

Path Optimization Technology for Robotic Arms Based on Visual Sensing Technology

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Abstract. Current path planning has become a key technology for robotic arm systems. However, in complex or dynamic environment, the path planning of mechanical arm still faces problems such as slow speed, unstable performance and weak human-computer interaction ability. Therefore, more intelligent algorithms and visual sensing technologies are needed to compensate for the limitations of traditional planning methods. The purpose of this paper is to analyze the advantages and disadvantages of traditional algorithms, intelligent algorithms and learning algorithms and the representative research results in various application fields in recent years. It is concluded that the combination of 2D vision technology and 3D vision technology and the integration of intelligent algorithm and learning algorithm is a research trend and has more application value.

Keywords: Vision Sensing, Deep Learning, Robot Arm, Path Optimization

1 Introduction

As the core equipment in the automation field, the industrial mechanical arm is experiencing the historical transformation from programmed and fixed operation tools to intelligent and flexible production partners. The driving force for this transformation is the global manufacturing industry's urgent pursuit of "intelligent manufacturing". Driven by international strategic initiatives such as "Industry 4.0", "National Strategy of Advanced Manufacturing Industry" in the United States and "Social 5.0" in Japan, the global manufacturing industry is accelerating to the digital, networked and intelligent development. The plant of the future will definitely be an intelligent ecosystem that can quickly respond to market changes, realize personalized customization and efficient resource allocation. In this context, the capability boundary of the mechanical arm as the "execution terminal" of the production line directly determines the intelligence level of the entire manufacturing system.

However, the traditional mechanical arm system mostly relies on the programmed control of preset and fixed trajectory. They perform well in a structured environment, but they become overwhelmed by unstructured scenarios such as random workpiece placement, dynamic line obstructions, and collaborative work with workers. At present, many researches have promoted the intelligent development of mechanical arm. Cheng Jinchan 's team proposed the artificial honeycomb algorithm based on reinforcement learning in the research of path planning algorithm, and verified in the experiment that the solution accuracy, convergence speed and path length of Artificial bee colony algorithm based on reinforcement learning

(QABC) are significantly superior to some existing traditional algorithms, improving the robustness of the system[1]. Liu Xun 's team used the improved RRT algorithm to construct the dynamic factor artificial potential field in the path planning research of the reconfigurable overhaul mechanical arm in a narrow and deep cavity. The simulation and experiment results show that the improved algorithm has certain advantages in path length, planning time, number of nodes and sampling times[2].

In view of this, the purpose of this paper is to conduct a comprehensive and systematic review and prospect of the research on path optimization of mechanical arm based on visual sensing technology. This paper firstly constructs the overall system structure of this technology, and then analyzes the core technology and method classification in visual perception (camera calibration, image processing, pose estimation) and path optimization (planning algorithm), and compares the performance boundary and application scenarios of various methods. Finally, based on summarizing the current core challenges, this paper will look forward to the future potential technical breakthroughs and research trends, and provide a clear technical panorama and valuable reference guide for researchers and engineers in related fields.

2 Composition of mechanical arm system based on visual sensing technology

2.1 Vision sensing technology

Visual sensing technology is the core and prerequisite to realize the robot arm's accurate sensing of the environment and intelligent path optimization. It can be divided into 2D vision technology and 3D vision technology according to different information dimensions and principles. The fundamental difference between the two is whether the depth information of the working scene can be directly provided, which also determines the different comparison and selection between the two in the mechanical arm path optimization technology. 2D and 3D vision technology is not simply an alternative relationship, but a complementary and coexistent relationship. 2D vision is suitable for cost - and speed-sensitive 2D planar operations, while 3D vision is the key to solve the complex path optimization problem in 3D space. In practical application, the two are often combined to take into account accuracy, efficiency and cost. These two types of technologies are discussed in depth below.

2D vision technology. The core of 2D vision technology relies on the monocular camera to obtain 2D plane information in the scene. This technology is mainly integrated into the path optimization of the mechanical arm in two visual servo ways.

The first is position-based visual servo (PBVS). The path planner generates an optimal path from the current position to the target position in the Cartesian space or joint space according to the pose information. Li Bin established the visual servo experimental platform of the big family E05-pro mechanical arm, established the visual servo model of PBVS[3], respectively analyzed the situation of single target point and multiple target points through Simulink simulation, established the mapping relationship between the image error and the joint speed of the mechanical arm, improved MPC algorithm for field of view and camera speed constraint, and made the convergence of the image error of the control system more smooth and faster. Tae-Jae Lee[4], based on the monocular vision sensor, uses Inverse Perspective

Mapping(IPM) algorithm and Markov Random Field(MRF) model to carry out accurate obstacle segmentation in the autonomous robot obstacle detection algorithm research, and realizes zero error rate in the barrier-free environment, and finally calculates the accurate distance between the robot and the obstacle. This study shows that 2D vision can provide an extremely efficient and safe solution in the path optimization task of the mechanical arm.

The second is image-based visual servo (IBVS). Liu Jun et al. adopted IBVS technology in the research, introducing distance adaptive gain to improve the convergence speed of the system when approaching the target, while reducing the gain in the obstacle avoidance stage to improve the track smoothness[5]. When the mechanical arm enters a complex area, they use a set algorithm to obtain the path planning, map the path direction to the image space, and generate dynamic guidance feature points linked with the real-time feature point coordinates, so as to guide the mechanical arm to complete obstacle avoidance.

3D vision technology. By directly acquiring 3D geometric information of the scene, 3D vision technology overcomes the fundamental defect of 2D vision in depth perception, and provides indispensable sensing capabilities for 3D obstacle avoidance, disordered grab and precision assembly of the mechanical arm in complex environment.g. Based on its working principle, it can be divided into two categories: passive stereo vision and active optical measurement.

Passive stereo vision technology is to analyze data through images obtained from different angles, and the typical representation is binocular stereo vision. Simulate the number and time of human eyes, collect images and information through two cameras (left and right eyes) at the same time, conduct stereo matching, calculate the depth value by triangulation method for corresponding pixels of the same physical point by two cameras, and finally generate the depth map or point cloud. Kendall A. built 4D cost volume for the first time in the research and aggregated and normalized it through 3D convolution.(GCNet)based on depth learning significantly improves the accuracy and robustness of matching [6]. From this study, it can be seen that 3D vision also has its own characteristics and advantages in the robot arm path optimization task.

Optical measurement technology directly calculates the depth by actively projecting a controllable structural light source (stripe, spot) to the scene, analyzing the pattern deformed by the shape of the object surface. To simplify the three-dimensional reconstruction problem. Raj T.'s team highlighted the low cost of 3D vision in their research on radar laser (LiDAR) scanning as an important reference for future solutions to robotics, measurement and agriculture[7].

By acquiring 3D geometric information, 3D vision technology completely solves the problem of "blind people" in 3D scene operation, which is the core to realize accurate path optimization. Although there is a high demand for cost and materials, the development trend is highly consistent with intelligent manufacturing.

Technical Comparison and Selection Analysis. To select the appropriate visual sensing technology for the robot arm path optimization system in practical application, it is necessary to consider the advantages and disadvantages of both and the task requirements, environmental characteristics and economic costs. This section will make a horizontal comparison between the aforementioned 2D and 3D vision technologies and provide selection guidance and analysis, as shown in Table 1.

Table 1 Horizontal Comparison of Visual Technology

Technical Dimension	2D vision (monocular)	Passive stereo vision (binocular)	Active 3D vision (structure light)	Laser radar (LiDAR)
Core Principles	Two-dimensional projection imaging	Passive triangulation survey	Active projection, triangulation, or flight time	Active scanning, flight time
Depth Information	No(to be inferred)	Yes(calculated)	Yes (direct measurement)	Yes (direct measurement)
Accuracy	High (in-plane)	Medium,with Distance	Height (close range)	excellent
Complexity of calculation	Low	High (stereo matching)	low	Low (excluding point cloud processing)
Cost	Low	Low	Medium	High
Impact of ambient light	Large (dependent on external light)	Large (texture and light dependent)	Structural light: weak anti-interference; ToF: strong anti-interference	Small (active light source)
Typical application scenarios	Plane positioning, QR code identification and dimension measurement	Outdoor robot navigation SLAM	Close-range 3D scanning, unordered capture, face recognition	Automated driving, large-scale environmental modeling
Role in path optimization	Provide 2D target pose (X,Y,θ)	Provide 3D environment information for obstacle avoidance and navigation	Provide high precision 3D information in the working space for fine operation and obstacle avoidance	Provide a wide range and high-precision 3D map for global path planning

Based on the comparison in Table 1, the following principles can be followed in selecting the visual system. If the task is limited to only one 2D plane, 2D vision is the most cost effective option and should be given priority. If the task involves obstacle avoidance in 3D space, unordered grab, etc., 3D vision techniques are recommended. However, in combination with

the above, there is no "only the best" solution, only the "most suitable" scenario. The current research and application trend is multi-sensor fusion, and the "2D+3D" hybrid vision system is becoming more and more common. The high speed and information processing of 2D vision are used for preliminary identification and positioning, and 3D vision is used for accurate 3D pose estimation in a small range. Therefore, the problem should be considered from multiple aspects in the selection scheme, so as to design a more reasonable path optimization scheme.

2.2 Mechanical arm motion system.

As the core part of the robot, the stability, working efficiency and working accuracy of the mechanical arm will directly affect whether the operation can be completed. In the visual grabbing task of the mechanical arm, the mechanical arm motion system is the direct representation of the transformation of visual information into motion. The actuator receives commands generated from the visual system, drives each joint and component to reach the target position, avoids obstacles and completes the operation. Therefore, the research and in-depth understanding of the mechanical arm motion system is the premise to realize the path optimization

Kinematical study of mechanical arm is mainly to analyze the mathematical relation of joint motion state, joint angle and position, without considering the force and moment generated by motion. It serves as the basis for path optimization and visual servo control, and its core task is to establish accurate mapping between joint space and Cartesian space.

Positive kinematics is the process of describing known joint variables to solve the pose of the end effector in the coordinate system. Denavit-Hartenberg (D-H) parameter method is the standard method for building mapping relationship, allocating coordinate system for each connecting rod and performing homogeneous transformation to complete the calculation[8]. Positive and reverse kinematics often complement each other to verify the accuracy of the calculation results, but it is deterministic and unique and provides the basis for real-time control and simulation.

Inverse kinematics is to solve the joint angle for the regularly expected end position. This is a critical and difficult problem in the path optimization process because planners often work in the Cartesian coordinate system and actuators require joint space instructions. Traditional numerical methods (e.g. Jacobi matrix, damped least-squares) and modern data-driven methods (deep neural networks) are commonly used in inverse kinematics, both of which have different advantages in different working environments.

3 Visual perception and information extraction

Visual sensing provides the robot with accurate working environment data, but these raw data (images) must be processed to transform into accurate spatial information that is meaningful for path planning. This chapter provides a systematic overview of the complete process: from system calibration to ensure measurement accuracy, to image pre-processing to improve data quality, to feature extraction to identify the target, and finally to obtain pose estimation. These four links are linked together to form the core of intelligent sensing of mechanical arm.

3.1 Calibration of vision system

Calibration is the bridge between visual measurement and robot motion control, and its accuracy determines the consistency between "what you see" and "what you get". At present, two widely used calibration methods are camera calibration and hand and eye calibration.

Camera calibration is to determine the internal parameter, external parameter and distortion coefficient of the camera. The most classic calibration method is Zhang Zhengyou's calibration method[9]. Xu Jia[10], used the Pyrone-OpenCV machine vision software library to complete the calibration of camera parameters based on Zhang Zhengyou's calibration method in the research and reduced the error by the method of re-projection. In recent years, many studies have focused more on automation and accuracy in complex situations.

In addition to camera calibration, another popular calibration method nowadays is hand-eye calibration. Taking the robot as the "hand" and the visual system as the "eye" fusion application, the transformation relationship between the robot and the visual system is obtained to obtain the target pose, that is, the hand and eye calibration. In 1989, Tsai and Shiu first proposed the hand and eye calibration problem and gave the classic $AX=XB$ hand and eye calibration equation[11,12], Its manifestation is as follows:

$$AX=XB \quad (1)$$

With the technological iteration in today's society, more and more algorithms have emerged for optimizing the hand and eye calibration technology. Chen ZM et al. proposed a new dual quaternary optimization algorithm based on dual quaternary vector 2-norm, and constructed a two-stage solution strategy by using regularization and patching techniques, so as to better improve the accuracy of calibration[13].

3.2 Image feature processing and pose estimation

Image feature processing includes image pre-processing and feature extraction. The former is to improve image quality and make the image clearer so as to carry out better feature extraction. Then, accurate coordinates of the target grab can be obtained through pose estimation.

In order to improve the image quality, Guan Hongyan[14], et al. adopted the filtering method commonly used in the digital image noise reduction process by median filter. The principle is to select the median value of the pixel in the template as the pixel size of the current template area, and the expression is as follows[15]:

$$g(x,y)=med\{f(x-m,y-n),(m,n \in W)\} \quad (2)$$

Where $g(x,y)$ and $f(x,y)$ respectively represent the original image and the processed image, and W represents the template size, typically 3×3 or 5×5 .

Feature extraction is to be able to find the target object from the image. At present, the main feature extraction methods are divided into traditional manual feature extraction methods and in-depth learning methods. Wang Ning et al[16], based on the improved YOnetwork structure and referring to CBAM attention mechanism in the research on the grab of the flight manipulator, the structure mainly includes input, feature extractor, feature fuse and detector (Head), as shown in Fig. 1:

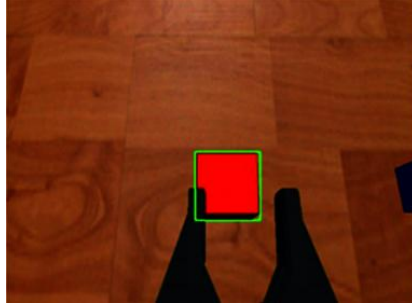


Fig. 1 Detection of Grab Position with YOLOv8n[16]

The improved detection accuracy increased from 92.5% to 96.3%, significantly reducing the risk of grab failure due to detection errors. When 2D coordinates of the target are obtained, the internal parameter matrix and the external parameter matrix are subject to inverse projection of coordinates through inverse matrix operation to finally obtain 3D coordinates.

The pose estimation is the final output result of the visual system, providing accurate position and pose of the target object for path planning. With the development of convolutional neural network, the monocular pose measurement based on depth learning has gradually become a research hotspot in this field due to its strong feature extraction ability and robustness. The method based on depth learning can compensate for the poor pose restoration effect of single RGB image and the problem that it is vulnerable to environmental interference[17]. HaraR M presents the solutions of four different pose estimation problems. For over-constrained 2D - 2D and 3D-3D pose estimation, a closed least-square solution is given[18]. For the 3D pose estimation problem of 2D perspective projection, a global convergence iterative technique is provided. Simplified linear solution and robust solution for 2D perspective projection - 2D perspective projection pose estimation are given. In the simulation experiment composed of millions of tests, the pairs of corresponding points in the experiment are different, the signal-to-noise ratio (SNR) changes, with Gaussian noise or uniform noise. The data shows that when the signal-to-noise ratio is less than 40 dB, it may require hundreds of pairs of corresponding points to accurately deduce the rotating and translational point set.

4 Classification of optimization methods for motion trajectory of mechanical arm

4.1 Environment based path planning method

In the daily use of the mechanical arm, the environmental awareness is closely connected with the operation. Perception refers to the mechanical arm's understanding and interpretation of the environment through multimodal information such as vision, sound, and haptics, while Operation performs specific tasks based on this sensing information. The premise of the robot arm path planning is to obtain and understand the surrounding environment information for map construction before optimization. Below is an analysis of the different environments.

Static environment. In a part of the operating environment, the object to be grabbed and the surrounding environment are in a static state. The main methods for map construction are grid

method, topology method, tangent diagram and octree tree modeling method. The 3D space segmentation data structure of the mid-period octree is highly practical. The spatial distribution of octree[19] is shown in Fig. 2:

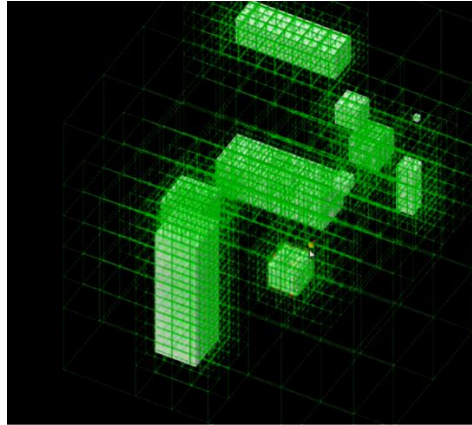


Fig. 2 Spatial distribution of octree[19]

White dots in the figure represent obstacles in the map. The more white dots, the thinner the square is divided. In the map, the octree map will first divide the entire map space into eight cubes with the same volume, and the cube divided will be stored in the memory as the sub-node of the octree. In this way, an octree data structure including the root node can be generated by continuously dividing the cube. Each cube divided in the octree has the ability to store map information. Each node has three storage states: blank, unknown, and occupied. Octagonal tree can continuously adjust the tree depth according to this mechanism according to different actual needs to meet the resolution requirements.

Dynamic environment. In most cases of complexity, obstacles, and target movement, some basic 3D recognition has some limitations, so other algorithms and feature recognition methods are required to improve more accurate environmental awareness and map construction.

Zhong Hang et al. proposed a dynamic obstacle avoidance method based on the combination of dynamic control obstacle function and model predictive control to solve the obstacle avoidance problem of the robot[20]. The control obstacle function can be used for the robot to avoid obstacles, and the solution time is reduced by reducing the MPC online solution freedom degree. He first detected the collision between the target point and the ESDF map and extracted the path point to obtain the initial track cost. Meanwhile, the dynamic obstacle avoidance is achieved, and the obstacle cost is obtained through the penalty term of the cost function. The two kinds of costs and the terminal pose constraint, the self-collision avoidance constraint, and the obstacle distance approximate constraint are brought into the OCS2 nonlinear optimization solver to calculate the joint angles, so as to realize the high-quality track optimization

This method improves the accuracy and stability of the robot under complex working conditions, and also provides reference and learning for other subsequent studies.

4.2 Algorithm based path planning method

Traditional algorithm. The operation process of the mechanical arm includes image recognition and system calibration, then map modeling to determine the surrounding environment, and finally path planning and motion. Many algorithms have been proposed since the 1950s. Initially, grid-based search methods were very popular in the area of autonomous navigation. Typical grid-based search algorithms include Dijkstra, A*, D* - lite, and Theta*. These algorithms can ensure completeness, making them suitable for path planning in deterministic environment. However, the path quality depends on the mesh size, and when the environment becomes complex, traditional algorithms cannot meet the accuracy requirements of the operation. So many scholars prefer to study the intelligent algorithm and learning algorithm to improve the operation accuracy.

Intelligent algorithm. For the path optimization algorithm of the mechanical arm, domestic and foreign experts have also proposed other new optimization algorithms, such as genetic algorithm, particle swarm optimization algorithm and whales algorithm to improve the optimization. Among them, the Whale Algorithm (WOA) is a metaheuristic intelligent optimization algorithm that mimics the Predation of Whale by Bubble Net. Its main steps are:

- (1) Surround the prey: constantly update its position according to the location of the target.
- (2) Bubble Net Attack: Simulating Whale Helix Bubble Predation.
- (3) Search for preys: Whales search for targets in global space.

Whale algorithm has the advantages of fast convergence and simple parameter setting, but it also has the disadvantages of local optima due to fast convergence.

Xie Huolin's team used the Whale Optimization Algorithm in path optimization, used chaotic mapping population initialization[21], added adaptive weights, adaptive threshold and mutation mechanism, and finally obtained that the planning time was reduced by 14.56% compared with the time before optimization through simulation, the maximum impact was reduced by 33.94%, and the average impact was reduced by 12.64%. It improves the accuracy and stability of the mechanical arm in operation and ensures the safety of the operation process.

Learning algorithm. With the updating of algorithms, various optimization methods emerge one after another. With the emergence of neural network, more and more learning algorithms based on deep learning, simulation learning and reinforcement learning begin to appear, which supplement the shortcomings of some intelligent algorithms.

This chapter will address Strengthening Learning (DRL). Strengthening learning as a powerful paradigm provides an effective way for robotic arms to impart motor skills. DRL combines learning characterization capabilities in Deep Learning (DL) with decision customization capabilities, so that it performs well in optimizing path selection strategies in interactions and trial and error, and can well solve the problem of volatility and location in the environment.g. Strengthening learning basically includes five parts: intelligent body, environment, state, action and reward. The agent receives the current state of the environment at each time step and determines the action according to this information to obtain the reward. The only goal is to obtain the reward as much as possible and repeat the cycle.

The Markov Decision Process (MDP) is the mathematical basis of reinforcement learning and an important concept of stochastic process, indicating that the future state of a process depends only on the current state and has nothing to do with the past state.g. Based on the state set S and action set A, through the state transfer function P and reward function R, depict the process of action selection, state transfer and reward acquisition of the agent in the state sequence.

Zhai Zhihao's team[22], adopted the PPO (Proximal Policy Optimization) algorithm in the in-depth reinforcement learning model to train the path planning ability of the mechanical arm in the path planning of the honey fruit bagged mechanical arm, and designed a weighted sum reward function composed of distance reward, attitude difference reward and additional reward, so as to effectively guide the gradual optimization of the mechanical arm in the training process and effectively learn the bagging action.

4.3 Comparison and analysis

This chapter provides a comprehensive evaluation of the various algorithms mentioned above, based on the environment, quality of route planning, efficiency, computational complexity, robustness, and difficulty in implementation, as shown in Table 2:

Table 2 Comparison of model selection

Method Category	Typical Method	Environment Path	Planning Quality	Efficiency	Calculation Complexity	Robustness	Implementation Difficulty	Mainly Applicable Scenario
Traditional search algorithm	A*, Dijkstra	static	Optimal/suboptimal	Medium	Medium	High	Low	structured environment, global path planning
Intelligent optimization algorithm	Genetic algorithm, Whales algorithm	Weak dynamic	Suboptimal	Low	HIGH	medium	Medium	High requirements for multi-objective optimization and track smoothness
Learning methods	Reinforcement learning, simulation learning	Strong dynamic	Adaptive	Training low/High execution	High (training)	Medium high	High	Unstructured environment, human-machine cooperation.Task generalization

Through the expression in Table 2, it can be compared and determined that a more appropriate algorithm can be selected for better path planning under different circumstances.

5. Conclusion

This paper describes the selection and comparison of the robot arm path planning technology based on visual sensing technology. 2D vision can quickly identify the target in a relatively static environment, but it is not stable in a complex environment; 3D vision can solve this problem by shaping the surrounding environment in 3D, so as to better plan the path.

In the path optimization section, different algorithm types and typical cases of each algorithm type are summarized in detail. Each algorithm has its own advantages. There is no unique solution for developing path optimization. Different algorithms shall be selected according to different scenarios. Traditional algorithms have poor adaptability, weak optimization ability and insufficient path flexibility when facing complex environment. The intelligent algorithm has the advantages of higher adaptability, excellent robustness and strong global planning ability. Compared with the former two, the learning algorithm has the unique ability of autonomous evolution, and the generalization and adaptive ability are also relatively prominent.

Despite the rapid development of current technology, in some extreme cases, achieving a low-cost, high-accuracy planning path to complete the operation is still a serious challenge. Future research trends also focus more on the paradigm application of multi-sensor fusion and learning intelligent algorithms, and finally achieve more accurate, safer and intelligent human-machine collaborative operation.

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