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Sensor Fusion-Based Perception Methods for Robotic Arms

Xinyan Cao

College of Mechanical and Electrical Engineering, Hohai University, Nanjing, China
2361710204@hhu.edu.cn

Abstract. Robotic arms are expanding from structured industrial scenarios to dynamic unstructured operation scenarios, which puts forward higher requirements for perception capabilities. A single sensor is difficult to meet the demands of robustness, real-time performance and completeness in complex operations. However, multi-sensor fusion technology, by integrating multi-modal information such as vision, force and touch, can significantly enhance the environmental perception and adaptability of robotic arms. This paper systematically reviews the classification and typical configuration strategies of robotic arm sensors, and focuses on analyzing the principles, applications and effects of multi-sensor fusion algorithms at different control levels. Finally, it summarizes the current challenges and looks forward to the future development direction, with the aim of providing theoretical references for related research.

Keywords: Robotic Arm, Multi-Sensor Fusion, Environmental Perception, High-Precision Control

1. Introduction

The robotic arm, as a mechanical device capable of replacing human labor to complete many high-risk and high-precision tasks, is essentially a multi-degree-of-freedom serial motion chain. Through precise transmission by the joints and connecting rods, its end effector can achieve the predetermined trajectory movement within the working space. As the core component of automation, its application is gradually expanding from structured industrial scenarios (such as welding and spraying) to unstructured and highly interactive scenarios (such as precise assembly [1], skilled grasping [2], Human-machine collaboration [3], medical operation [4]). These advanced operational task processes that occur in dynamic and unstructured physical environments are fraught with uncertainties, including variable external environmental disturbances and physical uncertainties in the interaction process. In this background, the traditional "blind operation" mode that relies on preset procedures has limitations and is no longer able to meet the requirements for high precision, strong adaptability and high security in operations. Meanwhile, as the requirements of the tasks increase in complexity and precision, a single sensor cannot independently provide robust, real-time and complete performance in the perception transmission, and the effectiveness of the robotic arm is limited. Thus, the capabilities mentioned above can be adequately enabled by providing the robotic arm with the power to adequately perceive the surrounding environment and the state of this arm, that is, the issue of closely engaging the multi-modal sensors is essential. Multi-sensor fusion

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technology offers the capability of incorporating and processing the data information of several dimensions including; vision, force perception and touch, thus providing the robotic arm to suit the usage demands of the surrounding environment in a better manner. The multi-sensor data fusion is critical in the attainment of information complements, increase of accuracy and recognition capacity of floating on target tracking and the system anti-interference capacity. It is an unavoidable component of the robotic arm. However, several studies have been conducted on the use of multi-sensor fusion in perception of the robotic arm, therefore, the appropriate information is present to support the review at the moment [5].

It is on this basis that this essay seeks to categorize the commonly used internal and external sensors in the robotic arms sector, the description of their performance properties, and the explanation that the weaknesses of one sensor result in the natural incorporation of multi-sensor fusion. It is also concerned with the summary of the studies of sensor configuration strategies and cooperative work in normal high-precision work analysis, its design concepts, and performance coupled with its use in robotic arms, and its effects on the robotic arms. Simultaneously, it systematically analyzes the mainstream multi- sensor fusion algorithms. It examined their principles, on which they can be applied and actual applications and performance in the robotic arm control by their levels in the control architecture. This also goes to point out how multi-sensor fusion in the optimization of robotic arms application. Lastly, the perception capability of the robotic arms towards the working environment and objects on which they are handling is improved through the research on multi-sensor fusion algorithms. The bottlenecks that currently occur due to data, algorithms, and hardware are outlined, and the technological integration tendencies of the future, as well as the formation of robotic arms, is projected and gives guidelines to the further research and theoretical support and practical references.

In order to realize the above-discussed purposes, the structure of the paper will be as follows, the second chapter will describe the classification on the sensors that will be used on the robotic arm and the common configuration research on the tasks that the robotic arm is destined to perform with a specific focus on the analysis of its functioning and the resultant effect; The third chapter will systematically examine the sensor fusion algorithms according to the real-time data layer and the decision control layer and how it will affect the overall efficiency of the perception system; Finally, the fourth chapter will summarize the research content of the entire article and provide an outlook for the future.

2. Common sensors and configurations of the mechanical arm

The configuration of the sensors should be planned in a systematic manner when designing a robotic arm system to perform a certain task depending on the nature of the operation, the environmental conditions and the level of precision needed. The dimension of information that can be received depends on the type of sensors that were chosen and the coverage and reliability of perception depends on the layout plan directly. The quality of the robotic arm's task completion is fundamentally dependent on whether its sensing system can provide sufficient precision, sufficient dimensions, and sufficient real-time environmental status and interaction information feedback. Therefore, the research on commonly used sensors and configurations of robotic arms is an important part of the intelligence of robotic arms. Therefore, studying the common sensors and configurations for robotic arms is an important part of making robotic arms intelligent.

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2.1. Common sensor classification and performance analysis

The sensor can convert the non-electrical quantity information being measured into quantifiable electrical signals, enabling precise transmission of information. It is applied in industrial automation, achieving precise perception of the production process and data-driven control. During the operation of different industrial equipment, there are differences in the measured objects and application requirements. Therefore, the sensors used are selected accordingly based on these requirements. The information perceived and transmitted by various sensors varies. In the use of robotic arms, some sensors such as visual sensors, mechanical perception sensors, acoustic sensors (including ultrasonic sensors), motion sensors, etc. are mainly used.The summary of the relevant sensors is presented in Table 1.

In the application of visual perception, laser, cameras and event cameras are all common visual sensors, and they can be selected based on the requirements of information acquisition. However, the application of a single visual sensor generally has certain limitations in information acquisition. For example, although the camera in a camera can capture more comprehensive information content, its performance is easily constrained by factors such as the intensity of light, and is greatly affected by the environment; the laser radar sensor actively emits laser, and is less affected by the surrounding environment, but it has limitations in recognition based on geometric reflectivity and lacks the perception of texture and color. Combining multiple visual sensors can more effectively perform visual perception. For example, the combination of thermal infrared cameras and laser radar sensors generates 3D point cloud data, which can achieve high-robustness detection and recognition of objects in more complex environments and improve accuracy [6].

In terms of sensing external forces, pressure sensors are one of the important types of sensors that achieve this function. Common flexible pressure sensors, as one of the pressure sensors with better performance and thus more widely applied in modern emerging fields, possess excellent performance. Their lightweight, thin and soft materials can ensure close contact with the measured object, and in some measurement processes, they play a role in obtaining more accurate and real data. Secondly, flexible pressure sensors have good toughness and can withstand a wider range of pressures and have a longer lifespan. Through innovative micro-structural design, flexible pressure sensors can have both high sensitivity and wide measurement range, making them applicable in a wider range [7]. Correspondingly, because the pressure sensor materials need to be repeatedly subjected to pressure application, they suffer significant material loss, are prone to cracks and other damages, and affect measurement accuracy.

An ultrasonic sensor is a type of sensor that uses ultrasonic waves for detection and recognition. Existing research on related ultrasonic sensors has demonstrated that the current ultrasonic sensors have strong material universality, good penetration ability, high environmental robustness, and excellent stability, enabling stable detection of data information. The material identification of the ultrasonic sensor is coupled with the robot safety control system as it is stated in the corresponding materials successfully gaining the safe control of the robotic arm in industrial conditions and in the process of sorting the materials in bins. This offers a very reliable and versatile answer to safe operation and effective handling of materials in the operations of the robotic arm towards greater adaptability and reliability of the robotic arm. The echo signal however may be influenced by unpleasant conditions or air streams and the substance may likewise constrain the omnipresence of the sensor [8].

Motion sensors are instruments that are used to detect the movement of objects or people. They use these to monitor the physical data on the environment and process it to get the information on the movement status. Their typical problems and shortcomings are their vulnerability to interference

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and lack of robustness which influences data measurement. Nonetheless, certain of these issues can be partially addressed using the available resources and technological innovations. They comprise a significant class of industrial automation sensor. Indicatively, a new form of magnetic motion reader having optical motion detecting and split magnets using gallium nitride photonic devices. The sensor is experiencing the benefits of easily fabricated, structural flexibility and rapid pace of manufacturing. Although having an ultra-high optical accuracy and speed, it has a good environmental robustness, manufacturing economy, and integration convenience, offering the best motion sensing solution to consumer electronics, precision industry, and advanced research [9].

Table 1. Sensor classification

classification	visual sensor	pressure sensor	acoustic sensor	motion sensor
sample	Laser, camera, event camera	Flexible pressure sensor	ultrasonic sensor	Magnetic force-assisted three-axis optical motion sensor
characteristics	Combining multiple visual sensors, 3D point cloud data	Longer lifespan. High sensitivity and wide measurement range	strong universality, good penetrating power, high environmental robustness, excellent stability.	Structural flexibility manufacturing speed environmental robustness.

2.2. Sensor configuration scheme for typical robotic arms

The robotic arm, as an important component of modern industrial automation, its practical capabilities and intelligence level largely depend on its perception ability. Traditional preset schemes cannot meet the requirements of complex scenarios. Sensor configuration schemes tailored for typical robotic arm needs can effectively achieve its intelligent interaction. The robotic arm and sensors form a "perception-decision-execution" closed-loop system, which is a cognitive system with perception ability and capable of continuously exchanging information with the environment. Therefore, a thorough understanding of the common sensor configuration schemes for typical robotic arms is an indispensable part of robotic arm perception. In the industrial production field, the functions of robotic arms vary, and the environments and objects they operate on also differ, so the requirements for sensors for robotic arms vary.

In circumstances where the robotic arm proves to be very unfriendly like high temperature condition, high moisture level and firm corrosiveness, the extreme sophistication state detection of the robotic arm is required. Relative to other control systems, MEMS sensors have a relatively small control error, and can be controlled to the level of the millimeter or micrometer. The MEMS inertial detection unit that is being designed by Zhang Cheng and his colleagues employs Bluetooth as a means of communication. This sensor has been positioned at the end of the robotic arm which allows measurement of the angle of the arm, the angular velocity and angular acceleration to be controlled accurately. They have planned a set of experiments of the inertial measurement units, and filtered and compensated the raw data, according to three axis accelerators, gyroscopes, and magnetometers. Simulation comparisons and a performance analysis of the two commonly used data fusion algorithms using the corrected sensor data have been performed, i.e. complementary filtering and Kalman filtering. With the MEMS sensors detecting the motion state, the robotic arm has been made less dependent on external environmental conditions, which is a weakness of the conventional methods of detection of the environment: the robots lacked the necessary degree of adaptability, were affected by interference, and were costly to install and maintain. In addition, the technology has also increased the efficiency, stability and level of intelligence of the robotic arm, since the real time and high-precision motion feedback has further optimized the accuracy and responsiveness of the robotic arm control [10].

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Moreover, in case of inspection of metal components, most of the components which are to be inspected have uneven and irregular surface shapes. The three-dimensional surface needs to be measured with high precision to assure their quality. Despite the high degree of accuracy of the general contact-based measures, they are also damaging to the pieces, whereas the non-contact measurement methods create lower levels of damage but the bouncing back of the metal surface can also lead to compromising the accuracy. Eddy current sensors (EC Sensors) could be used to overcome metal reflection and the use of these devices would be more appropriate in a variety of working conditions. It has been revealed that through incorporation of EC Sensors with the UR5 robotic arm system, real-time feedback signals have been offered towards the attitude control of the robotic arm, a move ensuring that the non-destructive testing process is optimized in the case of complex metal components. This technical solution has shown great promise in the modern industrial multi-scenario practice and can automatically determine defect features on the surface and sub-surface of metal parts, providing the robotic arm with tactile organs-like perception capabilities, and also utilizing its active adaptability and autonomous adjustment ability in detecting tasks [11].

Secondly, object grasp is a difficult task of robotic arms. An example is the particular issue of the ability to understand small objects in a messy environment, which has not been achieved absolutely yet. The process is quite a complex task, and basic form of tactile sensors cannot do much to finish grasping of items, and so more equipment is necessary to help. As an illustration, in the study by WK Do and B Aumann, a complete device, called DenseTact hemispherical tactile sensor (DenseTact Offers Enhanced Sensing) has been suggested. This sensor has been capable of improving the sensing capabilities and have higher deformation capability to give more benefits to compliance control. In this paper, the tactile sensor has determined the objects based on the point cloud data of deformation of the surface. DBSCAN algorithm has also been implemented to do real-time clustering and segmentation of the point cloud in order to define the contact area. It has used highly deformable soft fingertips in this research to effectively improve the success rate of grasping and even stability of grasping so that grasping is stabilized and classified [12].

Moreover, the robotic arm will also attempt to add multiple sensors with different functions to collect the same data for assisting the control of the arm body. In the research conducted by X Yang et al., two sensors, Kinect and data gloves, have been used to collect information on human arm postures. These signals have been fused and processed to achieve precise control of the robot, where Kinect has been used to collect posture data of the human arm, and the data gloves have been used to receive signals of human hand movements. This scheme has integrated body-sensing glove data with intelligent algorithms to achieve precise tracking and natural remote control of the humanoid dual-arm robot. The system has featured high flexibility, low energy consumption, and strong environmental adaptability, making it suitable for applications in industries, healthcare, and education [13].

There are also certain problems with the abovementioned sensors. As an example, MEMS sensors can be refined in three areas including extending to multi-node collaborative measurement, adopting more accurate algorithms as well as feedback control systems. The DenseTact control strategy on the other hand is dependent on using selected deformable surface sensors that limits its usage. The following improvements can be further made in the future: dual-finger tactile sensors can be used to improve the stability of grip and multi-object grasping, the expansion of the functions of the grasping can be used in the human-machine collaboration situations, and the combination of more perception modules can also be used to generate the precision of grasping of the target objects in a noisy environment. Moreover, such issues as insufficient environmental flexibility, too narrow-range functions, and impossibility to determine the balance between precision and real-time are also found

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in these sensors. Further studies can advance in order to enhance the configuration of the mechanical arm sensors towards intelligent integration and dexterous perception. The recognition bias, drift, degradation with accuracy, and total failures can be decreased by maximizing deep learning and aggressive algorithms to enhance the recognition strength and accuracy of multi-source sensing data and make the implementing of mechanical arms more prevalent.

3. Research on multi-sensor information fusion algorithm for manipulator

Various sensor combinations of the robotic arm will take a plethora of multifaceted information. At this stage, processing and assimilation of the gained information and controlling and operating the robotic arm are the critical elements.

In most cases, the subsequent fusion technology of various sensors may be subdivided into three layers, namely: data layer, feature layer as well as the decision layer. The system directly joins and harmonizes the raw observation of information of various sensors in the system in the data layer so that it forms a consistent base on which later processing of the data is to take place. Algorithms within the feature layer extract and combine important environmental and object features of the fused data in the feature layer e.g. shape, texture, spatial associations etc. The decision layer is where the collaborative analysis and judgment are executed based on the high-dimensional information generated due to processing of the last two layers and final operation directions like the pose control and path planning are produced which makes the robotic arm execute precise and robust working.

3.1. Fusion algorithm based on real-time data processing

The current robotic arms often treat different sensors as independent sources of information and separate the collected data. This does not take the full benefit of the complementarity of the various sensors to create stronger constraint relationships hence lacks robustness of the robotic arm in the event of the failure of one sense, which translates to how the robotic arm is used. Furthermore, despite a number of sensors being used, there are occasions where one sensor receives valid data at different times as compared to other sensors. Such delay and asynchrony result in information lag and outdated information conditions and the robotic arm is not able to give a precise response, which ultimately influences the accuracy of control. Hence, the fusion of algorithms of real-time sensor data processing is carried out through the placement of the fusion layer in front. It does intensive visualization of multi-source sensor data on the data level or feature level, which plays a significant role in enhancing the further task functioning. In data-level fusion, the model input layer combines time-frequency images in separate sensors with preprocessing to align the images after which the images are merged together along a channel in the model to create a multi-channel composite quantity, which will subsequently improve the robustness of the subsequent recognition and diagnosis in feature-level fusion approach, the time-frequency features in two sensors are independently extracted as deep features using independent parallel convolution and pooling operations and are then fused in an intermediate network layer thus obtaining effective abstraction and joint modeling of important discriminating information [14].

With respect to the various information provided by the mechanical arm sensors, various technical ways are followed to process and analyze the information in real time and pick up the most efficient way, and hence a better low level state estimation. An example of this is the Simultaneous Localization and Mapping (SLAM) technology which is commonly applied in the processing of data layer. The camera image contents as well as the angular velocity and acceleration information of the

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IMU is directly merged into the same optimization model to directly estimate the pose and velocity, among other states, in real time. It is a full integration scheme that takes full advantage of the complementary nature of sensors: data rates of the IMU work over fast rich movements and is able to correct motion distortion of the laser radar point cloud, whilst vision or laser radar mitigates the cumulative drift of the IMU. The SLAM system is made more robust and attains greater accuracy to the complex dynamic environment of tight coupling of the data layer [15]. Besides that, Qiu MW et al. obtained unbiased estimation by building estimators with the same mathematical expectation as the actual values of the parameters, and directly combined the observation records of every sensor. This essentially prevented the inception of system bias. This approach is independent of the previous noise variance of sensors and is capable of obtaining adaptive weighting by the use of the unbiased sample variance of the data at the data level ensuring the accuracy of the fusion estimation as well as the practicability of applications [16].

Furthermore, the fusion of the mechanical arm feature layer integrates the features extracted by multiple sensors for deep fusion and collaborative processing, significantly improving the accuracy and robustness of its environmental perception, pose estimation, and operation control. For example, Chen, F, et al. have proposed an enhanced hierarchical Poincaré graph index (EHPPI) without hyperparameters, extracting fault information of rotating machinery from multiple source signals through feature-level fusion. The study has adopted the feature-level fusion strategy, concatenating the EHPPI features extracted from multiple sensor signals, and combining them with random forests to construct a fault diagnosis model. Through comparisons with methods such as multi-scale entropy, as well as analysis of simulations, experiments, and actual cases, the effectiveness and engineering practicability of EHPPI in extracting abnormal information at the feature level have been verified, playing an important role in sensor data fusion [17]. Li, C et al. have designed a two-phase flow acoustic-optical sensing system. The signals collected by the acoustic emission and the near-infrared sensor have undergone empirical mode decomposition (EMD). Based on gradient boosting decision tree (GBDT), a new gas volume fraction model has been proposed through feature-level fusion. The average absolute percentage error (MAPE) of the gas volume fraction prediction model has been within 4% in all three flow modes, and a new precise method based on feature fusion has been created, which has been able to be applied to the perception of multiphase flow by robotic arms and has played an important role [18].

3.2. Based on the integration algorithm of the decision-making and control layers

One of the fusion procedures in the multi-sensor information fusion system involves the decision layer. It is able to do operations like intention estimation, task analysis on the information obtained after the data layer and feature layer have been fused, and produce the decision plans/action plans which achieve the task goals. Fusion method according to the decision layer makes the processing of data simpler and considers the reliability and accuracy of sensors much greater because of the fusion of data at the decision layer. The decision layer is the central part of the robotic arm autonomy because it receives environment and self-state estimation information by real-time combination of multifaceted perception information including vision, force, and touch and translates into motion plan and control strategies with task adaptability. This allows the robotic arm autonomy in decision making capability to perform multifaceted and versatile interactive tasks. The bottom-level execution module is the control layer in the system which could transform the tasks created by the higher level planning decisions to driving signals used by the actuators to move the machine in performing the given actions. The transformation between the multi-source sensor data and the autonomous intelligent actions is accomplished through the fusion algorithm between the decision

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and the control layers of the robotic arm. Various types of tasks, environmental factors and requirements of the system have been assigned different methods and models to effectively plan and make decisions on how to give instructions on them.

In the case when the robotic arm should execute high-precision tasks in complex and unstructured environments, a decision-level fusion model named DAWSIM was suggested by Yu, Y et al. due to the research conducted. This model identifies the best combination of input features by each of the organic acids by first fusing at the feature level. It thereafter implements a dynamic weighting framework anchored on random forests to dynamically weigh the forecast results of fundamental learners like PLS, ELM, SVR and MLP and chimes final decision-level fusion using the XGBoost meta-learner, which greatly improves the strength and precision of the forecast. Using the multi-sensor system of the robotic arm, the implementation of the DAWSIM dynamic fusion framework can be used to calculate the believability of each sensor at any moment and dynamically weight it, and make the best decision in real-time using XGBoost integration. The technique is an advancement of the level of decision and thus the robotic arm can adapt to changes in the environment and sensor disturbance thereby greatly improving the stability and achieveability of complex tasks [19].

When dealing with tasks that require high reliability in 3D perception and semantic understanding, the CLOCs algorithm proposed by Sun Junfeng can be used for decision-level fusion. This method is based on the dual consistency of geometry and semantics: it verifies the spatial overlap through the comparison of 3D/2D detection box projections, and associates multimodal results by category [20].In the implementation of the CLOCs algorithm to the multi-sensor fusion of the robotic arm, the 3D point cloud detection box will be projected on the 2D image, and the semantic consistency (IoU calculation) and the semantic consistency (category matching) checks will be performed with the visual detection box to filter the real targets and eliminate false detection. Lastly, cohesive and valid target space and semantic knowledge is delivered, hence the enhancement of the perception capabilities and accuracy of the functions of the robotic arm in complicated situations. In addition, the single radar classification result of the Bi-LSTM network studied by H Li et al. combined with the robust Naive Bayes combiner (NBC) has improved the multi-view perspective compared to the single radar situation, enhancing the classification accuracy of individual gaits, and also enabling the robotic arm to efficiently utilize non-structured and uncertain dynamic environments. The time series data of each sensor is first input into an independent Bi-LSTM network to extract features and output preliminary classification results. These results and their confidence levels are then sent to the robust NBC for decision-level fusion, integrating multi-source information, and ultimately generating more accurate and reliable environmental judgments and execution instructions, significantly improving the adaptability and success rate of the robotic arm in complex operational tasks [21].

4. Conclusion

This paper is dedicated to sensor fusion of the perception of robotic arms, and the influences of varying sensor fusions, as well as sensor combinations, on performance. It examines the current technologies and talks about the major advancements. The perception system of robotic arms has also developed to second-level integration at single-function sensing to multi mode system formed with complementary sensor configurations. First, highly-specialized sensors, like MEMS and DenseTact tactile sensors enhance performance and have greater flexibility than standard thresholds. Second, multi-sensor configurations (e.g. Kinect alongside data gloves) integrates various types of

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information to eliminate blind spots and interference which creates a more useful, smarter and stronger environmental perception.

Multi-sensor data processing is carried out with the help of layered architectures whereby data and feature layers minimize dimensionality, reduce noise, and extract correct features to facilitate decision making; decision and control layers interpret the result of the above process, make task decisions, and produce precise control commands. Such hierarchical representation makes understanding complex information easy and such robotic arms are able to work efficiently in dynamic and difficult environments.

Nevertheless, according to the materials of the article, we are still facing unsolved problems, including sensor malfunction resilience and information disputes. With a multi sensor, it is possible to encounter abnormal conditions whereby some of the sensors receive interferences or otherwise fail. And some such data-independent systems as the naive Bayesian combiner might not accurately handle conflicting evidence in time. In order to overcome these problems, anomalies can be detected by conducting consistency checking. In case of sensor failure, it is possible to create a model which will cover the absence of information and change the fusion strategy to guarantee the stable functioning of the system. This has a futher problem of analyzing the existing robotic arm and sensor system to optimize the above problems and further facilitate the perception of the robotic arm.

To sum up, multi-sensor fusion is one of the devices to improve the perception functions of the robotic arms, and the evolution of the robotic arms cannot be discussed without the evolution of multi-sensor fusion technology. The hardware of sensors will be moved towards greater integration and more performance, and a form will be encouraged in which sensors with awareness functionalities are closely integrated with the arms of the robotics themselves. The technology of the fusion will be futuristic to be more intelligent so that the robot arm would not only combine a number of different informational sources in real time, but also comprehend the intentions of the environment, assess the possibility of the feasibility of their own actions, and make more proper choices. With additional work in the future, robot arms can attain more dexterous operational capabilities nearly matching human-level behavior in a complex and unstructured environment.

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