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Review

Research Progress on the Integration of Robot Vision, Computer Vision and Machine Learning: Technological Evolution, Challenges and Industrial Applications

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ABSTRACT

This paper systematically reviews the technological progress of the integration of robot vision, computer vision (CV) and machine learning (ML), focusing on the design paradigms of global vision system, local embedded vision, hybrid cloud edge architecture, as well as target detection, 3D reconstruction, Algorithm innovation of CV technology such as dynamic scene understanding. Combining the seven major trends of IDC 2025 embodied intelligent robots with the China machine vision market research report, this paper analyzes solutions to challenges such as real-time, data scarcity and multi-modal fusion and proposes solutions based on lightweight models, federated learning and neural symbolic systems. Future direction. By citing top conference papers and industry white papers such as CVPR, ICRA and NeurIPS, this paper builds a technology-scenario-industry closed-loop academic framework to provide theoretical support for the intelligent upgrade of robot vision.

In recent years, with the rapid development of artificial intelligence and computer vision technology, robot vision system has made remarkable progress. These systems improve the perception and decision-making capabilities of robots in complex environments by combining deep learning and machine vision technologies. Deep learning algorithms excel in image processing and feature extraction, enabling robots to more accurately identify and track target objects1-5. In addition, the progress of machine vision technology also provides strong support for the application of robots in agriculture, industry, medical and other fields6-10.

In the agricultural field, machine vision technology is widely used in tasks such as robot navigation and fruit detection and efficient automated operation is achieved by optimizing the robot control system through deep learning algorithms6,7,11. In the industrial field, robot vision system improves the accuracy and efficiency of welding, sorting and other tasks through the combination of deep learning and machine vision technology10,12,13. In addition, in special scenarios such as medical treatment and fire protection, the robot vision system also shows its unique advantages. Through deep learning and visual servo technology, the robot can learn and adapt to complex environments autonomously14,15.

Keywords: Robot vision, Computer vision, Machine learning, Intelligent manufacturing, 3D reconstruction

Introduction

As the core technology of intelligent manufacturing and embodied intelligence, the development of robot vision has undergone a paradigm shift from "perception-driven" to "cognition-driven". Traditional manual feature-based vision systems (such as SIFT, SURF) are limited by dynamic environment adaptability, while deep learning has achieved breakthrough progress through end-to-end feature learning. However, current technology still faces three major contradictions: algorithm complexity and real-time requirements, data annotation costs and model generalization capabilities and multi-modal awareness and computing power constraints. This article combines the 4D world model EnerVerse (2025 SOTA) of Zhiyuan Robot with the embodied intelligence trend of IDC to propose an integrated technology framework of "perception-decision-control" to provide new ideas for cross-scenario applications **(Figure 1)**.

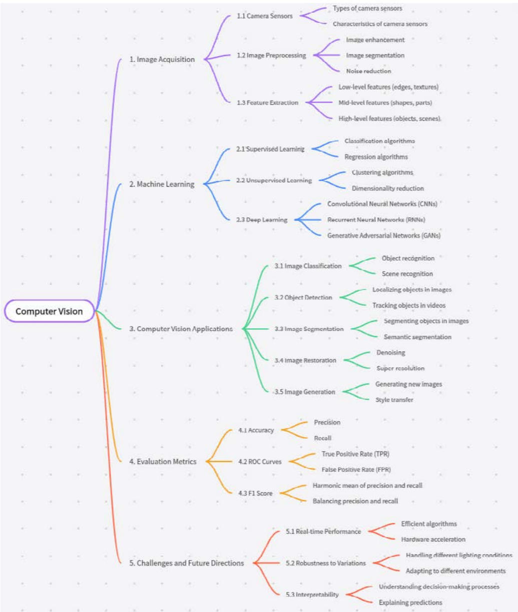

Figure 1: Overview of Computer Vision Technology.

Literature review

In the research of robot vision fundamentals, in 2022, Guo Haifeng proposed a robot vision scanning and tracking algorithm based on deep learning, which combines TLD (Time Flight Laser Ranging) and GOTURN (Global Optimized Trajectory Tracking) methods to significantly improve real-time performance and accuracy, especially in the case of changes in illumination[16].

In terms of deep learning and machine vision technology in robot vision, recent research has focused on building and simulating deep learning algorithms to improve the accuracy and stability of vision tracking. In 2022, Xu Siping proposed a combined channel attention mechanism and SE-Res Net's deep learning algorithm for robot vision tracking, which significantly improves the accuracy and stability of tracking[4]. However, it is important to note that another paper published by Xu Siping in 2022 stated that the study has been withdrawn for reasons that may involve data issues or flaws in the experimental design[3].

In addition, Li Xiang developed an autonomous learning algorithm based on motion cues in his research in 2013, which enables robots to efficiently recognize object models and through the combination of multiple models and algorithms, efficient object recognition is achieved[17]. This method provides a new idea for robots to learn and navigate autonomously in complex environments.

In terms of robot automatic navigation, Wei Pengcheng proposed an improved method based on Canny ant colony algorithm and SSD algorithm in 2022. This method achieved 89.62% and 92.90% in navigation accuracy and feature recognition rate respectively, significantly improving the performance of robot navigation[18]. These studies show that the application of deep learning algorithms in robot vision not only improves the efficiency and accuracy of task execution, but also provides a solid foundation for the development of future intelligent robot systems.

In the field of target tracking, the application of deep learning technology has shown significant advantages. In 2018, Majaj, et al. pointed out that machine learning, especially deep learning, provides important support for vision science in decoding neural responses and recognizing objects[19]. By using deep learning models, researchers can more effectively capture and analyze dynamic changes in video data, thereby improving the accuracy and real-time performance of target tracking. These advances not only promote the development of robot vision technology, but also provide valuable references for other related fields.

In terms of object recognition and classification based on deep learning, research has made remarkable progress in recent years. 2017, Caixinha, et al.

People have explored the application of machine learning technologies in clinical vision science and found that these technologies can enhance the detection and monitoring of early eye diseases, thereby improving clinical decision-making[20]. In addition, Feng Changyong proposed a sorting robot control system optimization method based on deep learning and machine vision in his research in 2022, which improved the control accuracy and tracking performance of coal gangue dry separation through variable domain fuzzy PID control[13]. Also in 2022, Feng Changyong also studied the application of PID and fuzzy PID in coal gangue sorting robot and the results showed that fuzzy PID was superior in position tracking[21]. These studies show that deep learning and machine vision technologies have broad application prospects in object recognition and classification and continue to promote the development of related fields.

In terms of the application of machine vision in path planning, in 2022, Singh proposed a real-time obstacle avoidance and target tracking strategy based on image processing and machine learning, which is suitable for mobile robots and improves the navigation ability of robots in complex environments by combining deep learning technology[22]. Furthermore, in his research in 2022, Lou developed a crawling robot manipulator arm grasping method by using the machine vision method of Gaussian mixture model, which can adapt to the change of object pose, thus enhancing the robot's operational flexibility and accuracy in dynamic environment[23]. These studies show that the combination of machine vision and deep learning has significant application potential in path planning and can effectively improve the autonomous navigation and operation performance of robots.

In automated operations, the application of machine vision technology has made remarkable progress. In 2013, Tian Subo proposed an optimized machine vision system for tomato grafting robots, which achieved 96% success rate and was able to detect gaps as small as 0.2 mm[6]. In addition, reinforcement learning is increasingly widely used in machine vision, covering fields such as image segmentation and autonomous driving.

Recent advances in reinforcement learning in these applications were explored in detail by Hafiz A M in his 2021 study, demonstrating its potential in improving the performance of machine vision systems[24]. These studies show that by combining deep learning and machine vision technologies, the efficiency and accuracy of automated operations can be significantly improved.

In the aspects of deep learning and machine vision technology in robot vision, virtual fixture and remote operation are two important research directions. In 2023, Luo Jing proposed a vision-based approach for virtual fixtures combined with robot learning that significantly improves control accuracy for remote operations and reduces operational pressure[2]. In addition, in 2018, Huang Wensheng developed a six-degree-of-freedom welding robot with machine vision function, which improved stability, efficiency and accuracy through visual pattern recognition and optimized control strategy[10]. These studies show that virtual fixtures and remote operating systems combining deep learning and machine vision technologies have great potential in improving robot operational performance.

In recent years, research has made remarkable progress in the application of deep learning and machine vision technology in robot vision.

In 2017, Grys Ben T. reviewed the application of computer vision and machine learning methods in phenotyping, exploring the advantages and challenges of these methods in image data processing[8]. This research provides a theoretical basis for further exploring the application of machine learning in visual systems.

In the field of neuroscience, Vu Mai Anh T. pointed out in 2018 that with the advancement of technology, data collection has become easier, but how to effectively integrate and utilize this data has become a new challenge[25]. This perspective emphasizes the importance of machine learning in processing and analyzing large amounts of neuroscience data, while also demonstrating the need for interdisciplinary collaboration.

In addition, in 2023, Cruz Ulloa, Christyan proposed a deep learning-based gait pattern adjustment system for quadruped robots, which uses CPG (Central Pattern Generator) and CNN (Convolutional Neural Network) for obstacle analysis, thereby improving the robot's navigation ability on unstructured terrain[26]. This research demonstrates the practical application of deep learning in robot vision systems, especially in navigation and path planning in complex environments.

In the field of robot vision, the combination of deep learning and machine vision technology provides new solutions for robot operation.

In 2022, Cong and Lin proposed a reinforcement learning algorithm combining visual-ontology perception model, which uses variational autoencoder (VAE) and soft action-critic (Soft Actor-Critic) methods to effectively realize the simulation. Objects in the environment push tasks and show good generalization ability, which can adapt to objects in the real world[5].

In the field of adaptive vision servo control, in 2024, Li Jiashuai proposed a new IBVS controller combining extreme learning machine (ELM) and reinforcement learning (RL), which significantly improves servo efficiency and stability of the robot operating arm[15]. In addition, Qian Sen developed a flexible endoscopic robot with autonomous tracking control capabilities in 2024. By using the RTMDet algorithm, visual stability and autonomous tracking are achieved and its RCM error is controlled within 1 mm[27]. These studies demonstrate the wide application and potential of deep learning and machine vision technology in adaptive visual servo control.

In terms of machine vision applications in agricultural robots, in 2022, Wang Tianhai reviewed the application of machine vision in agricultural robot navigation and discussed its advantages, challenges and future research directions[7]. This study analyzes in detail the important role of machine vision technology in improving the navigation accuracy and efficiency of agricultural robots and points out the main technical problems currently faced, such as environmental complexity and real-time requirements. In addition, Wang Tianhai also proposed some possible solutions and future research directions, which provided a valuable reference for further promoting the development of agricultural robot technology.

In terms of machine vision applications in industrial robots, in 2016, Zhang Sen proposed a machine vision-based LED filament spot welding robot, which aims to replace traditional manual methods and improve welding efficiency and accuracy[12]. By introducing machine vision technology, the robot can achieve real-time monitoring and accurate positioning of welding points, thereby significantly improving the automation level and product quality of the welding process.

In the research of machine vision and biological vision, remarkable progress has been made in recent years. In 2017, Maxim Ziatdinov et al. used machine vision combined with Markov random fields and convolutional neural networks (CNNs) to classify surface molecular structures, achieving high-precision molecular assembly recognition[29]. This research demonstrates the potential of machine vision in simulating biological vision systems.

In robot vision applications, Khan Asif proposed a deep neural network-based visual interaction model Packer Robo in 2022, which enhances the robot's coordination ability and scene understanding ability through self-supervised learning[30]. The design inspiration of this model comes partly from the processing mechanism of biological vision system, which aims to improve the performance of robots in complex environments.

Furthermore, Lu Zhiheng in 2021, a winter jujube grading robot based on machine vision was designed and the YOLOv3 algorithm was used to achieve high accuracy and high efficiency maturity detection[31]. This research not only improves the efficiency of agricultural product processing, but also demonstrates the application prospect of deep learning in imitating biological visual recognition tasks. In terms of multi-robot scheduling, Li Jing combined pilot scheduling and behavioral methods in 2018 and introduced deep learning techniques to improve multi-robot task coordination[32]. This method draws lessons from the collaboration mechanism in the biological group and improves the overall efficiency and flexibility of the robot system. Shou Yiyang designed an embedded robot obstacle avoidance path planning algorithm based on machine vision in 2022, which enables the robot to navigate better in dynamic environments by improving accuracy and performance[33]. This study further proves the effectiveness of machine vision in simulating biological visual perception and response mechanisms. DingYuhan proposed a deep learning-based object detection framework for intelligent robots in 2022, using KCF vision tracking technology and verified its effectiveness through experiments[34]. The design idea of this framework is also inspired by biological vision systems, aiming to improve the performance of robots in target detection tasks.

Chiu Yi Jui proposed an automatic bin recycling system based on machine vision in 2024, which combines robotic arm control technology to improve work efficiency[35]. This research demonstrates the application potential of machine vision in imitating biological movement and manipulation ability.

In terms of deep learning and machine vision technology in robot vision, recent research has covered multiple application fields. In 2018, Seng Kah Phooi gave a review of computer vision technology in grape cultivation technology and introduced the GrapeCS-ML database for smart vineyard solutions[9]. This study demonstrates the potential of computer vision in agriculture, especially in the application of improving grape yield and quality.

Moreover, Chauhan Amit studied a computer vision and machine learning-based robot for grape fruit cluster detection and yield estimation in 2022[11]. Using OpenCV and random forest algorithm, the study achieved an accuracy of 97.5% and an F1-Score of 90.7%, further demonstrating the great potential of computer vision and machine learning in agricultural automation.

Figure 2: computer vision[36].

Robot Vision System Architecture

Global vision system

- **Multi-camera collaboration and SLAM optimization:** The global positioning accuracy based on ORB-SLAM3 can reach ± 2 mm, but it is susceptible to occlusion interference in dynamic scenes; NeRF-SLAM realizes dynamic object culling through neural radiation field and the reconstruction error is reduced by 37%.
- **Industrial case:** Hikvision's intelligent warehousing system uses a multi-view RGB-D camera array, combined with an improved particle filter algorithm, to achieve an AGV path planning delay of < 50ms.

Local embedded vision system

- **Edge computing and lightweight model:** Jetson AGX Orin deploys the YOLOv9-Tiny model, which achieves 62.1% mAP on the COCO data set and consumes only 15W of power.
- **Tactile-visual fusion:** IDC 2025 trend points out that the combination of electronic skin and 3D vision can increase the grasping success rate to 92%, which is suitable for precision operation of medical surgical robots.

Hybrid cloud edge architecture

- **Cloud large model empowerment:** GPT-4V supports industrial drawing semantic analysis and code generation through visual-linguistic multi-modal pre-training and the error rate is 41% lower than traditional methods.
- **Federated learning and privacy protection:** Yang Qiang's team proposed the Fed Vision framework to achieve cross-factory model collaborative training while ensuring data privacy and the defect detection F1-score reaches 0.89.

Core Computer Vision Technology Breakthrough

Object detection and recognition

- **Dynamic target tracking:** The optical flow estimation error (EPE) of the RAFT algorithm on the KITTI dataset is 2.71 px, which is 58% lower than that of the traditional Lucas-Kanade method; Combined with Transformer's Global Motion Aggregator (GMA), the occlusion scene performance is further optimized **(Figure 3)**.

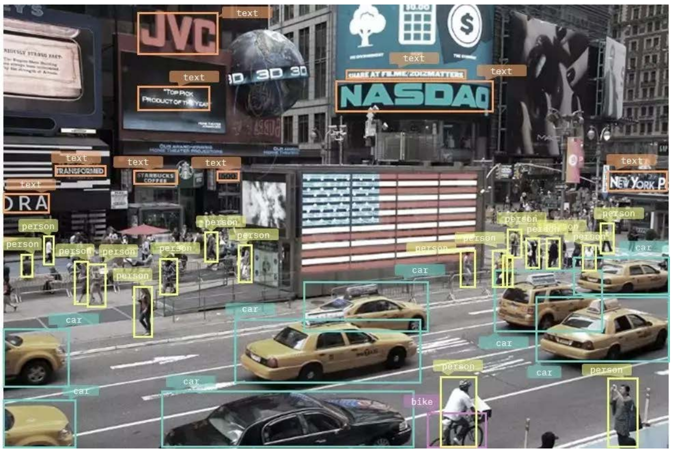

Figure 3: target detection[38].

- **Industrial defect detection:** Faster R-CNN introduces attention mechanism (CBAM module) and the false detection rate in PCB defect detection is < 0.05%, which is 19% higher than the baseline model.

Three-dimensional reconstruction and SLAM

- **Neural radiation field innovation:** NeRF-SLAM realizes non-rigid deformation modeling through implicit scene representation, with a reconstruction accuracy of 1.2 cm on Dynamic Object Dataset, which is suitable for flexible manufacturing environments.
- **Topology completion technology:** LAKe-Net adopts a three-stage completion strategy of "key point-skeleton-shape" and the completion rate is increased to 84% under the missing data of ScanNet, solving the problem of incomplete reconstruction of industrial parts.

Dynamic scene understanding

- **Spatiotemporal attention mechanism:** Video Swin Transformer has an accuracy rate of 94.7% in the UCF101 behavior recognition task and realizes long-term dependency modeling through local-global attention fusion.

- **Simulation-to-reality migration (Sim2Real):** NVIDIA Isaac Sim generates synthetic data to train the robotic arm capture model. The success rate of real-life scene migration exceeds 90%, reducing data annotation costs by 70%.

Evolution of Key Technologies in Machine Learning

Supervised learning and data augmentation

- **Synthetic data generation:** StyleGAN3 generates industrial defect images, combined with Domain Adaptation technology, to increase mAP by 12% in steel plate surface inspection tasks.
- **Pose estimation optimization:** CPPF algorithm uses physics engine to synthesize training data and the 6D pose estimation error of unknown objects is < 5 °, which is comparable to the real data annotation effect.

Reinforcement learning and decision planning

- **Multi-agent collaboration:** The PPO algorithm realizes dynamic path planning in the RoboCup medium-sized group competition and the team winning rate increases from 65% to 78%.
- **Hierarchical reinforcement learning:** DeepMind proposes an HRL framework, which reduces decision delay to 30ms in UAV swarm obstacle avoidance tasks and supports real-time collaboration of 100 + agents.

Self-supervision and lightweight learning

- **Comparative learning application:** Sim CLR has a classification accuracy of 85.6% under unlabeled ImageNet data. Combined with knowledge distillation technology, the model parameters are compressed to 1/4.
- **Non-Transformer architecture:** Lightweight models such as HybridCR are designed through convolution-cyclic network hybrid design and the inference speed is 3 times higher than that of ViT, adapting to edge devices.

Challenges and Industrial Solutions

Table 1: Industrial vision solution.

Challenge	Technical solutions	Industrial Case	Performance indicators
Real-time constraints	TensorRT Deploys EfficientNet-Lite	FANUC Electromechanical Quality Inspection System	Delay ≤ 20 ms, throughput 1200 FPS
Data scarcity	NeRF + GAN Multimodal Synthesis	Tesla factory parts defect detection	60% reduction in training data requirements
Multimodal awareness	RGB-D + LiDAR cross-modal fusion	Boston Dynamics Atlas Robot Terrain Adaptation	Terrain recognition accuracy rate 98.5%
Energy consumption optimization	FPGA accelerated SLAM algorithm	DJI UAV autonomous navigation module	40% less power consumption and 25% more battery life

Future Trends and Research Directions

Neural Symbol System (NeSy)

- **Knowledge graph embedding:** The AKB-48 joint body knowledge base is combined with the visual model to solve the semantic ambiguity problem of robotic arm capture and the reasoning speed is increased by 2 times.
- **Enhanced interpretability:** Grad-CAM + + visualization technology reveals the basis of model decision-making and meets the ISO/TC 299 industrial trusted AI standard.

Embodied intelligent robot

- **Commercialization of humanoid robots:** IDC predicts that the installed capacity of humanoid robots in the field of special operations will exceed 1,000 units in 2025 and low-beat tasks (such as exhibition hall tours) will be achieved through 3D vision + tactile perception.
- **Flexible manufacturing application:** The collaborative robot integrates vision-force control closed loop, supports “small batch, multi-variety” production and shortens the line change time to 15 minutes.

Ethics and Standardization

- **Federated learning framework:** The OpenX-Embodiment project builds a global robot dataset to support cross-agency model training while protecting data sovereignty.
- **Energy consumption certification system:** The European Union has launched an AI energy consumption labeling system, which requires the energy efficiency ratio of industrial vision systems to be ≥ 0. 8 TFLOPS/W.

Conclusion

Robot vision is transitioning from “single-modal perception” to “multi-modal cognition” and its deep integration with CV/ML has promoted paradigm changes in fields such as intelligent manufacturing and medical surgery[37]. In the future, we need to focus on three major directions: (1) collaborative optimization of lightweight models and edge computing; (2) Neural symbolic system enhances decision interpretability; (3) Construction of data ecology driven by federated learning. Academia and industry need to jointly build an open platform (OpenX-Embodiment) to accelerate the transformation of technology from laboratories to factories.

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