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Research on Visual Perception Method of Intelligent Robot Environment Based on Machine Learning

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Abstract: *With the development of modern science and technology, robots have begun to frequently appear in people's work and life, providing people with more and more diverse intelligent services. Human perception of the surrounding environment is achieved through visual observation in most cases, and environmental visual perception in the field of robotics has always been the focus and difficulty in research. In this paper, the research on the visual perception method of intelligent robot environment based on machine learning. In order to improve the robot's environment perception level, it is necessary to solve the problems in the perception of objects in the space environment and target objects. This paper analyzes the machine learning model, and improves the learning model through random variable analysis to improve the machine's ability to intelligently obtain information in the environment. At the same time, this paper analyzes the method of extracting the robot's three-dimensional shape category information, starting with the robot's perception of the target object space, and improving the robot's environmental visual perception ability. According to experiments, the recognition accuracy of the volume integral layer network model based on layer feature fusion in the ModelNet-40 dataset is as high as 90.57%, and the average recognition time is only 3.8ms, which is 37.71% faster than other similar models. Based on various data, the research in this article is very meaningful for improving the speed and accuracy of visual perception of intelligent robots in complex environments.*

Keywords: *Intelligent Robot, Visual Perception, Machine Learning, Neural Network*

1. Introduction

With the rapid development of robotics technology, intelligent machines are widely used in many fields such as aviation detection, disaster rescue, national defense security, and home services. The working environment of intelligent robots is usually complex and changeable. In order to make the robot complete tasks faster while ensuring safety, it is necessary to continuously improve the robot's perception of the working environment. The biggest difference between mobile robots and ordinary robots is that they can perceive the surrounding environment and their own position status through the built-in intelligent sensor system, so as to autonomously carry out direction movement and dynamic decision-making. The combined use of multi-sensor information is of great significance in the research of mobile robots. It can provide robots with more accurate environmental information and data, thereby realizing the construction of global maps.

In recent years, more and more scientists have focused on the research of intelligent robots and have achieved very good results. Bilal conducted research on the design of robot arms based on computer vision, using computer vision algorithms to identify objects and determine the coordinates of the specified objects, and finally let the robot arm complete operations on the specified objects. In the test experiment, the recognition accuracy of the robot arm can reach 97.6% [1]. Alcantara has carried out research on the topology of the waiting-free algorithm of mobile computing robots. He believes that asynchronous light emitting robots (ALR) can not only convey the actual position, but also convey more information. Asynchronous movement means that each robot can run at its own arbitrary speed. [2]. Hariyama proposed compact rectangular entities of three-dimensional objects for intelligent robot motion planning. This new architecture can perform matching operations between rectangular entities and discrete points in parallel, improving the efficiency of intelligent processors [3]. Keiichi's research showed that the robot's vision is robust to lighting changes. His team developed a powerful vision system that can adapt to changes in lighting conditions by positioning industrial parts. The

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experimental results confirmed the dynamics of the camera. Range expansion is very effective for realizing a powerful robot vision system [4].

With the advancement of science and technology, domestic research in the field of robotics has made more and more brilliant achievements. Lin Y M has carried out research on the robot vision system for 3D reconstruction in low-quality environment. He and his team designed a new type of vision system, binocular cameras and laser projectors can help robots better achieve obstacle avoidance and complete autonomous positioning in complex environments [5]. Zhang W believes that the framework of the fusion of vision and tactile methods can more effectively improve the perception of robots. His team proposed a framework for fusion of visual and tactile modal features, which is dedicated to solving the data fusion of various modes of robot perception functions. The problem [6]. Wang Q proposed a framework for intelligent operation robots, which includes an intelligent power system analysis system and an intelligent operation compilation system to solve common problems in the power system control center [7].

This paper conducts research on the visual perception method of intelligent robot environment based on machine learning, and analyzes the modeling process of machine learning and the recognition method of intelligent robot environment object type based on convolutional network. At the same time, this article starts from the two directions of intelligent robot environment visual perception and target object space state perception, builds the robot intelligent visual perception system, and confirms the feasibility of the perception method through experiments.

2. Analysis of Visual Perception Technology of Intelligent Robot Environment Based on Machine Learning

2.1. Multi-Sensor System and Information Fusion Technology

The intelligence of robots is largely reflected in their ability to adapt to the environment. If robots can quickly confirm their position in the environment, they can still perform good intelligent navigation capabilities even in a strange and complex environment. [8-9]. Smart sensors can help robots obtain sensing information and confirm their own position. At the same time, using multiple sensors to achieve mutual fusion of information can further achieve precise positioning.

Sensor information fusion is a relatively complicated process, because multiple information fusion algorithms may be involved in the information fusion system at the same time, such as Kalman filtering and weighted average methods [10-11]. In actual work, researchers will select the appropriate algorithm according to functional requirements. On the whole, multi-sensor information fusion technology is developing towards the integration and intelligence of data processing. Figure 1 is a schematic diagram of the multi-sensor information flow.

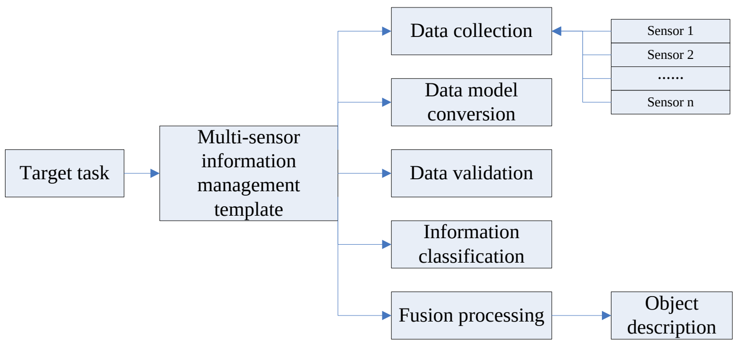

Figure 1: Multi-Sensor Information Flow chart

As shown in Figure 1, multi-sensor information processing includes five steps: data collection, data model conversion, data verification, information classification and fusion processing. The data collected from all sensors are processed and analyzed, and finally converted into detailed object descriptions. The reason why multi-sensor information fusion technology is widely used in the field of robotics is that it can help mobile robots better realize autonomous positioning in the environment, and promote the realization of intelligent guidance, obstacle avoidance and human-computer interaction [12-13].

ISSN 2616-5775 Vol. 7, Issue 9: 41-50, DOI: 10.25236/AJCIS.2024.070906

2.2 Modeling Technology Based on Machine Learning

Machine learning is an important way to improve the perception ability of mobile robots in environmental vision. Modeling the machine learning process is helpful to analyze the factors in the model that affect the effect of the robot's three-dimensional visual perception data information extraction, so as to guide the intelligent robot's environmental object recognition and target objects Design of spatial state-aware machine learning model [14-15]. This paper proposes a method to establish a machine learning process model using random variables, and analyze the design factors and variables of the machine learning model that have an impact on the model learning results.

Set x as the input feature, y as the convolution kernel weight, and z as the convolution output. Then the convolution information extraction function based on the parameter sharing mechanism satisfies:

$$z = x \cdot y \tag{1}$$

In the back propagation process, y'is the weight of the convolution kernel after iterative update, α is the training rate parameter, dy is the derivative of the convolution kernel weight, dz is the derivative of the back propagation error, then the weight of the convolution kernel is trained The formula meets:

$$y' = y + \alpha \cdot dy, dy = dz \cdot x^T \tag{2}$$

If only the input feature x matched by the convolution kernel y is considered, the value of the convolution kernel after the machine learning training is completed satisfies the formula:

$$\hat{y} = y_0 + \alpha \cdot \sum dz \cdot x^T \tag{3}$$

2.3 Environment Recognition Technology Based on Convolutional Network

(1) Convolutional neural network

Positioning is the core part of the entire system and plays a decisive role in the entire system. This article combines the efficiency of deep learning technology in image processing, and introduces the convolutional neural network used for positioning. In image processing, an image is composed of multiple pixels, and each pixel has a different number of channels, which is stored in the computer in the form of a matrix. Connecting the network structure will produce a large number of parameters, and the amount of calculation for each backpropagation is immeasurable [16-17]. The convolutional neural network can show good results because it can extend the concept of image feature recognition based on the local characteristics of the image itself. Through the corresponding convolutional layer operation, the image features can be effectively extracted, and gradually get Image local contour and global contour. With the deepening of the convolutional neural network, the greater the probability of obtaining more effective global information. Generally speaking, a complete convolution operation process is composed of input layer, convolution layer, pooling layer, fully connected layer and output layer [18-19].

This paper proposes a hierarchical network model based on layer feature fusion, which uses the layer feature fusion method to synthesize the features extracted by a single anisotropic convolutional network. The model adopts the global maximum pooling function to realize the layer feature fusion method. In the ordinary neural network model, the size of the pooling window is generally 2-4 units, which is used to fuse the local information of the input data. The window size of the global maximum pooling method used in this model is 128 units, which is used to fuse the overall characteristics of the three-dimensional shape.

Set f_i as the feature extracted by the anisotropic convolution function, h is the global feature of the three-dimensional shape with the same dimension as f_i, N is the size of the pooling window, and m_i is the pooling template, then the layer feature fusion function forward propagation formula Satisfy:

$$h = m_0 \cdot f_0 + m_1 \cdot f_1 + \cdots m_i \cdot f_i \cdots + m_N \cdot f_N \tag{4}$$

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Suppose df_i is the differential of the feature and dh is the differential of the fusion error, then the back propagation formula of the layer feature fusion function satisfies:

$$df_i = m_i \cdot dh \tag{5}$$

(2) Environment recognition based on point cloud convolutional network

Point cloud data P uses discrete coordinate point p_i to describe the surface topography of the object, and the mathematical set satisfies:

$$P = \{p_1, p_2, p_3, \cdots, p_i, \cdots, p_N\} \tag{6}$$

For the same three-dimensional shape, the point cloud expression and the tensor expression are completely equivalent and can be converted to each other. The point cloud data only records the coordinate values of the tensor data in the non-zero area, so the number N of non-zero areas of the tensor data is equal to the point cloud length. In general, the point cloud data is more compact and efficient in the expression of the topography [20-21]. Point cloud data can use the same data length to describe three-dimensional shapes of different sizes. The multiplication operation of the definable point cloud and the scalar s is:

$$P' = s \cdot p = \{s \cdot p_1, s \cdot p_2, s \cdot p_3, \cdots, s \cdot p_i, \cdots, s \cdot p_N\} \tag{7}$$

The point cloud data P is a collection of three-dimensional coordinate points in mathematical form, and is a 3*N sequence in data structure. Due to the disorder of the set, there are $N!$ kinds of equivalent arrangements to express the point cloud data P. The point cloud convolution function pcf can perform high-dimensional mapping on the generated local features to obtain highly nonlinear local feature expressions. Since the layer fusion function used in the layered network model can lead the reverse transfer error to the anisotropic convolution function that matches the layer feature, this paper focuses on the layer feature classification experiment to verify the layered network model from the two-dimensional shape the ability to extract object category information from a dimensional sketch.

2.4 Object Recognition Based on Color and Shape Features

(1) Robot visual perception system

Robot vision systems usually need to process a large amount of data, so there are high requirements for the system's data processing speed. Machine vision will recognize objects based on color and shape features, but the current robot visual perception system still has certain limitations. For example, the environment may change the characteristics of the surface of the object, causing the target color to change accordingly, which increases. The difficulty of the robot to dynamically track the target color [22-23]. Figure 2 is a schematic diagram of the overall structure of the robot vision system.

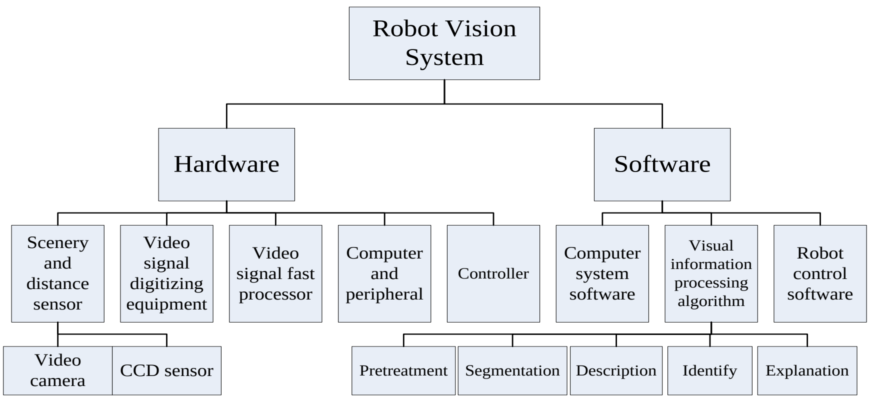

Figure 2: The Composition of the Robot Vision System

(2) Object recognition based on color features

Although the visual sensor can realize the dissemination and analysis of information, it also has certain drawbacks, for example, it takes too much time in image processing and calculation. In addition,

ISSN 2616-5775 Vol. 7, Issue 9: 41-50, DOI: 10.25236/AJCIS.2024.070906

smart sensors at this stage are still difficult to achieve accurate transmission of complex information. In order to meet the real-time intelligent planning of mobile robots, it is also necessary to improve the image processing technology. The color-based real-time multi-day mark recognition algorithm can extract the required signal from the complex signal and make the image clearer. When performing target recognition in the color area, the intelligent algorithm will automatically ignore the connected domains with less area, improve the robustness of recognition while improving the anti-noise ability, and better improve the accuracy of image recognition [24-25]. Set a to represent the area of the connected domain of the recognition image, A to represent the total area of the image, and c to be a constant in the range [0, 1]. Then the formula for calculating the reliability of the image satisfies:

$$F_c = \begin{cases} 1 & a \geq (c \times A) \\ a/(c \times A) & (c \times A) > a \geq 0 \end{cases} \tag{8}$$

3. Intelligent Robot Environment Visual Perception Experiment

3.1. Experimental Background

This paper is based on the modeling process based on machine learning, focusing on the perception of the types of objects in the environment of intelligent mobile robots and the perception of the spatial state of target objects. In order to test the feasibility of object recognition of the convolutional layer network and point cloud convolutional network proposed in this chapter, this paper established a large amount of geometric model data to investigate the classification and recognition ability of the convolutional network. In addition, this article establishes a number of different environmental scene characteristics for the perception situations that the robot may encounter when exploring in the actual environment, and publishes a number of environment perception tasks to simulate the autonomous perception process of the robot.

3.2. Experiment Setting

The ModelNet-40 data set contains a total of 40 kinds of object data in different environments, and each category involves a variety of three-dimensional shape examples, from common beds, desks, and sofas at home, to cars, flower beds, and street lights in outdoor scenes. Among the thousands of three-dimensional objects, there are many objects that are similar in body shape but contain many special features, such as the same chair, which can have obvious differences in size and shape. We compared the convolutional layer network and point cloud convolutional network mentioned in the article with traditional 3D visual recognition technology. Table 1 is the accuracy comparison data of various 3D shape recognition methods.

Table 1: Accuracy Comparison of Three-Dimensional Shape Recognition Methods

Method	Input Data	Classification Accuracy	
		ModelNet-10	ModelNet-40
Shape Net	Topography Data	82.91%	76.83%
Vox Network		92.36%	82.78%
Automatic Encoder		89.17%	83.20%
3D Convolution		90.85%	84.11%
Hierarchical Network		93.23%	90.57%
Point Cloud Convolutional Net		87.49%	78.02%

It can be seen from Table 1 that the hierarchical network model has relatively good performance in ModelNet-10 and ModelNet-40, and the point cloud convolutional network can basically achieve similar accuracy with the topographic network and the voxel network. After comparing the efficiency of several types of identification methods, it can be found that the hierarchical network has a shorter identification time while ensuring high accuracy. On the whole, object recognition modeling based on anisotropic volume integral layer network has a very high competitive advantage.

3.3. Experiment Process

When using 3D vision data to describe the shape features of an object, the data features may be subject to errors in the shape acquisition sensor. In addition, due to the complicated arrangement of

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various objects in the real environment, some objects lack complete morphological features. In the course of the experiment, it can be found that the hierarchical network model can maintain good recognition ability even in the face of objects with incomplete morphological features. In order to verify the processing ability of this method in actual scenes, this paper uses typical environmental objects to build an experimental office environment to investigate the perception and processing of events that occur in the environment by the robot platform.

During the experiment, the camera of the robot head will visually perceive the environment scene, and intelligently recognize different objects in the scene through smart sensors and visual information processing algorithms. At the same time, combined with the iconic physical characteristics, the system will automatically simulate the environment and further infer the results. For example, if there are keyboards, staplers, and laptops in the environment, the robot will recognize them as an office scene; if there are beds, wardrobes, and dressing tables, the robot will determine that it is now in the bedroom. After completing object recognition and scene perception, the robot can better implement subsequent autonomous operations.

4. Experimental Analysis of Visual Perception of Intelligent Robot Environment Based on Machine Learning

4.1. Experimental Analysis of Robot Indoor Environment Object Perception

(1) Modeling and analysis of object recognition based on convolution hierarchical network

The intelligent robot's three-dimensional visual perception data analyzes environmental information through the shape of the object, and directly recognizes the type of object in the three-dimensional data to avoid errors caused by information judgment and remapping. However, the robot's 3D visual perception data only records the shape information of the object. Compared with the image data, the shape data will lose the texture information and increase the data dimension, which increases the difficulty of identifying the object type. The object recognition modeling based on the volume integral layer network judges the object category from the tensor data, which can not only improve the speed and accuracy of the robot's environmental object recognition, but also realize the real-time perception of the environmental object category based on the robot's three-dimensional vision data. Table 2 is the comparison of the efficiency of the volume integral layer network in 3D shape recognition.

Table 2: Comparison of the Efficiency of Three-Dimensional Shape Recognition Methods

Method	Parameter (M)	CPU core	Training time (h)	Recognition time (ms)
Shape Net	32	2680	46	-
Vox Network	0.95	2680	13	6.1
3D Convolution	8	2680	7	-
Hierarchical Network	0.22	1840	8.37	3.8

It can be seen from Table 2 that the convolutional layer network has lower parameters and CPU cores than the topography network, voxel network, and three-dimensional convolutional network, and the training time and recognition time are relatively shorter. While the accuracy rate is as high as 90.57%, the recognition time of environmental object types based on tensor anisotropic convolution only takes 3.8ms, which is 37.71% faster than the voxel network. Figure 3 is the PR curve of the hierarchical network model on the geometric model data set.

The classification accuracy and the recall rate can form a PR curve describing the shape search process, and the underline area represents the feature extraction ability of the model. According to Figure 3, the object recognition accuracy of the convolutional layer network performs best under the premise of different recall rates. By calculation, the area of the PR curve of the convolutional layer network in ModelNet-40 is 0.746, which is significantly better than the spherical harmonic method and the light field method.

ISSN 2616-5775 Vol. 7, Issue 9: 41-50, DOI: 10.25236/AJCIS.2024.070906

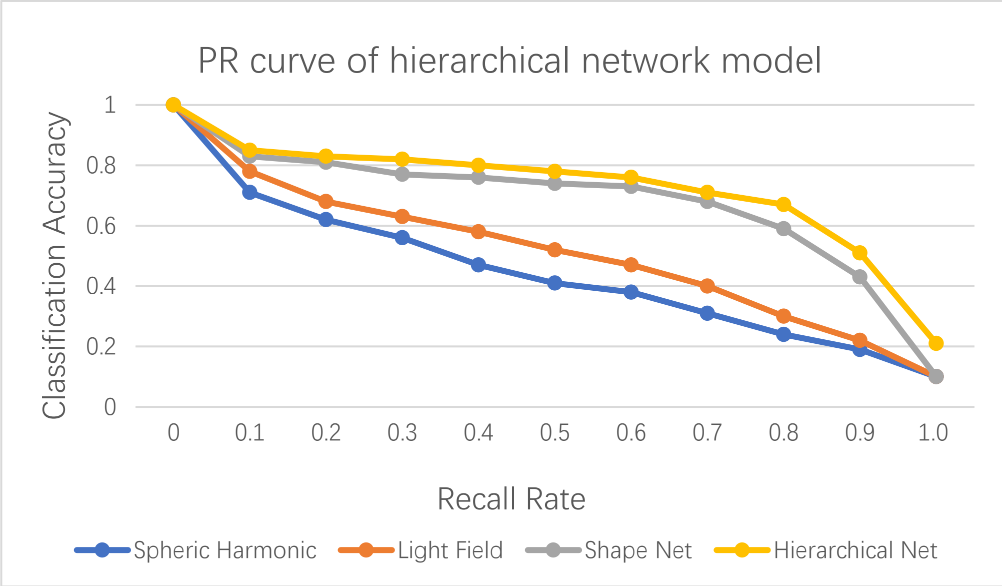

Figure 3: PR Curve of Hierarchical Network Model on Geometric Model Data Set

(2) Object recognition modeling analysis based on point cloud convolutional network

The local features of the topography are of great significance to the object type information. The convolution function based on the repeatability of local features can efficiently extract local information from data in a specific order, such as vectors, matrices, and tensors. For the same three-dimensional shape, the point cloud expression and the tensor expression are completely equivalent and can be converted to each other. The point cloud data only records the coordinate values of the non-zero area of the tensor data, so the number N of non-zero areas of the tensor data is equal to the point cloud length. Of course, if there is an excessively large difference between the saliency target area and the target as a whole in the image recognition process, it is easy to cause the saliency value to be lost.

It can be seen from Figure 4 that the point cloud convolution function can improve the classification accuracy of the point cloud convolution model, and it is first verified that the local topography can provide important information for the judgment of the three-dimensional topography category. In categories where local features change slowly, the point cloud convolution function improves the model's classification ability less. However, for objects with rich local information, such as beds, desks, and toilets, the point cloud convolution function improves recognition accuracy by about 10%.

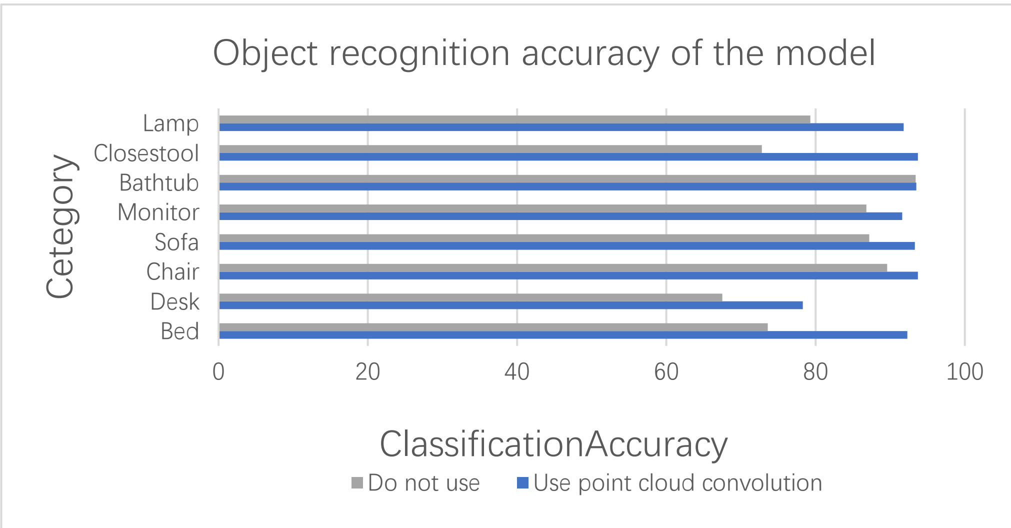

Figure 4: Effect of Point Cloud Convolution Function on Classification Accuracy

ISSN 2616-5775 Vol. 7, Issue 9: 41-50, DOI: 10.25236/AJCIS.2024.070906

4.2. Experimental Analysis of Robot Target Object Space State Perception

(1) Experimental analysis of robot multi-target object recognition and space state estimation

This article focuses on the target aircraft, bed, monitor, chair and bookcase to investigate the robot's multiple target recognition capabilities. Figure 5 is a scatter plot of the three-dimensional shape recognition result based on the nonlinear mapping result as a function of the sampling rate. It can be seen from Figure 5 that for different three-dimensional topography, the change trend of the recognition accuracy is roughly the same. Without sampling, the recognition rate of the three-dimensional topography of the nonlinear mapping network is close to 100%. When the sampling rate drops to 30%, The recognition accuracy of each three-dimensional topography has begun to decline significantly. But even if only 10% of the point cloud is retained, the 3D shape recognition accuracy of the nonlinear mapping model can still be maintained above 80%. It is worth noting that when the sampling rate of the 3D shape drops to 10%, most of the object Local information has been lost, and even the global topography has become difficult to distinguish. But at this time, the recognition model based on the nonlinear mapping network can still maintain a high profile recognition accuracy.

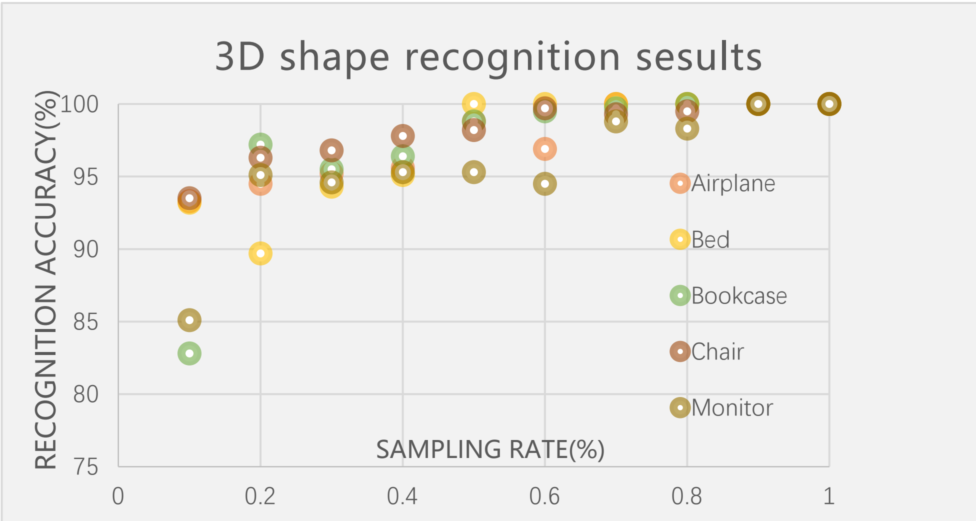

Figure 5: Scatter Plot of 3D Shape Recognition Results with Sampling Rate

In summary, for the situation where it is difficult to extract the local information of the three-dimensional topography from the disordered point cloud data, the point cloud convolution function can play a good effect. Experiments show that this method can directly identify unknown objects from point cloud data, and the average amount of point cloud data is only 5.2% of the same information tensor data. At the same time, the point cloud convolution function can effectively identify objects on average and accurately. Degree increased by 6.8%.

(2) Perception experiment of target object space state based on visual system

Detecting the space state of the robot grasping target through the robot vision system is an important application of the method of sensing the space state of the robot target object. The linear single feedforward mapping analyzed by the degenerate QR decomposition method can avoid the problem of point cloud mismatching and improve the perception accuracy of the spatial state of the target object. This experiment verifies in detail the performance of the single feedforward linear mapping model in target recognition accuracy and spatial state calculation accuracy. Figure 6 is a diagram of the matching error of each method identifying the bedside table when the sampling rate is 0.5.

ISSN 2616-5775 Vol. 7, Issue 9: 41-50, DOI: 10.25236/AJCIS.2024.070906

Figure 6: System Identification Matching Error Map when the Sampling Rate is 0.5

According to Figure 6, compared with the method based on descriptors, the QR decomposition method proposed in this paper has higher matching accuracy because it can adapt to a variety of different features of the three-dimensional topography and does not depend on the local topography of the target object feature. Compared with other methods, the three-dimensional shape recognition and spatial state calculation model based on linear mapping has higher recognition accuracy and spatial state estimation accuracy, and also has higher efficiency.

5. Conclusions

This paper conducts experiments and further analysis based on the perception of the space state of the robot target object. In the experiments of robot multi-target object recognition and space state estimation, this paper randomly selected several common objects to investigate the recognition accuracy of three-dimensional topography under different sampling rates. The results show that when the sampling rate is kept above 50%, the recognition rate of the three-dimensional shape of the nonlinear mapping network is close to perfect. This paper studies the visual perception method of intelligent robot environment based on machine learning. In the research process, this article has already harvested some valuable research results, but comprehensively speaking, the research still has certain limitations. When carrying out the environmental object type recognition experiment, this article normalized the object volume, so the comprehensive consideration of the object size is lacking in the machine recognition. Although the ModelNet-40 data set used in this experiment already contains most of the image data, the images in the database are still too simple compared to the real environment. In order to ensure that the robot can achieve accurate positioning and dynamic path decision-making in complex real scenes, many researchers need to continue to carry out algorithm optimization and various methods in the future.

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