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Research on Video Image Vehicle Tracking Algorithm Based on Random Forest Method

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Abstract. On the basis of apparent tracking theory of discriminant model, we put forward a vehicle video tracking improvement algorithm based on the random forest classifier to seek a better classifier confidence figure, so that we can improve the tracking accuracy. After getting the degree of confidence of the rectangular image block predicted by the classifier, the pixels and the distance information between rectangular image blocks have different impacts on the degree of confidence. According to this feature, using the pixel confidence estimation method based on weighted distance information to improve the confidence estimation accuracy of pixel, and then improve the tracking accuracy.

1. The introduction

Intelligent transportation system is based on machine vision and image processing method to establish intelligent traffic management system, the effective monitoring to intelligent transportation through the moving vehicles in the statistics of traffic, traffic density within a certain time to implement the corresponding road traffic flow information management and control\cite{1}.

2. Another section of your paper Basis of random forest theory

Due to its own algorithm characteristics\cite{2}, it has been widely used in research fields and engineering applications in science, engineering, medicine and management. Random forest\cite{3} is composed of a group of independent and disparate random CART trees. Each random CART tree grows to its maximum depth according to the greedy algorithm and does not perform any pruning operations\cite{4}. Self-help sample set in random forests in the random selection makes random forests not only retained the efficient and simple advantage of the classification decision tree, and reduce the high variance in the calculation of the classification decision tree, but the feature of the random choice of optional node weakened correlation between random CART tree in the forest, and reduce the error limit of generalization in random forests, classifiers.

3. An overview of vehicle video tracking based on discriminant model

The target location is the greedy searching confidence diagram peak area in the confidence diagram of the interest area, and then the target location is locked. The main purpose of the model updating is to enhance the robustness of the classifier to the target's own changes or background changes to ensure its tracking accuracy. Generally, the update of the model is divided into three parts: the update of the sample set, the updating of the classifier parameters and the update of the tracking strategy\cite{5}. As shown in figure 1, it is the update process based on the Adaboost classifier. According to the positive and negative samples trained by the current frame input to the Adaboost classifier, according to the
new samples, adding a new weak classifier in the feature space, eliminate the original weak classifier which has the high error rate. New weak classifier in the figure corresponds to the hyperplane represented by the red line, the eliminated weak classifier for the hyperplane and black lines represent, as you can see the updated Adaboost classifier has stronger classification ability.

![Updated classifier](image)

**Figure 1.** Updating of classifier.

4. **Random forest vehicle tracking algorithm based on HOG+HSV features**

Based on random forest discriminant classifier vehicle tracking research idea is: As the basic processing unit of the image, we use the rectangular image block[6] to extract the HOG feature and HSV color feature, training the random forest classifier, establishing discriminative model based on image block feature. In the process of vehicle target positioning, in combination with prospect probability function of the rectangular image block, we adjust the current frame sampling frame size to improve the input samples of classifier and establish a more reliable confidence figure. After positioning target based on kernel density mean shift algorithm successful, the positioning results returned for online updating the apparent model based on random forest classifier. The block diagram is shown in figure 2.

![Main framework](image)

**Figure 2.** Main fram

The framework is mainly divided into rectangle image block segmentation and feature extraction module, offline training model module, online tracking module of kernel density mean drift, and update module of online model. In the first module, the rectangle segmentation of image is realized by sliding window method, and HSV feature and HOG feature are extracted for each rectangular image.
block. The second module mainly includes the initialization interested area in the image (the background of the target vehicle and the surrounding area) rectangular image segmentation, extraction of each rectangular image block HSV feature and HOG feature and marking category information, as the random forest classifier sample, trained classifier to determine its internal parameters; The third module in rectangular blocks within the new target and background region segmentation and HSV feature and HOG feature extracting, the input of HSV feature and HOG feature combination test sample, getting the goal of the current frame - background incredible figure, according to true figure outputted by the random forest using fusion kernel density function of the mean shift algorithm is used to search for the optimal location of the target. In the fourth module, the tracking results are returned to the random forest classifier for update operation.

4.1 Mean drift tracking[7]
In the process of vehicle tracking, it is necessary to define a tracking template for the target vehicle in advance, and then find the candidate target which is the most similar to the target template through the nuclear density mean-shift algorithm. The target template based on kernel function combines the category information of the pixel and the contribution of its spatial location information to the target template.

4.2 Experimental results and analysis
Usually the distance between the center of the tracking results to the center of the actual vehicle is less than 20 pixels (called precision index). This tracking meeting the range of the precision tracking. Tracking results box and the target of minimum external rectangle overlap area of more than 50% (called overlap index). The video tracking is accurated[8]. This chapter will analyze the results of the vehicle tracking by these standards.

In the actual vehicle driving scene, the vehicle has a variety of models and various colors, and also has different driving trajectories. In this paper, the tracking experiments are carried out on three kinds of vehicle models, vehicle trajectory and vehicle color. A total of 21 small cars, 12 midsize cars and 8 large trucks were tracked in the experiment. The trajectory of the vehicle included turning left, right and straight. The algorithm respectively to different colour vehicles (green taxis, gray vans, blue big trucks), different model vehicle (small taxis, large trucks, medium vans), different movement track (vehicles go straight, turn left, turn right) to track test, and have reached the steady tracking performance. Through the analysis, the horizontal displacement and vertical displacement error of the vehicle can be increased with time, and the target frame center is farther and farther away from the actual center of the vehicle.

The following results are shown as follows: 445th frame, 459th frame, 473rd frame, 487th frame, 501st frame and 510th frame of the minibus.

As can be seen from the figure 3, the overlap area of the minimum external rectangle and tracking frame of the van is greater than 50%, so the van is successful. In 445th frame, the van was interferenced by the shadow, but the vehicle was successfully tracked from 445th to 501st frame. At 510th frame, the vehicle travels out of the camera range (which can be seen as a block) but is successfully tracked.
Figure 3. Van tracking effect

Table 1. Horizontal displacement table (unit: pixel)

| category | Frame | 445 | 459 | 473 | 487 | 501 | 510 |
|----------|-------|-----|-----|-----|-----|-----|-----|
| Actual location | 687 | 690 | 698 | 722 | 752 | 774 |
| Tracking location | 680 | 697 | 690 | 731 | 741 | 796 |
| Pixel displacement | 7 | 7 | 8 | 9 | 11 | 13 |

Table 2. Vertical displacement table (unit: pixel) in the center of the minibus

| category | Frame | 445 | 459 | 473 | 487 | 501 | 510 |
|----------|-------|-----|-----|-----|-----|-----|-----|
| Actual location | 44 | 105 | 182 | 288 | 442 | 520 |
| Tracking location | 51 | 113 | 191 | 298 | 431 | 544 |
| Pixel displacement | 7 | 8 | 9 | 10 | 11 | 14 |

From the table 1 and table 2, within the frame of 445th to 487th the horizontal displacement and vertical displacement errors of the taxi stay within 10 pixels, it satisfies the requirement of tracking precision, but the precision of tracking is reduced after 501th frame.

The tracking results of 892nd frame, 906th frame, 920th frame, 934th frame, 948th frame, 962nd frame and 967th frame are shown as follows:
As can be seen from the figure 4, the overlap area of the minimum external rectangle and tracking frame of the right transfer vehicle is greater than 50%, so the van is successful. At 892nd frame, the right turn vehicle was interferenced, but the vehicle successfully tracked 445th to 948th frame. In 962nd frame and 967th frame, the vehicle travels out of the camera range (which can be seen as a block) but is successfully tracked.

**Table 3. Horizontal displacement table (unit: pixel)**

| category         | Frame | 892 | 906 | 920 | 934 | 948 | 962 | 967 |
|------------------|-------|-----|-----|-----|-----|-----|-----|-----|
| Actual location  |       | 572 | 563 | 542 | 526 | 497 | 473 | 465 |
| Tracking location|       | 579 | 571 | 550 | 516 | 486 | 461 | 488 |
| Pixel displacement|     | 7   | 8   | 8   | 10  | 11  | 12  | 14  |

**Table 4. Vertical displacement table (unit: pixel)**

| category         | Frame | 892 | 906 | 920 | 934 | 948 | 962 | 967 |
|------------------|-------|-----|-----|-----|-----|-----|-----|-----|
| Actual location  |       | 86  | 123 | 183 | 266 | 381 | 518 | 551 |
| Tracking location|       | 79  | 131 | 192 | 275 | 391 | 531 | 573 |
| Pixel displacement|     | 7   | 8   | 9   | 9   | 10  | 13  | 14  |

From the table 3 and table 4, within the frame of 892nd to 948th turn right horizontal displacement and vertical displacement errors of the vehicle always stay within 10 pixels, it satisfies the requirement of tracking precision, but the precision of tracking is reduced after 948th frame.
5. Conclusion
Firstly, we introduce the characteristics of HOG and HSV in the target presentation stage to describe the target vehicles, and two random forest classifiers are initialized with these two characteristics. Then in the process of predicting, calculating the image block when calculating the pixel confidence through weighted distance information to improve the confidence of the target figure estimates; At last, strengthening the learning abilities of two classifiers, improving the vehicle tracking robustness and accuracy. The algorithm for different models, different movement track of the vehicle tracking, we can see in the rendering, at the same time analyze and compare the tracking effect of the collaborative training and the self-training, getting the result which is the collaborative training tracking accuracy is better than the self-training tracking accuracy, and the tracking precision has a certain improvement.

Although this paper implements a variety of effective tracking moving vehicles, but there are still many insufficient places, the research in the future needs to improve and expand: understanding the behavior of the vehicle established on the basis of long time tracking, but this article is only to study the vehicle tracking in a single camera, camera gathering poor information so that it can not describe the vehicle behavior, so research direction in the future can be set up in the vehicle tracking of cameras.

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