Research on Real-time Visual Processing Algorithm for Dynamic Obstacle Avoidance of Bionic Mechanical Arm Using YOLOv5

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Abstract: With intelligent manufacturing technology entering a new era, the bionic mechanical arm has also developed quickly. Centered on innovation-led development ideas, researchers need to propose dynamic obstacle avoidance methods that meet the needs of industrial automation. Based on the dynamic evolution of deep learning, we construct a theoretical analysis framework for real-time visual processing algorithms according to the inherent logic of visual processing and explain the dynamic obstacle avoidance mechanism related to YOLOv 5's manipulator and the obstacle avoidance strategy generated by the real-time visual feedback loop mechanism. In addition, the potential to achieve more efficient and safer goals in intelligent manufacturing is explored in terms of the practical derivation of deep learning algorithms and mechanical arm control. In this research, by constructing a dynamic obstacle avoidance model of a bionic mechanical arm based on YOLOv5, the influence of various visual processing parameters, neural network structure, and error level on the avoidance results is analyzed, which provides theoretical support and technical reference for the real-time visual processing algorithm of a bionic mechanical arm.

1. Introduction

Dynamic obstacle avoidance of intelligent mechanical arms is one of the primary responsibilities of intelligent manufacturing technology and one of the research topics in industrial automation [1]. It can be divided into primary static obstacle avoidance and complex dynamic obstacle avoidance. They consist of traditional sensors and advanced visual processing algorithms. The intelligent mechanical arm uses deep learning algorithms to sense and process dynamic environments in real-time to improve the flexibility and adaptability of intelligent manufacturing. Since the advent of deep learning technology, real-time visual processing has been the key to intelligent mechanical arms [2]. Dynamic obstacle avoidance is an essential metric for evaluating the performance of intelligent mechanical arms. Unlike traditional sensors, deep learning-based visual processing emphasizes real-time accuracy and robustness. Therefore, we propose a real-time visual processing algorithm based on YOLOv5 dynamic obstacle avoidance with a bionic mechanical arm, and this paper provides theoretical and technical support for this issue.

The dynamic obstacle avoidance algorithm with a bionic mechanical arm based on YOLOv5 proposed in this research originates from the development of intelligent manufacturing with innovation as the core [3]. The theory reflects the advanced nature of deep learning. It is a tool for realizing the modernization of intelligent mechanical arms. From the perspective of intelligent manufacturing, we combine deep learning with mechanical arm control to achieve adaptive avoidance in a dynamic environment. However, it is only a theoretical discussion. Today, intelligent manufacturing has implemented a unique way based on deep learning. The advancement of intelligent mechanical arms has changed the production mode of traditional industry and reflected the advanced nature of manufacturing. In addition, it will affect the pattern of future industrial production and profoundly impact industrial automation. In conclusion, we must have a forward-looking and global pattern when it comes to dynamic obstacle avoidance. In the context of intelligent manufacturing, we proposed a research object in this paper.

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To sum up, dynamic obstacle avoidance with a bionic mechanical arm based on YOLOv5 is a necessary condition and guarantee for intelligent manufacturing. From the current research, intelligent mechanical arms have made significant progress in dynamic obstacle avoidance, but there are also some technical shortcomings. For example, an effective way to adapt to complex and dynamic environments is needed, and researchers work hard to improve the performance and practicability of the algorithm. Therefore, further research is needed in intelligent manufacturing, which not only helps improve the performance of intelligent mechanical arms but also promotes the development of the industry.

Based on the above background, this paper proposes a YOLOv5-based dynamic obstacle avoidance algorithm for bionic mechanical arms, which aims to improve the adaptability of mechanical arms in complex dynamic environments. Researchers used deep learning theory and real-time visual processing to solve the problem of dynamic obstacle recognition and avoidance. The main content includes constructing a bionic mechanical arm model based on YOLOv5. In addition, we analyze the influence of various visual processing parameters, neural network structure, and error levels on the avoidance results. The experiment effectively deals with risks in intelligent manufacturing, which have theoretical and practical significance.

2. Basic Theory of YOLOv5

YOLOv5 algorithm is developed from deep learning, which embodies real-time processing, emphasizes the efficiency orientation of computer vision, and reflects the rapid development trend of artificial intelligence in recent years. However, it isn't easy to get a comprehensive explanation when we use some image recognition standards to construct the definition and essence of YOLOv5. YOLOv5 (You Only Look Once, Version 5) is an object detection algorithm based on a deep convolution neural network, which can quickly and accurately identify and locate objects in images and videos [4]. The workflow includes the following steps:

In preprocessing, the input image is scaled to a fixed size and normalized to standardize pixel values. The image is then sent to a neural network that employs the CSPDarknet53 convolutional neural network architecture. The architecture consists of several convolution layers and pooling layers, which are used to extract complex features of images.

The network then combines feature maps at different scales to create a feature pyramid (PANet) that balances accuracy and efficiency for object detection at different scales. At each scale of the feature pyramid, the network uses a series of convolutional layers to predict bounding boxes and category probabilities. Each bounding box contains the object's location information and confidence value, and the category probabilities indicate the likelihood that the object belongs to each category.

To delete redundant bounding boxes, YOLOv5 uses a non-maximum suppression algorithm. By comparing the confidence scores, the algorithm selects the bounding boxes with the highest scores and suppresses the bounding box that overlaps with other bounding boxes with high scores.

Finally, YOLOv5 outputs a non-maximum suppressed bounding box and corresponding category labels, which can be used for further processing or analysis, such as object tracking or behavior recognition. YOLOv5 is designed to achieve real-time processing while maintaining high detection accuracy, so it is trendy in application scenarios that require fast response, such as autonomous driving, video surveillance, and robot navigation.

3. Bionic Mechanical Arm Modeling Based on YOLOv5

The modeling of bionic mechanical arms based on YOLOv5 is an important part of intelligent manufacturing, which shows the performance of intelligent mechanical arms. Regarding the design and function of an intelligent mechanical arm, we discuss its application scenarios from the perspectives of kinematics and dynamics. In addition, some scholars think that a bionic mechanical arm is an advanced robotics level or an ideal choice for intelligent manufacturing. Bionic mechanical arms have high flexibility and adaptability to some extent, which belongs to advanced manufacturing science aimed at improving production efficiency [5]. The modeling of the bionic mechanical arm based on YOLOv5 is shown in Figure 1.

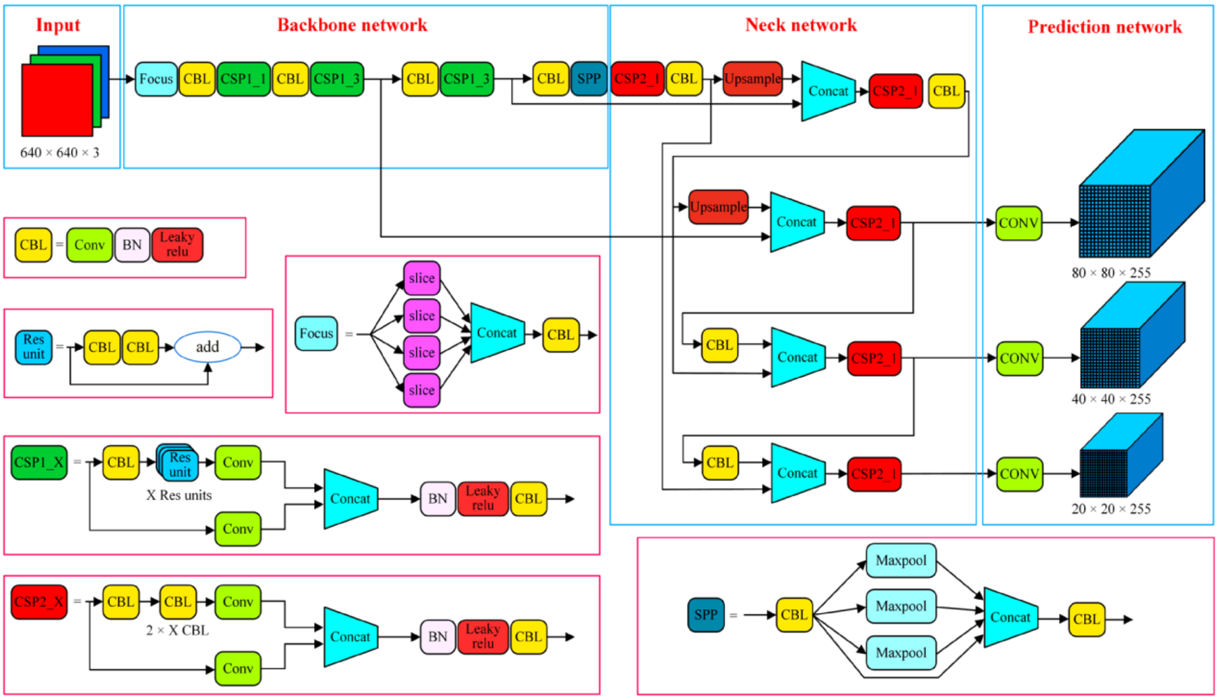

Figure 1 The modeling of the bionic mechanical arm based on YOLOv5

The design concept of a bionic mechanical arm is related to the early industrial robots, and its main activities include automatic production, precise assembly, and operation in complex environments. In addition, visual processing and dynamic obstacle avoidance based on deep learning are closely related to the function and performance of intelligent mechanical arms. By integrating the YOLOv5 algorithm, the bionic mechanical arm has become essential in intelligent manufacturing.

The main contribution of bionic mechanical arms in modern intelligent manufacturing is to improve production efficiency and safety. Therefore, the concept of bionic mechanical arm modeling based on YOLOv5 initially focused on real-time visual processing and dynamic avoidance. The bionic mechanical arm can complete efficient and safe operations in a complex and changeable environment through this modeling. The dynamic performance and functions based on visual processing of intelligent mechanical arm are as follows:

$$\tau = \frac{J\theta'' + c\theta' + k\theta}{1 + e^{-\alpha(d-d_0)}} \tag{1}$$

In the formula:

- τ represents the torque of the mechanical arm joint.
- J stands for a moment of inertia.
- θ'' represents joint angular acceleration.
- c represents the damping coefficient.
- θ' represents the joint angular velocity.
- k represents the spring constant.
- θ represents for joint angle.
- α represents the obstacle detection sensitivity parameter based on the YOLOv5 algorithm.
- d represents the current distance between the mechanical arm and the obstacle.
- d_0 represents the safety distance threshold.

Equation (1) combines the mechanical arm's dynamic parameters with YOLOv5-based vision processing capabilities for efficient and safe operation in complex environments.

4. Dynamic Obstacle Avoidance Neural Network

Unlike static obstacle avoidance, dynamic obstacle avoidance neural networks emphasize the relationship between environment perception and mechanical arm control and have the characteristics of real-time learning and adaptation. Some scientists doubt that the neural network model directly relates to the environment; most advocate that neural networks can rationally evaluate the dynamic environment.

Some researchers proposed a classical neural network model of dynamic obstacle avoidance with deep learning, which has since become a typical tool for intelligent mechanical arms to avoid dynamic obstacles, thus developing a new model. They believe that neural networks are adaptive and that mechanical arms can effectively avoid dynamic obstacles only if neural networks can sense and process environmental changes in real-time. Thus, dynamic obstacle avoidance neural networks result from intelligent mechanical arm self-adaptation to the environment. The dynamic obstacle avoidance neural network is shown in Figure 2.

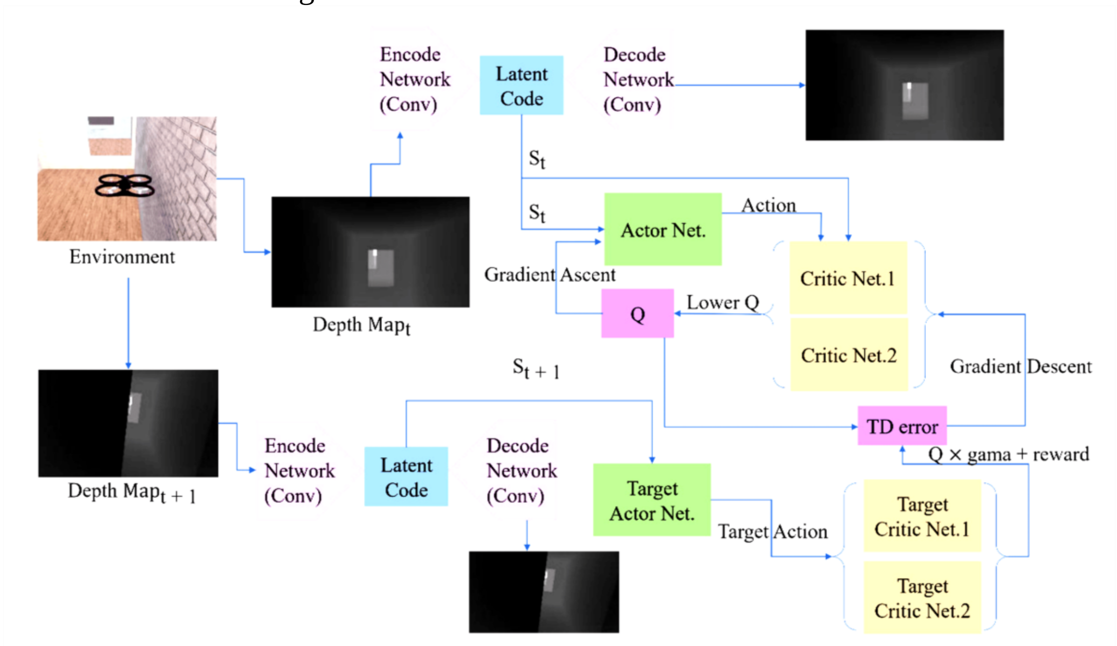

Figure 2 Dynamic obstacle avoidance neural networks

In addition, some scholars generalize dynamic obstacle avoidance into two models, namely, rule-based and learning-based avoidance models. The former focuses on predefined rules and logic, while the latter focuses on data-driven and deep learning. Although researchers have experienced some practical failures, it can improve mechanical arms' intelligence level and operational safety in the long run. Dynamic obstacle avoidance based on neural networks has gradually become the consensus of intelligent manufacturing research and practice [6]. Formula (2) considers the role of neural networks in real-time environment perception and dynamic obstacle avoidance to reflect the characteristics of neural networks.

$$N(s)=\frac{w_1e^{k_1s}+w_2e^{k_2s}}{1+\sum_{i=1}^{n}v_ie^{-\beta_i(s-s_0)}} \tag{2}$$

In the formula:

- $N(s)$ represents the control signal output by the neural network.
- s represents the state variable of the mechanical arm.
- w_1 and w_2 represent weight parameters, representing the response strength of the neural network to different states.

- k_1 and k_2 represent adjustment parameters, which determine the neural network's sensitivity to state changes.

- v_i represents the environmental perception weight, representing the neural network's perception intensity of the i-th obstacle.

- β_i represents the obstacle avoidance coefficient, which determines the speed of the neural network to avoid obstacles.

- s_0 represents the safety status threshold. When the status of the mechanical arm exceeds this value, the avoidance mechanism needs to be activated.

Through a combination of polynomial and exponential functions, this formula describes how the neural network dynamically adjusts the control signal according to the state of the mechanical arm and the position of environmental obstacles, to realize effective obstacle avoidance.

5. Visual Processing Principal Component Analysis

The essence of principal component analysis (PCA) in visual processing is data dimension reduction. Principal component analysis is the application of statistical thinking in image processing. It has entered the research field as an alternative model: PCA framework to make up for the shortcomings of high-dimensional data processing. The basic ideas of this framework are as follows. First, visual processing should ensure that crucial information is extracted. Second, set professional standards for feature extraction. Third, the main features in the data are captured by eigenvalue decomposition and other techniques. Fourth, the variance and covariance of data are measured by mathematical methods. PCA framework changes the extraction of visual features, improves data interpretability, and attaches importance to features' variance, independence, and usefulness. Visual processing algorithms can extract the most essential features from the original high-dimensional image data, thus improving the efficiency and accuracy of subsequent processing steps [7]. The formula (3) is designed to reflect the mathematical model of principal component analysis (PCA) in visual processing:

$$Z = \frac{\sum_{i=1}^{n} \lambda_i v_i x_i}{\sqrt{\sum_{j=1}^{m} \sigma_j^2}} \tag{3}$$

In the formula (3):

- Z is the feature vector after dimensionality reduction.
- λ_i is the i-th eigenvalue.
- v_i is the i-th eigenvector.
- x_i is the i-th element of the original data vector.
- σ_j^2 is the variance of the j-th variable.
- n is the dimension of the original vector.
- m is the dimensionality after dimensionality reduction.

Formula (3) achieves data dimensionality reduction through a linear combination of eigenvalues and eigenvectors and takes into account the variance of the original data to ensure that the most important information is preserved during dimensionality reduction. A principal component analysis of visual processing is shown in Figure 3.

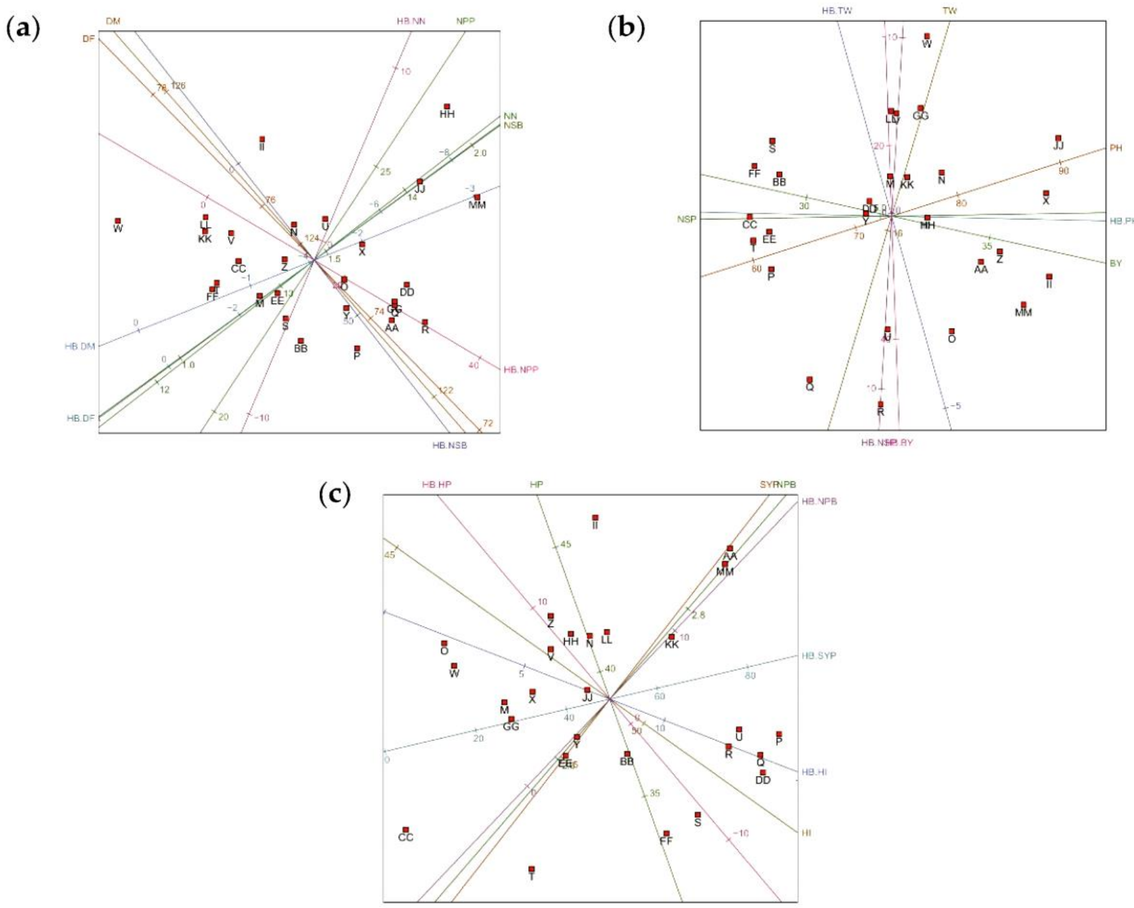

Figure 3 Visual Processing Principal Component Analysis

6. Numerical Examples of Real-time Visual Processing

6.1 Dynamic Obstacle Recognition Based on Deep Learning

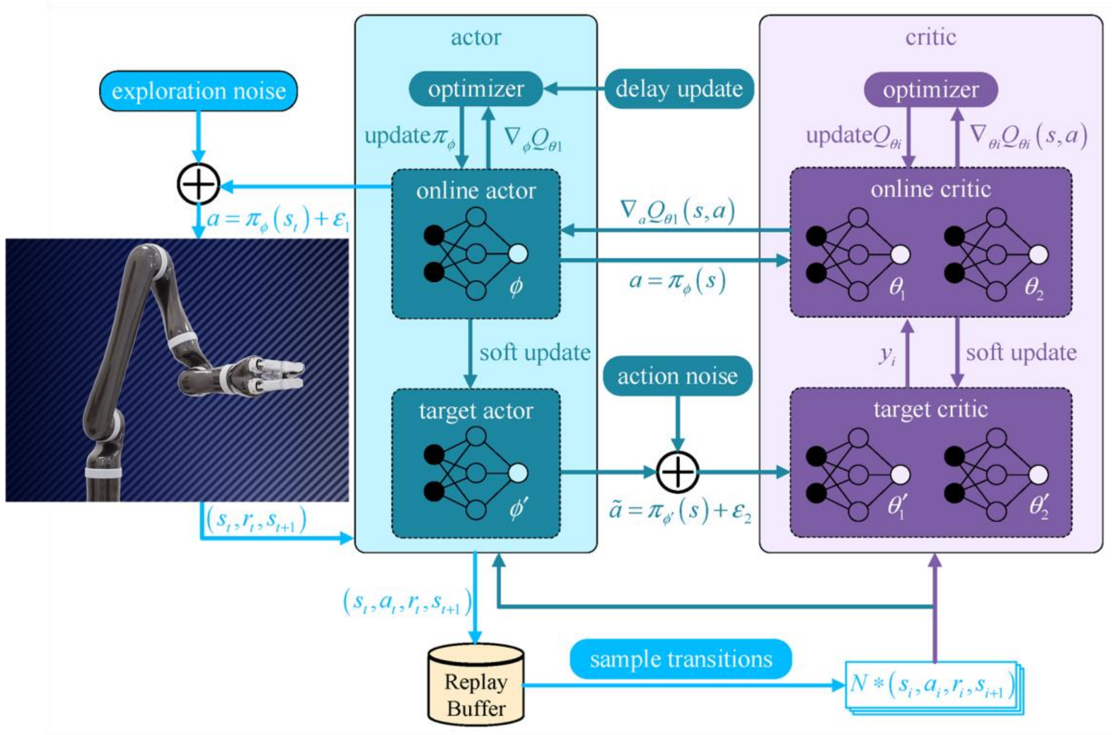

Figure 4 Dynamic obstacle recognition based on deep learning

Dynamic obstacle recognition based on deep learning is a function of a real-time visual processing algorithm, which focuses on the environmental perception level of an intelligent mechanical arm. The YOLOv5 algorithm reflects the position and speed of dynamic obstacles. Some key technologies and application scenarios for developing intelligent mechanical arms are gradually taking shape. Deep learning models and various performance evaluation systems are gradually gaining attention. However, from the application point of view, some dynamic obstacle recognition practices still need to be developed in the theoretical research, contrary to the logical framework and generation mechanism of intelligent manufacturing, resulting in some problems. Figure 4 shows the dynamic obstacle recognition based on deep learning.

6.2 The Influence of the Area of Dynamic Obstacles in the Sample Library on the Experimental Results

From the library construction example perspective, the range of dynamic obstacle values is the basis of the avoidance strategy and is central to the algorithm's performance. Therefore, the dynamic obstacle avoidance strategy takes data diversity as the generation logic. The sample library is the leading resource for training neural networks and an essential subject for evaluating model performance. We strengthen sample library control from the perspective of data quality control. There are three forms: First, we expand the type and quantity of dynamic obstacles. Sample libraries contain diverse and complex data. The second option is standardized data collection and processing. Administrators achieve standardized data quality control by developing and publishing data collection and preprocessing standards to the community. The third is to optimize data enhancement and expansion methods. In recent years, data-driven research has leveraged data to improve model performance and strategies' robustness. However, the representativeness of the sample library needs improvement. The influence of the range of dynamic obstacles in the sample library on the avoidance results is shown in Figure 5.

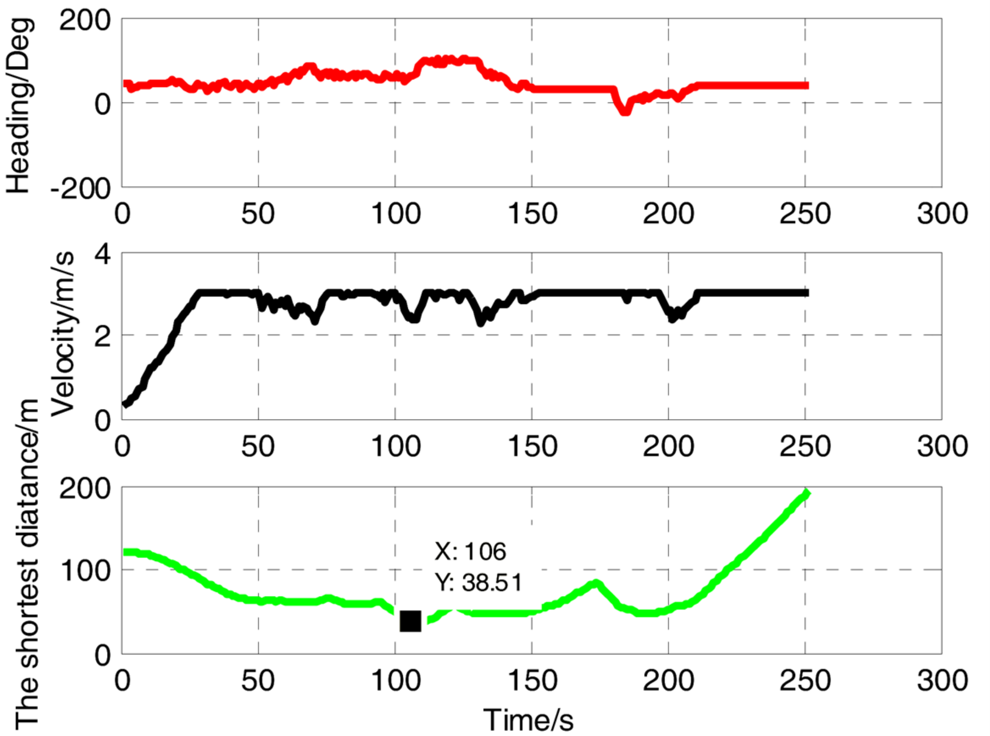

Figure 5 The influence of the range of dynamic obstacles in the sample library on the avoidance results

6.3 The Influence of Visual Processing Parameters on Avoidance Results

The fundamental difference between the YOLOv5 algorithm and the traditional visual processing method lies in its deep learning attributes. YOLOv5's performance standards and optimization criteria are aimed at real-time processing, and its development primarily reflects fast response and accuracy. In the framework of real-time vision processing, fast detection, accurate recognition, dynamic avoidance, and stability are the core values and highest criteria for developing intelligent mechanical arms. The variety of dynamic obstacles and environmental changes lead to the diversification of visual processing. YOLOv5 has significant performance advantages but has shortcomings, such as imperfect parameter configuration and model tuning, and vision processing algorithms need adaptive mechanisms. Therefore, they are "short boards" of real-time vision processing, affecting the overall performance of dynamic obstacle avoidance.

6.4 The Influence of Deep Learning Neural Network on Avoidance Results

From the perspective of practical application, traditional visual processing methods cannot accurately provide the dynamic environment information required by an intelligent mechanical arm. Users are particularly concerned about the safety of the avoidance performance of mechanical arms, and there is a lack of accurate identification and real-time response mechanisms for dynamic obstacles. The root of this problem may be the limitation of the algorithm. In deep learning, the ability of neural networks to identify dynamic obstacles directly reflects the intelligence level. At the same time, traditional methods have a poor ability to deal with dynamic environments. In general, the real-time information of dynamic obstacles is difficult to obtain or measure. Information asymmetry and imperfect algorithms have become obstacles for mechanical arms to avoid dynamic obstacles. In conclusion, applying a deep learning neural network is very important to improve the dynamic obstacle avoidance strategy with an intelligent mechanical arm. Figure 6 proves the influence of deep learning neural networks on the result of avoidance.

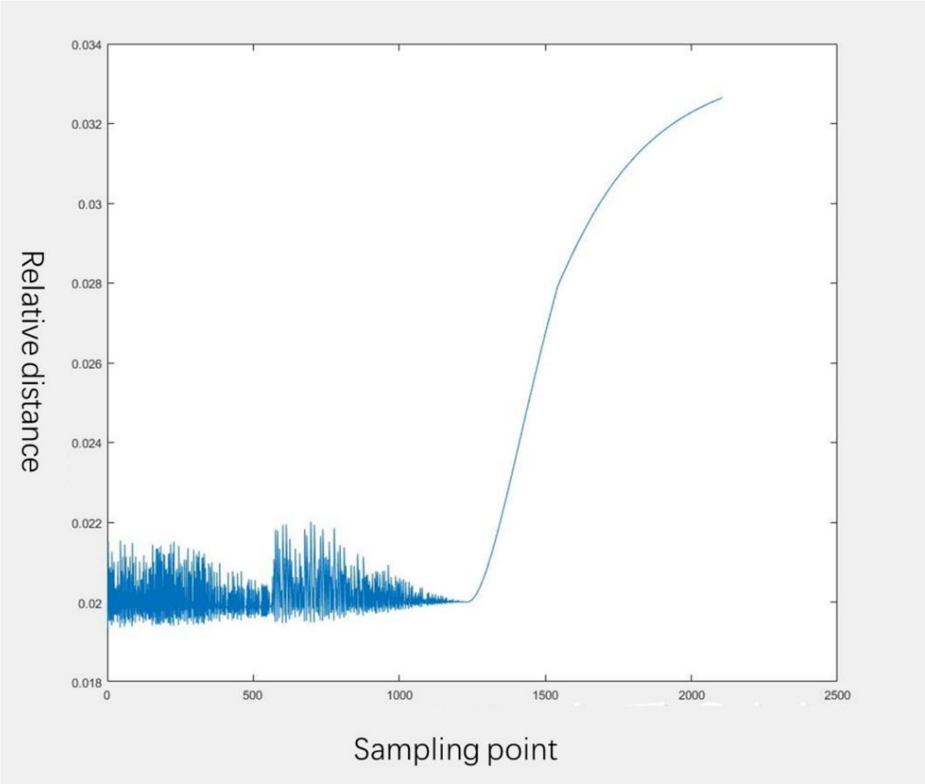

Figure 6 Robotic arm obstacle avoidance path results

6.5 Error Levels and Avoidance Effects

From the perspective of practical application, the error level has restricted the avoidance speed of intelligent mechanical arms for a long time. Since the 21st century, intelligent mechanical arms integrated with multiple sensors have transformed the ability to perceive the environment through sensor fusion. However, traditional visual processing methods' drawbacks restrict mechanical arm performance improvement. Due to the limitations of the sensor itself and environmental noise and interference, the visual processing algorithm needs to be improved. On the premise of ensuring real-time performance, sensor fusion is regarded as a direct way to improve performance. However, the effect of the avoidance strategy based on sensor data on the mechanical arm remains to be discussed. The difficulty of data processing makes the mechanical arm unable to perceive the dynamic environment accurately. Therefore, sensor fusion has yet to reach the ideal goal of evasion. To sum up, dynamic obstacle avoidance with an intelligent mechanical arm is a technical problem, and it also faces problems with algorithm optimization and data processing.

7. Conclusion and Prospect

Scientists have made progress in the dynamic obstacle avoidance of a bionic mechanical arm based on YOLOv5, which poses new challenges and requirements for intelligent manufacturing. YOLOv5 is a symbol of intelligence and an essential means to improve production efficiency. Furthermore, it meets the urgent needs of realizing production safety and protecting workers and reflects the inherent requirements of intelligent manufacturing. Due to the progress of advanced technology, we build a theoretical analysis framework and practical mechanism of dynamic obstacle avoidance model of a bionic mechanical arm based on YOLOv5. In recent years, modern information technologies such as deep learning have promoted the development of intelligent manufacturing. It empowers the mechanical arm through YOLOv5 and improves the speed and accuracy of the avoidance strategy. The research value fits the logic of the intelligence industry. Therefore, YOLOv5 provides a new method for a bionic mechanical arm's dynamic obstacle avoidance model. In conclusion, the sustainable improvement and development of a dynamic obstacle avoidance model of a bionic mechanical arm based on YOLOv5 help scientists cope with the challenges in intelligent manufacturing and promote the development of intelligent manufacturing to a higher level.

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