate thermal imaging with deep Q-learning, the system would generate a thermal mask indicating heat signatures and overlay it with RGB and depth data. Training the deep Q-learning network using a combination of color, depth, target, and thermal masks can improve inference accuracy. Developing policies that prioritize actions in regions with significant thermal signatures ensures efficient uncovering and identification of targets.

Future Directions for Multi-Modal, Multi-Expert Models

The future of robotic manipulation lies in the integration of multi-modal and multi-expert models. These models combine information from various sensors and leverage the expertise of different algorithms to make informed decisions. For AGGRO, incorporating insights from RFusion, thermal imaging, and advanced visual systems can create a robust framework capable of handling a wide range of scenarios.



[FIGURE 29: EXAMPLE OF DISASTER RECOVERY SCENARIO]

Research should focus on developing training paradigms that incorporate data from RGB, depth, thermal, and RF sensors. Collaboration among specialized models for different tasks, such as thermal detection for identifying living beings and visual segmentation for object recognition, can enhance comprehensive decision-making. Implementing reinforcement learning techniques that allow the system to adapt to new environments and challenges can improve its resilience and effectiveness.

What's Next for AGGRO

The AGGRO framework has demonstrated significant potential in various applications, from agricultural robotics to disaster recovery. Future work should focus on expanding its capabilities by integrating advanced sensory inputs and improving its learning algorithms. By leveraging technologies like RFusion and thermal imaging, AGGRO can

become a more versatile and powerful tool for robotic manipulation in complex environments.

Key areas of improvement include enhanced sensory integration, where continuous improvement of new sensors, such as thermal cameras and RF receivers, will provide richer environmental data. Advanced learning algorithms, exploring the use of transformers and other advanced AI architectures, can enhance the decision-making process. Developing scalable solutions that can be easily adapted to different tasks and environments will ensure AGGRO remains relevant and effective in diverse applications.

Clear Expectations for AI and Robotics

The advancements in AI and robotics have set high expectations for the capabilities of autonomous systems. It is crucial to establish realistic and achievable goals that guide future research and development. Ethical considerations must be at the forefront to ensure that the integration of strong machine intelligence into robotic systems aligns with societal values and promotes positive outcomes. This includes safeguarding privacy, ensuring transparency in AI decision-making processes, and preventing biases that could lead to unfair or harmful consequences.

Robotic systems should be designed with safety protocols to minimize risks to humans and the environment. Developers must also consider the long-term impacts of AI and robotics on employment and the economy, advocating for policies that support workforce transitions and education. Additionally, fostering inclusivity in AI research and

development ensures that diverse perspectives are considered, leading to more equitable and universally beneficial technologies.

CLOSING THOUGHTS

The journey of developing AGGRO, detailed within this thesis, represents a comprehensive exploration into the convergence of advanced machine learning techniques and robust robotic hardware. This work has traversed through the intricacies of reinforcement learning, visual perception, and dynamic manipulation, culminating in a system capable of addressing the significant challenges posed by cluttered environments. This closing section aims to provide a holistic reflection on the key insights and contributions of the entire work, followed by final reflections on the broader implications of this research.

Key Insights and Contributions

Integration of Deep Reinforcement Learning

One of the pivotal contributions of this thesis is the effective application of Deep Q-Learning (DQL) in robotic manipulation. The transition from simple Atari game environments to complex real-world scenarios illustrates the versatility and power of reinforcement learning. DQL's ability to learn optimal policies through interaction with the environment has enabled AGGRO to perform sophisticated tasks such as object grasping and manipulation with high efficiency. This work has demonstrated that

reinforcement learning can bridge the gap between simulated and real-world applications, ensuring that robots can adapt and improve over time.

Advanced Visual Perception Systems

The integration of Intel RealSense RGB-D cameras into AGGRO has significantly enhanced its visual perception capabilities. By adopting a top-down, wrist-mounted camera configuration, this work has overcome common challenges such as occlusion and the need for frequent recalibration. This innovative approach has ensured consistent and high-quality data input, which is crucial for accurate decision-making and task execution. The improved visual data quality has directly contributed to AGGRO's ability to navigate and manipulate objects in cluttered environments effectively.

Robust and Scalable Hardware Design

The choice of FarmBot Genesis V1.6 as the foundational hardware platform has proven to be a strategic decision. Its modular and scalable design allows for easy customization and adaptation to various research and operational needs. The integration of custom-designed grippers, advanced power management solutions, and high-performance computing infrastructure (NVIDIA GPUs) has resulted in a robust and versatile robotic system. AGGRO's ability to perform tasks typically handled by more complex and expensive robotic systems at a reduced cost and complexity highlights its practical applicability and potential for widespread adoption.

Sophisticated Synergy

The development and refinement of the "Grasping the Invisible" (GTI) framework represent a significant advancement in the field of robotic manipulation. By leveraging segmentation techniques such as K-Means and Lightweight RefineNet, and employing emergent behaviors guided by reinforcement learning, AGGRO has shown remarkable proficiency in handling occluded objects within cluttered environments. The GTI framework's structured approach, combined with an effective reward structure and advanced learning mechanisms, has ensured efficient exploration and coordination, leading to successful grasps even in challenging scenarios.

Dynamic and Effective Exploration Policies

The creation of structured and dynamic clutter scenarios has strengthened AGGRO's training paradigms, preparing it for real-world applications. The development of baseline, penalty, and strict policies has provided a robust framework for effective exploration and uncovering of target objects. These policies have been crucial in enhancing AGGRO's performance in large-scale environments, ensuring accurate target identification and efficient object manipulation. The integration of pseudo-target masks and the fine-tuning of exploration policies have further refined AGGRO's capabilities, enabling it to handle full occlusion scenarios with greater precision.

Final Reflections

Reflecting on the entirety of this thesis, it is evident that the development of AGGRO has not only addressed significant technical challenges but also laid a strong foundation for future innovations in robotic manipulation. The holistic integration of advanced machine learning techniques, robust hardware design, and innovative visual perception systems has resulted in a versatile and efficient robotic system capable of performing complex tasks in real-world environments.

This work has underscored the importance of interdisciplinary collaboration, combining insights from machine learning, robotics, and computer vision to create a cohesive and functional system. The iterative process of development, testing, and refinement detailed in this thesis highlights the value of practical experimentation and real-world validation in advancing theoretical concepts.

Moreover, the contributions of this thesis extend beyond the specific achievements of AGGRO. They provide a blueprint for future research and development in robotic systems, emphasizing the need for scalable, adaptable, and efficient solutions to complex problems. The methodologies and principles developed here can serve as a foundation for further exploration into autonomous systems capable of intelligent and autonomous manipulation in diverse and dynamic environments.

In conclusion, this thesis represents a significant step forward in the field of robotic manipulation, demonstrating the transformative potential of integrating advanced

machine learning techniques with robust hardware design. The insights gained and the innovations achieved through the development of AGGRO pave the way for a new era of intelligent and adaptable robotic systems, capable of addressing the increasingly complex challenges of the real world. This work stands as a testament to the power of interdisciplinary research and the relentless pursuit of innovation in the goal to advance the capabilities of autonomous systems.

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