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Intelligent Target Tracking of Unmanned Vehicles Considering Convolutional Neural Networks

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Abstract: The target tracking system and remote control system of unmanned vehicles have been paid more and more attention by major automobile manufacturers. As mobile Internet giants such as Apple and Google begin to combine mobile devices, mobile systems and in-vehicle systems, this has revolutionized the intelligent system of unmanned vehicles. However, target tracking systems and remote control systems for unmanned vehicles are in their infancy, especially when implemented on mobile devices. Aiming at the difficulties in tracking tasks, this paper proposes a tracking algorithm based on deep learning. First, offline pre-training is performed on tens of thousands of general target images through a convolutional deep neural network. Since the types of pre-trained images are extensive and the features used are structural, when the target is occluded and changed, the changed target can still be re-represented by retraining the parameters of the feature. The tracking method based on convolutional neural network and particle filter framework provides a good experimental framework for solving problems such as target changes. The tracking method proposed in this paper shows good tracking ability in multiple test video sequences with good real-time performance and accuracy.

1. Introduction

When driving a car, drivers often have visual blind spots due to vision problems, which lead to car accidents. In the past, the detection and object tracking system of blind spots of obstacles was usually obtained by ultrasonic or infrared to obtain information on the road conditions ahead, but this has many limitations and drawbacks. Most importantly, it is impossible to identify a particular object among multiple objects. However, the road conditions of the car are often complex during the driving process, so how to identify a specific object among multiple objects and then track it is very important. This is also an inevitable trend for smart cars to be intelligent. It must simulate how people control the motion state of vehicles through road conditions, which requires smart cars to realize information collection, data analysis, data transmission and control strategies for complex road conditions. As a new branch of image processing, machine vision has very broad development prospects in various intelligent applications such as computer science and engineering, signal processing, physics, applied mathematics and statistics, and automobiles. The environment in which the car is located is complex, and often times, the surrounding information is a blind spot for the driver. Therefore, when the smart car uses machine vision technology to obtain the external information through the camera, and processes the information through the algorithm in the intelligent system, it can then give a warning to the current situation or control the state of the vehicle movement based on the processing result [1-2].

In the research on intelligent target tracking of unmanned vehicles considering convolutional neural network, many scholars have studied it and achieved good results, for example : Rohan A proposed to find the target by finding corresponding feature points in adjacent images Motion optical flow vector. With the invention of the optical flow method, dynamic imaging research became popular. However, due to the background of camera technology, the noise in the recording will affect the image quality, making it difficult to find the corresponding point with the optical flow method [3]. The search-based TLD tracking method proposed by Yudin DA uses online learning to make the three modules of tracking, learning and search work together to track the target online and achieve good results [4].

This article starts from the two points of accuracy and real-time, and monitors the speed of progress in the case of insurance. Starting from the network learning method and neural network model, a network target algorithm based on feature extraction is proposed. First, the network selects a deep neural network model with strong feature extraction capabilities, integrates the concept of transfer learning, and adopts the "offline learning + online update" function. Then, in order to improve the accuracy, a frozen regression model is added, and at the beginning of tracking, the frozen regression model is trained with the information of the original frame, so that the predicted frame is closer to the actual frame. Two different update methods, long-term update and short-term update, are used to address tracking verification issues. Finally, compared with other algorithms in the OTB technology collection, the experimental results show that the proposed algorithm can deal with the problems of distortion and blocking in the tracking process, improve the tracking accuracy, and obtain the results quickly. Improve tracking speed.

2. Research on Intelligent Target Tracking of Unmanned Vehicles Considering Convolutional Neural Networks

2.1. Point-Based Object Tracking

The point-based target tracking method is to match the corresponding points in the front and rear video frames to complete the trajectory tracking of the target. Due to the use of point-based features, when the target's rotation, scale and affine change, the point will not be tracked. However, once the target is occluded, the illumination changes, and the disappearance or appearance of the target will directly affect the matching of object points [5-6] .

Deterministic point matching:

The deterministic point matching method matches the feature points of the preceding and following frames in consecutive video frames, and minimizes the matching cost for multiple matching relationships according to the motion constraints of the feature points. to find the best match. Hom and Schunck proposed an optical flow method, which matches the corresponding points of the front and rear frames, calculates the motion vector of the object that is relatively moving, and forms an optical flow field. In recent years, in the method of target tracking using optical flow, SIFT feature and color feature are used for feature point matching to obtain better tracking effect.

Statistical match

In the process of target tracking, the quality of video images cannot be guaranteed, and the video contains a lot of noise, which has a huge impact on the matching of feature points in the target tracking process. In the tracking method using statistical matching, the position of the target in the picture is obtained first, and the state space such as the position and velocity of the target is modeled. The state prediction equation is as follows [7-8]:

$$X^t = f^t\left(X^{t-1}\right) + W^t \tag{1}$$

Among them, W t (t=1,2,...) is white noise, and f t is the state transition function.

The relationship between the measured value and the target state information is calculated by formula (2), and N t is white noise:

$$Z^t = h^t\left(X^t, N^t\right) \tag{2}$$

Although the Kalman filter algorithm has achieved good results in dealing with linear Gaussian noise, the Kalman filter cannot handle the task of nonlinear non-Gaussian noise.

Particle filter algorithm is also one of the important algorithms for statistical matching. The tracking method in this paper adopts the particle filter framework, and the particle filter method is introduced in detail later.

2.2. Method of Intelligent Vehicle Target Tracking System

The intelligent car target tracking system analyzes and tracks the motion trajectory of a target in front of the car through the target tracking algorithm. The whole process is shown in Figure 1: the smart car captures the front tracking target through the camera, and transmits each frame of the image captured by the camera to the smart car target tracking system. Then, the system uses the target tracking algorithm to calculate the moving direction of the target object, and finally feeds the system to the smart car to change the trajectory of the smart car to achieve the tracking effect. The core technology of this process is the target tracking algorithm. Target tracking is to process a video rather than a still image. Understanding the motion of the target object mainly includes two parts: recognition and modeling. Recognition refers to finding objects of interest in each frame in subsequent frames of the video stream. The modeling is to estimate the motion trajectory of the object obtained by this rough measurement [9-10].

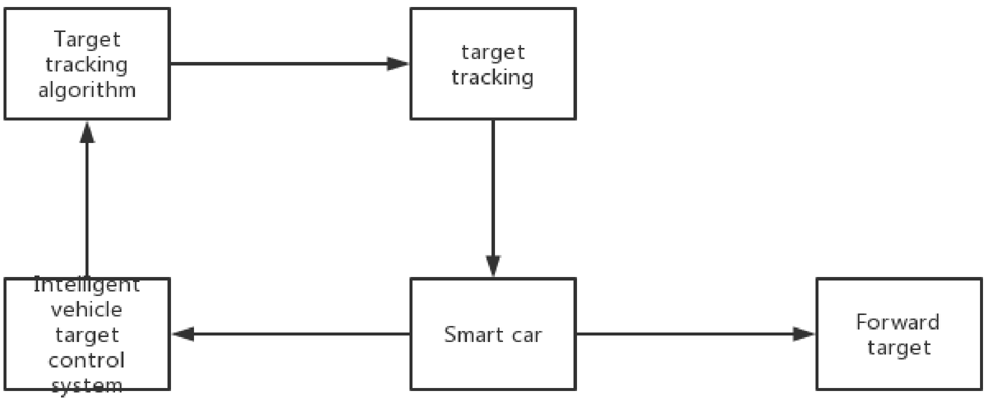

Figure 1. Schematic diagram of the intelligent car target tracking system

2.3. Improvement of Convolutional Neural Network Tracking Algorithm in Intelligent Tracking of Unmanned Vehicles

Video target tracking can often only acquire prior knowledge based on the information of the first frame, which cannot meet the training data requirements of convolutional neural networks. Most of the existing convolutional neural network tracking algorithms use the Imagenet data set to train large-scale deep networks offline, and select a certain amount of positive and negative sample sets to input into the network during tracking, resulting in repeated calculations in similar areas, resulting in very high real-time tracking. Low, and many scholars sacrifice accuracy to gain speed, but accuracy is critical for tracking tasks. Therefore, this paper studies from two aspects of network construction and learning methods [11-12]. Taking neural network as feature tracker and using the concept of transfer learning, a neural network tracking algorithm based on unified feature extraction is proposed. The network calculates once, removes the feature once, and then finds the positive and negative samples at the corresponding position in the generated feature map, which reduces the number of recalculations for similar areas of the sample and speeds up the tracking speed. And for added improvement, a frozen regression model was added. At the beginning of tracking, a frame regression model is trained using the information from the first frame to make the predicted frame close to the actual frame. In addition, two different update methods, long-term update and short-term update, are adopted to deal with the tracking effectiveness problem [13-14].

3. Research Design Experiment of Intelligent Target Tracking of Unmanned Vehicles Considering Convolutional Neural Network

3.1. Tracking Algorithm Implementation Details

The following introduces some details of the algorithm in this paper and introduces the tracking algorithm in this paper.

(1) Training data: We select 20 positive samples and 20 negative samples around the target according to the position invariance of the convolutional neural network in the feature map of each frame, where the positive samples have an overlap rate greater than 0.7 with the real frame, The overlap ratio of negative samples and ground-truth boxes is less than 0.3.

(2) Network learning: During offline training, after several parameter adjustments, the training network is determined to perform 100 iterations . When updating online, momentum and weight decay are set to 0.9 and 0.0005, respectively [15-16] .

3.2. Experimental Design

This paper mainly compares six different convolutional neural networks in experiments, compares the performance differences and tracking speed differences between this paper and other convolutional neural networks, and then compares the performance of the algorithm in this paper with the traditional algorithm, and compares the tracking accuracy respectively. and algorithm operation time.

4. Experimental Analysis of Unmanned Vehicle Intelligent Target Tracking Considering Convolutional Neural Network

4.1. Real-time

Another important test criterion in target tracking is real-time performance. Due to the use of single extraction features to reduce the amount of repeated calculations, the tracking algorithm proposed in this paper has a certain improvement in the tracking speed of the algorithm. Table 1 compares the current popular tracking accuracy. Higher tracking speed of the convolutional neural network algorithm in two experiments.

Table 1. Popular convolutional neural network speed comparison

	MDNet	SANet	CCOT	MVT	TCNN	SO-DLT
Test1	1	1	0.5	3	1	0.5
Test2	2	2	0.7	5	2	1

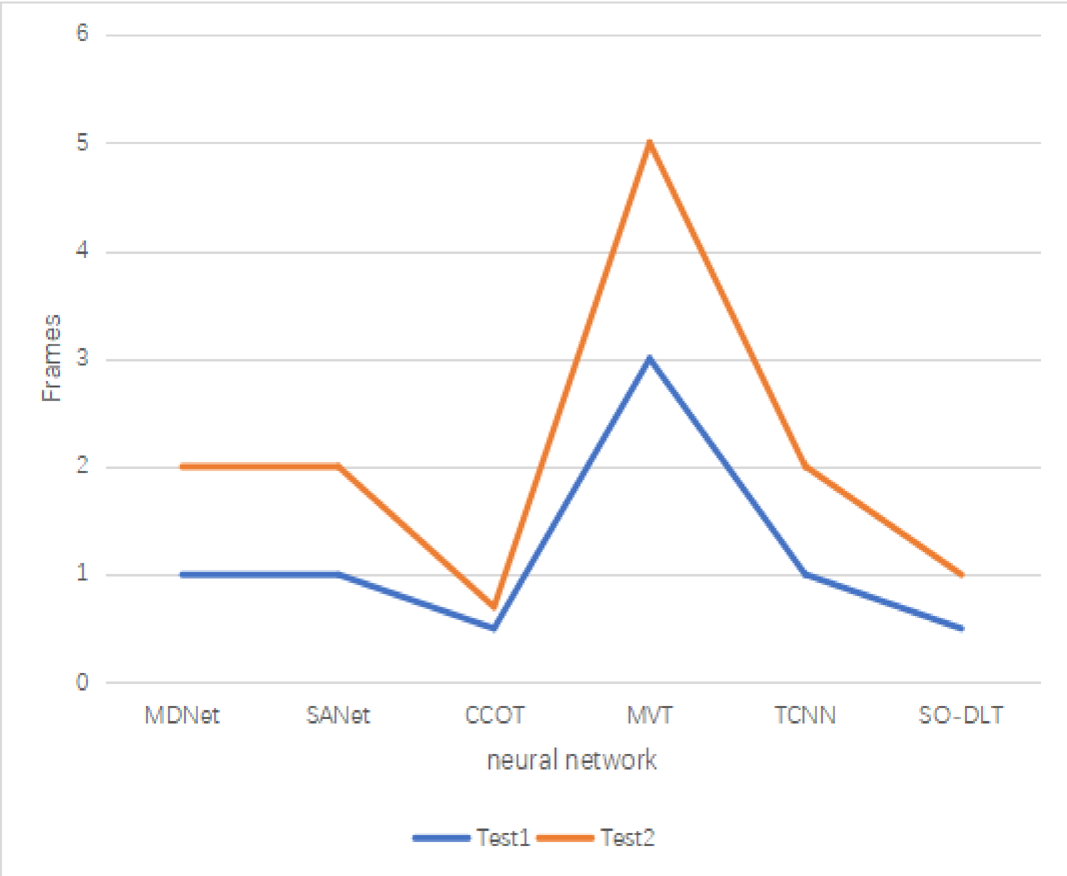

Figure 2. Comparison of the processing speed of the different convolutional neural networks in the two experiments

2 that the speed of target tracking algorithms based on convolutional neural networks is relatively low. The tracking speed of the algorithm in this paper has been improved to a certain extent, reaching 3-5 frames per second, while the speed of other algorithms is 1-2 Frames/second or so, the reasons for the slow speed are as follows: (1) After the image is input to the network, the

convolutional neural network obtains high-dimensional and large numbers of edge, color, and color from the bottom layer through the mapping and learning of multi-layer neurons. From features to high-level structural features, the acquisition process requires a large amount of computation, resulting in low tracking speed. (2) At the beginning of tracking, select positive and negative sample sets on the input image according to a certain rule. The positive sample set is a set of candidate regions whose overlap rate with the tracking target is greater than a certain threshold, and there is a large overlap between the positive sample sets. The input of these overlapping regions into the network will cause a large amount of computation, duplication of computation, and data redundancy, resulting in slow tracking. (3) In the tracking process, in order to improve the accuracy, the information of the first frame is used to update the network parameters, and the update of the model during the tracking process will also slow down the tracking speed [17-18]. On the basis of reason 2, this algorithm adopts the method of single extraction of features, which avoids the calculation of overlapping areas, and can improve the tracking speed to a certain extent. However, due to the huge amount of computation in the online fine-tuning and template update modules, it is difficult to further improve the tracking speed of this algorithm.

4.2. Experiment of Target Tracking System with Improved Convolutional Neural Network Algorithm

This paper , these two methods are used to conduct 100 and 150 object tracking experiments on the same moving car in the same video, respectively. Among them, if the center of the target area calculated by the algorithm exceeds the actual target area to be tracked, the tracking fails. Finally, the algorithm operation time is the average operation time of the entire algorithm obtained by 100 successful traces. The data are shown in Table 2.

Table 2. Performance performance of convolutional neural network algorithm

	Tracking accuracy for 100 times	Tracking accuracy for 150 times	Algorithm run time
Traditional tracking algorithm	91.2%	86.1%	0.583
Improved convolutional neural networks	97.9%	96.1%	0.404

It can be clearly seen from Figure 3 that the accuracy of the improved convolutional neural network algorithm in this paper is significantly improved compared with the traditional algorithm, and compared with the traditional algorithm, the operation time of the improved algorithm in this paper is also greatly reduced, which can effectively Cope with more target tracking scenarios for unmanned vehicles.

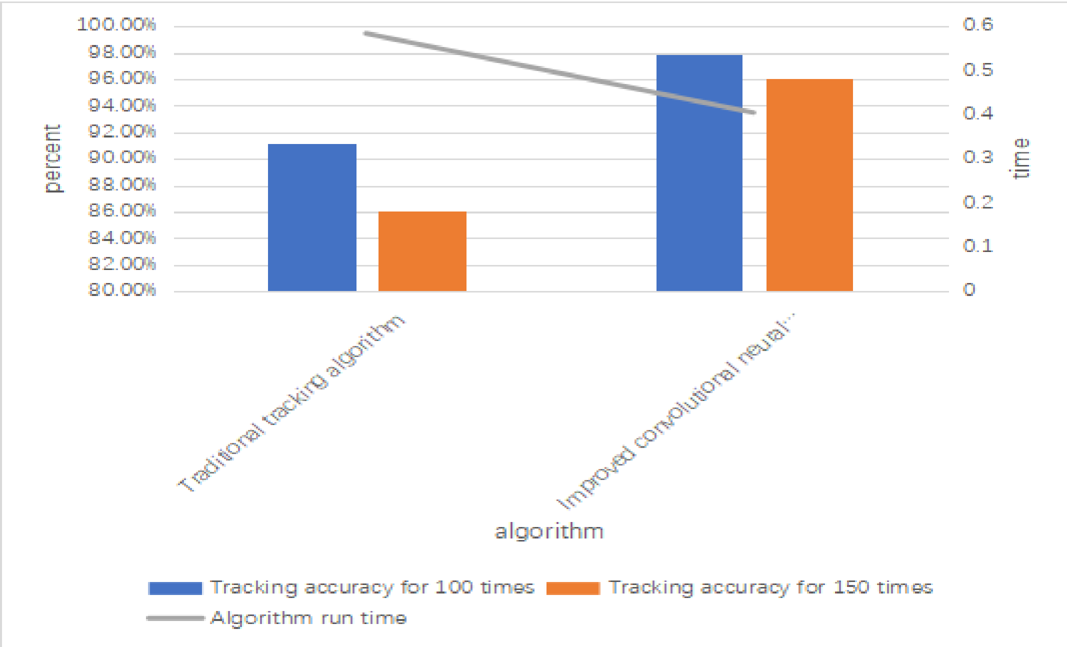

Figure 3. Target tracking comparison of the two algorithms

5. Conclusion

Object tracking is an important research direction in the field of computer vision applications, and it is of great significance for military and civilian applications such as military, transportation, and sports events. At the same time, video target tracking is also one of the difficulties in the field of visual tracking. Traditional target tracking algorithms cannot further meet the requirements of tracking accuracy. Convolutional neural networks have more powerful feature extraction capabilities. However, due to the huge computational load of neural networks, the real-time performance of target tracking is generally low. The research starts from the two aspects of network training method and neural network model, and finds out the essence of the target object through advanced structural features, which further improves the accuracy of tracking and accelerates the tracking speed. According to the current development trend, convolutional neural network is undoubtedly the most promising model in the field of deep learning. Aiming at the problem of poor real-time tracking based on convolutional neural network, this paper proposes a convolutional neural network target tracking algorithm with single feature extraction. In the tracking process, the input image is directly input into the convolutional neural network for one forward operation, that is, The convolutional neural network only takes one input and extracts features once. According to the position invariance of the convolutional network, the positive and negative samples are directly found at the corresponding positions in the generated feature map, which reduces the repeated calculation of similar areas of the samples and reduces feature extraction. Time, reduce the calculation amount of the algorithm to speed up the tracking speed, improve the real-time tracking of the target, and have the ability to distinguish the target from the background. Through the performance evaluation of the algorithm on the OTB data set, the experimental results are evaluated from both qualitative and quantitative aspects. From the tracking results, the algorithm proposed in this paper is superior to most tracking algorithms in accuracy. Changes, illumination changes, deformations, in-plane rotation, out-of-plane rotation, similar backgrounds and other complex situations have good accuracy. (3) A smart car remote control system is developed using the three-axis gyroscope of the Android mobile terminal. Through this system, the steering wheel effect of the official driving vehicle can be well simulated. (4) Equipped with WE-40C bluetooth module on the smart car hardware system, and use serial port mode and design the bluetooth module of smart car Android mobile terminal for information transmission.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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