Application of Neural Network and Computer in Intelligent Robot

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Abstract. Autonomous mobile robot is widely used in security patrol, freight, autopilot, and family life and other fields, improve the application effect is one of the most important factor is to be able to accurate navigation path, so how to design a highly efficient, intelligent autonomous mobile robot navigation path algorithm has been a popular research topic in the field. This paper mainly studies the application of the combination of neural network and computer in the field of intelligent robot. The Pnninet model is used to simulate the 3D simulation environment built in this paper, and the path navigation method of the autonomous mobile robot based on the end-to-end model is realized, and an algorithm based on ray detection is proposed to achieve obstacle avoidance. Through several groups of comparative experiments (such as comparison with Pilotnet model, etc.) and analysis, it is proved that the algorithm in this paper improves the efficiency of robot navigation research and the robot developed has a better performance in navigation in unknown or familiar environments.

Keywords: Neural Networks, Intelligent Robots, Path Navigation, End to End

1. Introduction

In recent years, autonomous mobile robots have become a research hotspot in the fields of automation, artificial intelligence and computer. Compared with traditional industrial robots, autonomous mobile robots can realize the functions of autonomous perception, execution and decision making, which has a very broad application prospect [1]. The realization of environment perception and control technology of mobile robot is one of the most critical problems in navigation and control of mobile robot, which is also the core of intelligent robot. Industry and academia have made great efforts and contributions in hardware design and algorithm research, but there are still many problems to be solved. On the one hand, the traditional path navigation algorithm of mobile robot is mostly built on...
the premise that the robot is familiar with the environment (indoor or outdoor), and the movement is limited to several fixed routes. In the face of unfamiliar environment, the generalization ability of identifying targets and obstacles is poor. However, the environment in which robots live usually changes greatly. Therefore, traditional mobile robots have certain limitations in the expansion of environmental adaptability. On the other hand, many autonomous mobile robots need to store complex navigation algorithms or detailed map information in advance to realize navigation, which requires a large memory space. Therefore, the research on the path navigation method of autonomous mobile robot needs to be further developed.

For the problems existing in the path navigation methods of autonomous mobile robots, scholars at home and abroad have proposed many solutions, including methods based on machine learning, methods based on sensor fusion and methods based on virtual reality technology, etc. Saeedi completed the autonomous navigation of the robot through practice. In this method, the image information collected by monocular camera is used as the model input, and the decision system goes through three iterative processes: exploration, optimization and evaluation. From randomly initialized parameters, the algorithm can use monocular images as input to learn strategies for lane tracking in a few training sets [2]. Pandey proposed an end-to-end obstacle avoidance robot based on vision, which used a six-layer convolutional neural network as the learning system. The input was the steering angles of human drivers under different types of obstacles, and the output was the obstacle avoidance steering. Experiments proved that the system was robust to various situations in the field environment [3].

This paper mainly studies the path navigation method of autonomous mobile robot based on the end-to-end neural network model. Firstly, an end-to-end convolutional neural network model with higher training and computation efficiency, better learning performance and better generalization ability is designed. Then, the path navigation method of autonomous mobile robot based on the end-to-end neural network model is implemented in a three-dimensional simulation environment.

2. End-to-End Convolutional Neural Network Robot Navigation Model

2.1. Theoretical Basis of Convolutional Neural Network

(1) Convolutional Neural Network Structure

Artificial Neural Networks (Artificial Neural Networks), referred to as Artificial Neural Networks, is a mathematical model of algorithms, mainly used to deal with distributed and parallel information. It is built on the basis of the behavior characteristics of animal Neural Networks. Convolutional neural network is a kind of artificial neural network, but it has some changes in the form and function of layers. It can be said that it is an improved artificial neural network, and can also be regarded as the multi-layer perceptron of artificial neural network. The hierarchical structure of the Convolutional neural network can be divided into data Input Layer, Convolutional computing Layer, ReLU Layer, Pooling Layer and Fully Connected Layer [4]. The convolution calculation layer is the most important layer in the neural network, including activation function and filters. This layer involves many hyperparameters, such as the size of filters, the number of steps and the filling value. Convolutional neural networks generally choose ReLU (modified linear unit) as the excitation function, with caution Sigmoid function (S-shaped growth curve). The role of the pooling layer is to compress the amount of parameters and data and prevent the model from overfitting. The full connection layer is usually located at the last layer of the model and connects in the same way as the neurons in a traditional neural network.

(2) Working Principle of Convolutional Neural Network

Contained in the convolutional neural network is used for image conversion of two-dimensional matrix filter, filter cover images, then the elements multiplication and summation of the coverage area, after calculating an area mobile (mobile location according to the size of the value of setting step) to other regions of the image to repeat the same process, until the image area is cover image produced new characteristics, that is the convolution operation. The characteristic image obtained in the
convolution operation highlights the unique features of the original image, and the types of extracted features are determined by the trained filter [5]. The machine can learn the parameters of the filter through a large amount of data to design the feature filter, and then the convolutional neural network can continuously extract the features from the local to the overall through the designed filter, so as to realize the functions of image recognition.

(3) Application of Classical Convolutional Neural Network Model

Pilotnet is a convolutional neural network-based unmanned driving system created by NVIDIA engineers. Using raw road images from a camera mounted directly in front of the robot as input to the system, Pilotnet trains a convolutional neural network to automatically learn to detect useful road features, thus realizing road contour recognition. Pilotnet system is so powerful that the system's core convolutional neural network plays an important role in the model structure. Through a series of experiments, NVIDIA proved that this algorithm based on the end-to-end neural network model is very powerful. It can not only realize the training of the model with the least training data, but also realize the self-optimization of the internal components of the system to maximize the performance of the system.

Network in Network (NIN) Model: a novel deep network architecture for classification tasks. The model consists of a series of MLP-conv layers, a GAP layer, and a classification layer. Two major innovations of this model are that two new structures MLP Convolution Layer and Global Average Pooling are added to the network structure. The biggest innovation of this model is that a number of 1×1 Convolution are added after the conventional Convolution and each feature graph is regarded as a neuron. The feature graph of 1×1 Convolution can be regarded as multiple linear combinations of neurons, which is similar to MLP (multi-layer perceptrons) [6]. That is, Network In Network. The conventional convolutional layer GLM (Generalized Linear Model) can be regarded as a single-layer network with limited abstract expression capacity. MLP CONV is used to replace the traditional GLM in this Model to improve the abstract expression capacity of the Model. The calculation formula of the feature graph in the MLP CONV layer is as follows:

\[
\begin{align*}
    f_{i,j,1} &= \max(w_{k1}^1 x_{i,j} + b_{k1}, 0) \\
    \vdots \\
    f_{i,j,n} &= \max(w_{kn}^n f_{i,j}^{n-1} + b_{kn}, 0)
\end{align*}
\]

2.2. PninNet Models Based on PilotNet and Network In Network Improvements

By learning the theoretical basis of the convolutional neural network model, combining the respective characteristics of Pilotnet and NIN models and the characteristics of the end-to-end path navigation method, this paper designs a new model based on Pilotnet and NIN, which is referred to as the PNNINET model for convenience description.

The design of Pninnet model is a 10-layer convolutional neural network handwritten by the Sequential model in Keras. Although it is a linear model with a seemingly simple structure, it can build a very complex network. The model structure consists of a local response normalization layer (LRN), six convolution layers and three full-connection layers [7]. LRN, as the first layer of the network to perform image normalization, ensure all the data on the dimension on a change, then the convolution layer adopts three layer 2 x 2 step 5 x 5 convolution kernels and two layer 3 x3 convolution kernels of cross feature extraction, convolution convolution of the last layer adopts 1 * 1 step 1 * 1 convolution, the connection layer designed a controller to control the direction of the [8]. At the same time, 20% Dropout is used as regularization for all the hidden layers to randomly discard the neural network units to reduce the dependence of the model on some local features. The entire network uses the ReLU function as the activation function for nonlinear activation.

\[
f(x) = \max(0, x)
\]
Where, \( f(x) \) represents the output of the neuron at the next layer, \( \text{Max}(0, x) \) represents the linear transformation function, and \( x \) represents the input vector of the neural network at the next layer.

The problem of predicting the steering value of robots through images or videos is essentially a regression problem, so this paper adopts the internationally common Mean Square Error (MSE) as the index to evaluate the network model. MSE is calculated by taking the ratio of the square sum of the distance between the deviation of the predicted value and the true value to the predicted times to evaluate the deviation between the observed value and the true value [9-10].

\[
mse(y_i, y_i') = \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{n} 
\]

3. Experiment on Path Navigation Method of Autonomous Mobile Robot Based on PninNet Model

3.1. Experimental Environment
The operating system used in this paper is Windows 10 64-bit, the processor is Intel (R) Core (TM) i7-6700 CPU @ 3.40GHz, the RAM (memory) is 16.0GB, and the graphics card is NVIDIA GeForce GTX 1050 Ti. The development platform of robot path navigation system is 3D simulation environment Unity3D, IDE (integrated development environment) is Spyder in Anaconda.

After a series of studies and comparisons, this paper realizes the construction of 3D simulation environment in Unity3D, because it has high-quality 3D scenes and character models, which can make the simulation closer to reality and more convenient to transfer to the real world. In addition to supporting multi-user platforms, it also has access to a lot of resources to speed up development.

3.2. Data Acquisition
In this paper, based on the end-to-end algorithm of neural network model to realize autonomous navigation of mobile robot path, in particular, a convolution neural network through training, to make it through the way of supervision and learning to learn the robot camera taken between original image and the robot steering Angle mapping, and supervised learning method requires a large amount of data collection and data features tag.

3.3. Implementation Process
The end-to-end system in this paper is a deep convolutional neural network, the input is the original image obtained by the monocular camera installed directly in front of the robot, and the output is a set of continuous possible steering commands obtained through training, which can control the robot to walk towards the feasible road area.

The algorithm has only one prediction result from the input end to the output end. After the prediction result is compared with the real result, an error is obtained. Then the back propagation algorithm is used to transfer the error in each layer of the model, and the parameters are adjusted according to the error until the desired effect is achieved or the model converges.

The main processes include environment model building, data acquisition, neural network model training and robot navigation method testing.

4. Experimental Result

4.1. Model Performance Comparison Experiment
In order to verify the better performance of the Pninnet neural network model designed in this paper, we compared the Pninnet model and Pilotnet model in this paper with the average loss function value and the average iteration period of all samples in the training set as the evaluation index.
Table 1. Comparison of model performance

| Model structure | Data set | Average loss | iterations | Mean iteration period |
|----------------|---------|--------------|------------|-----------------------|
| PninNet        | 6000    | 0.0031       | 128        | 12                    |
| PilotNet       | 6000    | 0.0042       | 139        | 15                    |

As shown in Table 1, after comparison, it is found that the final output loss function value of the neural network model Pninnet in this paper is lower, which decreases by 22% compared with the Pilotnet model, and the average iteration period also decreases by 20%, which proves that the neural network model in this paper not only has smaller error, better learning performance, but also has faster convergence speed.

4.2. Comparison of Correct Autonomous Navigation Time of the Model Transformation Control Robot

The proposed end-to-end neural network model algorithm is evaluated on 3D road simulation and real-time robot in square environment including static obstacles and pedestrians, to determine whether the robot really realizes navigation, adaptability of the robot to unknown environment, and generalization ability of targets and obstacles. Multiple experiments were carried out, and the navigation performance of PilotNet model was recorded and compared.

![Figure 1. Pilotnet and Pninnet turn to control the correct autonomous navigation time of the robot](image)

As shown in Figure 1, it can be seen from the figure that after the same training, the neural network model in this paper can control the correct autonomous navigation of the robot for a longer time.

4.3. Model Controls the Correct Navigation Time of the Robot

A well-trained neural network that performs well in the unknown environment (it can well navigate the robot) is the premise for the application and expansion of autonomous mobile robot. Therefore, under the condition of good training of the above model, we carried out tests in 7 different new road environments without data collection to verify the generalization ability of robots trained by different neural network models.
Figure 2. Comparison of correct navigation time of robot controlled by PILotnet and PNINNET neural network models

As shown in Figure 2, it can be found that although the adaptive ability of autonomous mobile robots to different environments is different, the end-to-end neural network model PNINNET proposed in this paper has better environmental adaptability and generalization ability than the robot trained by Pilotnet model.

5. Conclusions
In this paper, based on the end-to-end neural network model of autonomous mobile robot navigation path method directly to the original environment image as the training data, changed the traditional feature extraction apparatus used in robot navigation path method designed by using the classifier to classify the complex operation way, and use less training data to achieve the better training effect, saving the cost and time. Several experiments have verified that the end-to-end neural network model designed in this paper has good learning ability, robustness and generalization ability, and has achieved good results when applied to the path navigation of autonomous mobile robots. In addition, the path navigation algorithm of the autonomous mobile robot based on the end-to-end neural network model in the simulation environment adopted in this paper can, on the one hand, realize the reproduction of various scenes in a short time, and solve the problems such as high cost of training and testing, long time of research, and low algorithm efficiency in the existing methods.

Acknowledgement
This research was financially supported by Teaching Reform Research Project of Jiangxi's Universities (Grant NO.JXJG-20-50-9).

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