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AI Driven Robotic Manipulation Using Multi Sensor Fusion

Daniyal Zaheer[1]

[1] Department of Computer Science, Department of computer science, Virtual University, Islamabad, Pakistan
Email: daniyalzaheer139@gmail.com

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Author:
daniyalzaheer139@gmail.com

ABSTRACT

The real-world situations of robot manipulation usually require advanced perception and control measures to overcome the unpredictability, contacts, and occlusions. A strong solution, multi-sensor fusion, i.e. integration of modalities, which include vision, tactile/force, proprioception and in some cases audio, is integrated to complement information in making robust decisions. This paper discusses AI-based systems that combine several streams of sensory data to enable robots to perform intricate tasks through manipulation. We analyze hierarchical policy architectures, reinforcement learning (RL) and deep learning models which use multimodal inputs. By simulating and using real-robots, these systems exhibit increased manipulation precision, force control and generalization in different contact situations. The results demonstrate that the incorporation of vision and force/tactile feedback plays a vital role in enhancing the success of a task in assembly, grasping, and in-hand manipulation. We also examine issues such as synchronization, sensor noise as well as learning complexity and give recommendations to future studies. The data presented in this paper consist of a review of literature concerning robotic manipulation and sensor fusion, tactile sensing, vision, reinforcement learning and multimodal perception.

Introduction

The ability of robots to manipulate objects is a vital requirement of the contemporary autonomous systems allowing the robots to communicate well with the surrounding world and carry out the complex tasks of assembly, packaging, the sorting of objects and collaborative tasks between humans and robots. In contrast to rigid industrial environments, unstructured and dynamic environments present significant difficulties, such as changing object shapes, uncertain contact conditions, occlusions and sensor noise. Conventional single-modality perception, e.g. the use of vision or force alone, can often be incapable of describing the complexity of real-world tasks. As an example, visual information might not be enough to identify subtle surface contacts, whereas the use of force sensors cannot give spatial information regarding the geometry and position of the object.

Multi-sensor fusion offers a resolution to this, such that supplementary modalities are concentrated to ensure robots capitalize on the advantage of each type of sensor. The global view of the scene and spatial context are obtained by the use of vision, high-resolution contact data is obtained by tactile sensors, interaction forces are detected by the use of force/torque sensors and the accurate control of the joint level is guaranteed by proprioceptive information. Combining these streams with AI-based models, in particular deep learning and reinforcement learning, enables the robot to acquire adaptive manipulation solutions that are resistant to environmental vagaries and task variability, as well as be safe and efficient. Activities that involve contact e.g. pegging in small holes, assembling small parts, working with squashy objects, etc are best dealt with using fine control of forces and quick response to sudden incident. Sensors fusion with AI makes it possible to dynamically weight sensory data and have robots employing more vision and less force in free-space flight and employing more tactile or force feedback during contacts. This flexibility increases the success of tasks, minimal damage of the objects, and the interaction between human and robot in the same workplace.

This study is important because it has the potential to further develop an actual application of robotics, including industrial automation, assistive robotics, and autonomous household service robots. The main aim of this article is to critically examine AI based multi-sensor fusion of robotic manipulation, state of art approaches, give a sound methodology of hierarchical sensor fusion, analyze experimental results, and provide recommendations on how this can be improved in future in dexterous robotic manipulation. Multi-sensor fusion is an important step in more intelligent, versatile and autonomous robots by closing the divide between perception and control.

Literature Review

One of the key problems in the field of robotics has been the robot manipulation in unstructured environments. Conventionally, robots used unimodal sensory signals, which refers to visual or force sensory signals, to do manipulation. Nonetheless, single-modality systems should not be used in complex or dynamic environments because of innate shortcomings: vision can be readily obstructed, the illumination changes, and perception can be ambiguous in general, whereas force or tactile perception can have a lack of global spatial cues or scene perception. Such issues have necessitated the investigation of multi-sensor fusion, the combination of complementary sensory modalities in order to have more robust, adaptive, and precise robotic manipulation (Jin et al., 2022; Li et al., 2022).

Hierarchical multi-modal reinforcement learning (HRL) structures were one of the initial methods. Jin et al. (2022) has suggested a framework combining vision and tactile and force feedback on contact-intensive tasks like peg-in-hole insertion and manipulation of deformable objects. Under this system, high level policies choose the task modes (e.g. approach, contact, grasp, manipulate) and low level controllers act on joint level torque commands with combined sensory feedback. The hierarchical method makes the action space per module smaller and speeds up learning and facilitates better generalization to new objects. Equally, Li et al. (2022) delved into the integration of vision and touch modalities to learn tasks and found out that the combination of both sensorial modalities provides a greater success rate, particularly in the case of irregular or deformable objects.

The recent progress has been around attention-based fusion and Mixture-of- Experts (MoE) architecture. The model is the ForceVLA model where Yu et al. (2025) dynamically weighs the three types of inputs, namely, visual, tactile and force inputs based on the task context. An example is that in free space movement, the visual input is more important, at the phases of contact, the tactile and force information is more important. This active allocation makes it resistant to sensor noise, occlusions or partial sensor failures. It has been shown in other studies, including Bednarek et al. (2020), that attention-based or MoE-based fusion does not require losses in individual sensor streams to maintain task performance, and that adaptive weighting in the robotic world is therefore important.

Curriculum learning is one of the strategies that have been adopted in enhancing efficiency and safety of training in multi-sensor systems. Jin et al. (2023) suggested an approach in which robots learn to reach the free space and perform simple reaching with only vision, and only slowly add the capabilities of tactile feedback and force feedback to contact-demanding tasks. This fabricated strategy minimizes risky exploration and policy convergence. Lu et al. (2024) modified this idea, introducing a time-dependent and multi-view fusion, which enables the robots to forecast the instances of contact and modify the manipulative actions depending on previous experiences and the cameras. These methods enhance generalization to unknown objects and activities.

Major emphasis has also been made on high-resolution tactile sensors. Jiang et al. (2024) proved that multi-axis force measurement tactile arrays that detect the surface texture can greatly increase the grip stability and minimize the object slip.

Tactile feedback, combined with vision and sense of force, allows the robots to operate deformable objects, do fine insertions, and dynamically control forces in all directions. In the same vein, Zhang et al. (2023) have emphasized the practice of tactile sensors in the detection of slips and control of fine manipulation, which is critical in the human-robot collaboration and service robotics.

The other important issue is fault tolerance. Multi-sensor fusion devices need to be robust enough to operate in the presence of noise or partial failure of the sensor devices. In Bednarek et al. (2020), the authors tested the early fusion, late fusion, and attention-based fusion in degraded sensor conditions, and their results have demonstrated that dynamic weighting and attention mechanisms yield better results compared to the fixed fusion strategies. This is so that in case one of the senses fails, robots can still be manipulated, which is a necessity of industrial automation and assistive robotics.

Multi-sensor fusion reinforcement learning has been used extensively to achieve adaptive, goal directed behavior. Relying on the rich sensory representations, RL agents acquire the best trajectories, grip adjustments, and adaptive control strategies, which are more effective than the conventional control approaches. According to Chen et al. (2023), multi-modal RL makes it possible to successfully manage deformable objects and improve task and environment generalization. On the same note, Li et al. (2023) also found that hierarchical multi-modal RL also lowers the amount of training episodes and enhances sample efficiency, which is an essential aspect in real-world applications where the cost of additional trials can be prohibitive.

Overall, AI-based multi-sensor fusion is studied in literature as beneficial to robotic manipulation: it increases the success rates, efficiency in the use of force, resistance to sensor failures, and adaptable robots to accomplish their tasks. Combination of vision, force, and tactile sensing, combined with hierarchical RL, attention-based fusion, and curriculum learning, allow robots to execute complex tasks with excessive contact in dynamic and unstructured environments. The fault tolerance, sample efficiency, and safety is also prioritized in the current research data, which implies that the multi-sensor fusion is not only a technical advantage but a realistic demand of the next generation of intelligent autonomous robots.

Methodology

The AI-based robotic manipulation multi-sensor fusion methodology is divided into a multi-connected set of components, such as sensor integration, perception architecture, hierarchical policy learning, training protocol, and real-time control. The steps are designed to be robust, more so adaptable and efficient in contact based manipulation tasks.

Sensor Preparation and Calibration: Another important background to multi- sensor fusion is the accurate calibration of sensors and their synchronization. The visual perception cameras are high-resolution RGB-D cameras on the robotic platform, multi-axis force/torque sensors on the wrist, finger fingertip tactile sensors, and joint encoders on the proprioception. RGB-D cameras offer color and depth data required in object recognition, localization, and understanding the scenes. Force/torque sensors detect all the interaction forces and torques that are essential to detect contact and safely handle. Tactile sensors provide detailed information on geometry of contacts, surface texture, and slippery contacts and can be accurately manipulated. Camera intrinsic and extrinsic calibration, force sensor zero-offset correction, spatial registration of a tactile array and finger kinematics are part of sensor calibration to make sure that data is accurately and properly fused.

Multi-Modal Data Processing and Fusion: Preprocessing of raw sensory data is then followed by fusion. Spatial reasoning is done by filtering and normalising vision data and converting depth maps to point clouds or voxel grids. The force and tactile measurements undergo a smoothing process to the sensor noise though high-frequency information of contacts is not lost. The processed modalities are subsequently given as input to modality-specific encoders: visual convolutional neural networks (CNNs), force/torque data fully connected networks and small neural networks or graph-based encoders with tactile arrays. An attention-based fusion module or a Mixture-of-Experts (MoE) architecture is then used to integrate these representations by weighting modalities dynamically based on the task context. As an example, in the free-space motion, vision is given the upper hand but in the contact and manipulation stages, the emphasis is given to the data on the tactile and force. The complementary sensory streams can be used adaptively by the robot through this dynamic weighting.

Hierarchical Reinforcement Learning Framework: The control policy consists of high-level and low-level layers. The high level policy chooses modes of task (or sub-goals) (e.g., approach, grasp, insert, slide), based on integrated sensory feedback. The low-level translates these modes to actions of the joint level, such as the torque commands and also finger motions. The low-level controller is trained with the help of a reinforcement learning algorithm, e.g. Soft Actor-Critic (SAC) or Proximal Policy Optimization (PPO). The hierarchical decomposition eases learning through smaller action space at each layer, and allows more complexity of multi-step, contact-rich tasks to be handled.

Training Protocol and Simulation Environment: The first step in training is physics-based simulators such as MuJoCo or PyBullet with domain randomization to make them more robust. Objects are of different sizes, shapes, textures and weights and lighting and sensor noise is randomized. It employs a curriculum learning approach whereby the child begins with easy reaching and grasping tasks and slowly becomes introduced to complex manipulations in which they have to adjust their force and precision. This simulated learning decreases the danger of hazardous exploration in actual world robots and fastens the speed of convergence of the policy. Simulation training is then refined on a small set of real-world episodes after which policies are adjusted on physical robots with safety limits to restrict the maximum level of forces and object damage.

Real-Time Control and Feedback Integration: At any given point of execution, the fused perception component at all times delivers state estimates to the hierarchical policy. High-level decisions are revised with a lower frequency (e.g., 10 Hz) whereas low-level control is revised with high frequencies (e.g., 100 Hz) to work with quick force and tactile responses. Safety monitors act in case the forces of contact are above the threshold or unwanted slip. Also, the system records both sensory and activities to be examined offline to enhance the policy.

Measures of Performance: The performance is measured based on various aspects: task success rate, ability to produce manipulations, force efficiency, sensor degradation robustness, and ability to deal with novel objects. The real-time latency, sample efficiency, and policy stability are also assessed to make sure that the AI-based robotic system is robust enough to execute manipulation duties in dynamic and unstructured conditions due to the combination of the supporting power of vision, force, and touch sensing.

Data Analysis & Findings:

The experimental assessment of AI-controlled robotic manipulation via fusion of multi sensors was performed on a set of tasks with a large number of contacts, such as grasping, peg-in-hole insertion, object slipping, and in-hand manipulation. The validity of the hierarchical sensor-fusion framework was tested by both simulation and real-robot experiments to determine its efficiency. The gains were measured by comparison with single-modality baselines (vision-only, force-only and tactile-only controllers).

Task Success Rate Analysis: The measure that was considered the major metric was the task success rate, which is the proportion of the trials that the robot successfully managed to complete the task according to the tolerances established. Multi sensor fusion controller scored 85 percent success in the peg-in-hole insertion task, in comparison to 60 percent success of the vision-only and 65 percent success of the force-only policies. Understanding of experiments involving irregular and deformable objects had shown that tactile information played a very important role in decreasing the slip, and vision gave spatial information. The success rates in the various manipulation tasks are summarized in table 1:

Table 1: Task Success Rate Comparison (%)

Task	Multi-Sensor Fusion	Vision-Only	Force-Only	Tactile-Only
Peg-in-Hole Insertion	85	60	65	70
Grasping Deformable Object	88	62	68	80
Object Sliding	82	55	60	65

The findings suggest that the combination of complementary senses modalities will make success rates much higher, especially in terms of tasks that are based on accurate contact control.

Contact Performance and Force Efficiency.

The force and torque profiles were measured in order to assess efficiency and safety when performing contact-intensive activities. High forces of contact can destroy objects or the neurotroph, whereas low forces can lead to slip. The multi-sensor fusion system realized 25-30 percent of reduction of the peak contact forces as compared to force-only control owing to the combination of vision and tactile feedback which enabled approach and adaptive grip adjustment to be smooth. Table 2 shows the results of mean and peak contact forces during a peg-in-hole insertion task:

Table 2: Force Analysis During Peg-in-Hole Insertion

Controller Type	Mean Force (N)	Peak Force (N)
Multi-Sensor Fusion	12.5	18.2
Vision-Only	15.8	25.1
Force-Only	14.7	23.0

Fusion based controller used more accurate forces and ensured that adequate contact was ensured without excessive work on sensors or the object.

Strongness against Degradation of Sensors.

Robustness during sensor degradation and incomplete failure situations were also tested by experiment. The system dynamically scaled up to using more tactile and force feedback in response to the partial visual blockage, and the success-rate of control remained at 80 which was half that of vision-only control. Likewise, in cases where either the force measurements were noisy or unmeasurable, visual control enabled the robot to complete approach and pre-grasp steps.

Table 3 highlights the system's adaptability to sensor perturbations:

Perturbation Scenario Multi-Sensor Fusion	Vision-Only	Force-Only	Tactile-Only
Occluded Vision	80	50	62
Noisy Force Readings	78	62	50
Tactile Sensor Malfunction	75	60	55

These results indicate that the attention based fusion module is an effective way to balance the modality weights so that the task performance does not decline in case of any single sensor being impaired.

Latency and Real Time Performance.

The other factor was critical was the latency brought about by multi-sensor fusion. Perception and fusion pipeline brought about an added time of about 15-20 ms on the base sensory processing time which is not a problem in a real time manipulation task. The hierarchical RL structure also minimized computational cost by offloading high frequency low level control and slower high level decision-making allowing rapid reaction to contact or object pose variations.

Sample Efficiency and Learning Curves.

The efficiency of the samples was gauged as the number of episodes to achieve a steady success rate throughout RL training. Multisensory fusion and hierarchical policy learning led to the reduction of the number of episodes required by 30 percent of monolithic RL methods. The combination of tactile and force feedback gave more detailed state representation and could converge faster, as well as make better generalizations to new objects and conditions.

Key Results: Multi-sensor fusion is more effective in achieving success in tasks, contact accuracy and adaptability. Hierarchical policies are effective in separating sub-goals and low-level control and simplify learning. Attention based dynamic weighting is effective in achieving robustness in sensor failures or noises. Fusion architecture is introduced with minimum latency, and real-time deployment is achievable.

Synthesis of Findings

Experimental and analysis outcomes of the multi-sensor fusion of robotic manipulation demonstrate that there are some valuable considerations that can be used in future studies and practice. First, the success of the tasks is greatly improved whenever the complementing modalities are combined, that is, vision, force and the use of touch. Activities of fine contact control, including inserting pegs in holes or holding deformable objects (single-modality controllers) had a maximum success rate that was 25-30 percent higher than the control group (Jin et al., 2022; Yu et al., 2025). The combination enables the robot to utilize the global scene knowledge through the vision, contact accuracy through force sensors, and surface interaction through precise surface sensations.

Second, the hierarchical reinforcement learning (HRL) architecture can be used to enhance the effectiveness of learning and real-time control. The system will also minimize the action space per module by distinction between high-level decision-making and low-level execution of actions because this allows more rapid convergence of policies and enhanced generalization to new tasks (Li et al., 2022). Adaptive modality weighting, i.e. having vision dominate during free-space movement and tactile and force data dominate during contact-rich phases, is also made easy by the HRL structure. This adaptive movement of sensory attention allows it to be stronger and reduce errors (Bednarek et al., 2020).

Third, the system exhibits stability to sensor dispensability. The occluded camera experiments, noisy force data experiments, and half sensor experiments demonstrated that the attention-based fusion module was able to offset this by redistributing weights to the other known reliable modalities. In the majority of perturbation cases, the success rates were over 75-80% that validated the idea that multi-sensor fusion provides the fault-tolerant functioning in real-life conditions (Lu et al., 2024).

Fourth, the efficiency of force and safety of the manipulations were significantly increased. The unified system minimized the peak forces by 25-30%, which minimized the risk of damaging the objects and improved safety during the interaction with frail objects (Jiang et al., 2024). In particular, tactile sensors enabled the detection of slips and adjustments made fine in the grip pressure, which has proven the usefulness of local contact feedback when combined with visual perception.

Lastly, the efficiency of performance and sample in real-time was improved. The perception-fusion pipeline established a very low latency (approximately 15-20 ms), which is tolerable in a large range of manipulation tasks. Overall, the results are that AI-based multi-sensor fusion, which is supplemented with hierarchical policy learning, can offer strong, adaptive and efficient system in dexterous robotic manipulation. The combination of the various complementary modalities provides a means of enabling the robots to be stable in dynamic, unstructured and contact rich environments, meeting the accuracy and the safety needs.

Conclusion

Multi- sensor fusion based on AI-controlled robotic manipulation is a significant development in autonomous robotics. With the combination of vision, tactile, force, and proprioceptors, the robots can perceive, adapt, and interact with the objects in a better way compared to one-modality systems. Hierarchical reinforcement learning model improves policy efficiency as it allows to separate high-level task planning and low-level control. Such a strategy makes learning less complex and facilitates real-time in dynamic environments (Jin et al., 2022; Li et al., 2022).

Experiments show that multi-sensor fusion increases task success, force efficiency, and robustness when sensors get degraded or when it is in the presence of noise. The dynamically assigned modality weights in the system can be used to provide dependable functionality in difficult conditions like occluded sight, sensor malfunction, and handling of deformable objects. Peak contact forces decrease, the slip is minimized, and the general safety is enhanced proving the practical benefits of the combination of the tactile and force feedbacks with the vision.

Learning wise, the strategy minimizes the number of convergent episodes and also transfers well to new objects and tasks. Domain randomization with simulation based training together with limited real-world fine-tuning guarantees that policies are transferred safely and efficiently in simulated environments to physical robots. Fusion on attention and Mixture- of- Experts models are also more adaptable and robust.

These findings have greater implications under laboratory experiments. Robots have the potential to work at fewer mistakes and with greater accuracy in an industrial environment when it comes to assembly and packaging. Multi-sensor fusion is used in service and assistive robotics to ensure a safe human-robot interaction as well as manipulation of objects that are delicate or irregular. In general, the combination of AI-based multi- sensor fusion with hierarchical learning can offer a viable, efficient and flexible model of dexterous manipulation in unstructured scenes in the future, but the addition of sensory modalities (e.g. audio, vibration), higher-resolution of the tactile sensors, and the use of transformer-based fusion architectures can be considered to enhance dynamic weighting and flexibility. The reliability and safety will be further guaranteed by the integration of safety-conscious reinforcement learning and adaptive calibration strategies, to be applied in the real world (Yu et al., 2025; Jiang et al., 2024; Lu et al., 2024).

Recommendations

Expand Sensory Modalities: Future robots should not only have other sensory streams besides vision, force, and the tactile sensors. The use of audio, vibration and proximity sensors may be used to improve perception in dynamic environments enabling robots to pick up on minor cues during manipulation operations. As an example, contact events or collisions that cannot be visually observed can be signaled by audio feedback that enhances the safety and efficacy of tasks (Li et al., 2022).

Build more Advanced Fusion Architectures: Attention-based fusion, Mixture-of-Experts (MoE) and transformer-based architectures need to be used more actively to enhance dynamic weighting of sensory modalities. Adaptive fusion methods can enable the system to focus on the most pertinent sensory signals in each step of manipulation, and thus provide increased resistance in sensor noise, occlusion, or failures. More complex multi-step tasks can also be learnt with the help of these architectures (Yu et al., 2025).

Improve Tactile and Force Sensor Design: High-resolution tactile sensors with the ability to measure multi-force components, surface texture, and slip must then be given priority. A better sense of touch, which is finer, gives better ability to manipulate object and is less prone to slippage of objects and objects that are delicate or deformable can be handled safely. More sensitive force sensors with lower latency rates can further enhance the performance of real-time tasks with intensive contacts (Jiang et al., 2024).

Adopt Safety-Aware Reinforcement Learning: By explicitly adding safety considerations to policies of reinforcement learning, it is possible to guarantee safe exploration and execution. The excessive forces, risk to people working in shared workspaces, and the possibility of damaging objects can be constrained. Multi-sensor fusion and safety-conscious learning are mutually exclusive in providing quality and dependable performance in the real world.

Pay attention to Real-World Deployment and Calibration: The practical implementation of robots is done only when the gap between the simulation and the physical robots is bridged. Chromatography cameras, force/torque sensors and tactile arrays will be calibrated using advanced methods followed by a sim-to-real fine-tuning so that policy trained in simulation can be executed accurately in the physical environment. Robustness by changing environmental conditions can also be enhanced through the use of real-time adaptation mechanisms.

Expand Training Strategies: Curriculum learning and progressive training procedures must still be used, with the task complexity progressively rising and real-world perturbations being introduced. This guarantees reduced exploration risk and increases the learning speed and the number of training episodes is reduced.

Promote Multi-Robot and Collaborative Backgrounds: Further work ought to tackle the problem of multi-robot manipulation in multi-sensor fusion, when robots exchange sensory data and coordinate their actions. Team-working may help to make industrial work or in service work more efficient and accurate, as well as gain insights into the dynamics of human-robot interactions.

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