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VEHICLE RECOGNITION BASED ON MULTI-SCALE OF GAUSS BACKGROUND MODELING

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ABSTRACT

In the intelligent traffic system, vehicle recognition is always a hot topic. However, because the environment is easily influenced by the light, the weather, the shadow and the noise. It's difficult to get ideal vehicle segmentation effect. This paper studies the existing background modeling algorithm and proposes a vehicle recognition method based on multi-scale of Gauss background modeling. This algorithm divides traffic image into several parts and multi-scale analysis, and extracts multi-scale features of the image. Describe the multi-scale features by using the mixed Gauss model, thus realize background modeling of the complex traffic image. This algorithm can be well suited to sudden change in the image, and restrain discrete noise points. As the research shows, the effectiveness of this algorithm solves the problem of the false alarm pixels interference.

Keywords: *Multi-Scale Features,; Mixture Gauss Model, Vehicle Recognition, Background Subtraction*

1. INTRODUCTION

With the development of the computer, image processing technology has been widely applied in intelligent transportation system in recent years. Accurate recognition and analysis of the moving target is very important for the process of the target classification, tracking and behavior understanding in intelligent monitoring system. The most commonly used and most effective target recognition method is background subtraction. However, the key to the background subtraction algorithm is how to obtain a clean background image. Quality of the background image for moving target recognition accuracy has a great impact.

Background modeling algorithm has been studied by many people at home and abroad and also received a lot of different methods. Such as the median method, the mean method, the Gauss distribution model, the Surendra method, the mixture Gauss modeling, the non-parametric kernel density estimation model, the Kalman filter method. Friedman proposed mixture Gauss modeling method in the transportation monitoring [1]. Each pixel in the image consists of three Gauss components, respectively corresponding to the road, vehicles and shadow. Stauffer proposed a more general mixture Gauss background modeling method [2]. He used online K-means approximation method instead of a strict expectation maximum (EM) algorithm in the process of learning the model parameters. It improves the learning efficiency of the Gaussian mixture model. Since then the researchers made a variety of improvements to the mixture Gauss background modeling [3-4].

During the last decades, much attention has been given to model based techniques to model the uncertainty in a probabilistic manner [5-9]. In model-based techniques, standard GMM is a well-known method used in most applications [10]. An advantage of the standard GMM is that it requires a small amount of parameters for learning. Another advantage is that these parameters can be efficiently estimated by adopting the expectation maximization (EM) algorithm to maximize the log-likelihood function [11]. However, a major shortcoming of this method is that it does not take into account the spatial dependencies in the image. Moreover, it does not use the prior knowledge that adjacent pixels most likely belong to the same cluster. In this family of Bayesian segmentation methods, prior probabilities of class membership are considered constant for every pixel of an image. Thus, the performance of Bayesian segmentation methods is too sensitive to noise and image contrast levels.

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A possible approach to overcome this problem is to impose spatial smoothness constraints to incorporate the spatial relationships between neighboring pixels [12]. Recently, several mixture models based on Markov random field (MRF) for pixel label are proposed in [13-15]. According to these approaches, prior probabilities capture spatial information by using a MRF. The primary advantage of this family of mixture models is that it incorporates spatial information and reduces complexity and computational cost. Hence, it improves segmentation results, particularly when image is corrupted by high levels of noise.

This paper studies the existing background modeling algorithm and proposes a vehicle recognition method based on multi-scale of Gauss background modeling. The image is divided into sub-images without overlap, and then decomposed sub-images using the wavelet decomposition algorithm. Obtain sub-images' multi-scale statistical feature. On this basis, build sub- image multi-scale feature vector and use a mixture Gauss model to describe it. Determine which sub-image belongs to the background and build traffic background image which has strong robustness features. Finally, using the background subtraction method recognizes vehicle. The algorithm can better adapt to sudden events in the image and suppresses the noise spot. Through with the Gauss mixture modeling comparative trial and it has confirmed the algorithm validity.

2. VEHICLE RECOGNITION

Mixture Gauss modeling is based on pixel, it will generate an error judgment in foreground when massive changes are in image content or slow-moving objects. It 's because relatively too long time to train for the slow-moving objects on the model and make the wrong foreground image added to the background model. Gaussian mixture modeling approach does not consider the mutual relations of pixels and surrounding pixels,which leads to errors in the foreground segmentation and makes the foreground image noisy. In view of these problems,this paper proposes a multi-scale Gaussian modeling method based on image block. Make full use of the information on the correlation between pixels to make up for the traditional pixel modeling methods shortcomings. Use multi-scale decomposition method to decompose the sub-image segmentation. Make the vehicle featured and noise separated in the traffic image. Then build multi-scale feature vector and use the Gaussian mixture model to describe it. Here are the specific steps of the multi-scale Gaussian background modeling algorithm.

2.1 Mallat Algorithm

The wavelet transform can be changed in time and frequently, which has the function of stretching and shortening camera focus. The basic idea is to use a family of wavelet functions to represent and approach signal. In fact, Mallat decomposition algorithm equals to the input signal through the filter, then sampling of the filter output and take even part of it. Discrete wavelet transform Mallat algorithm the general formula as follows:

$$A^0_{2^{j-1}}(m,n)=\sum_{x,y}A^0_{2^j}(x,y)h(x-2m)h(y-2n) \quad (1)$$

$$D^1_{2^{j-1}}(m,n)=\sum_{x,y}A^0_{2^j}(x,y)h(x-2m)g(y-2n) \quad (2)$$

$$D^2_{2^{j-1}}(m,n)=\sum_{x,y}A^0_{2^j}(x,y)g(x-2m)h(y-2n) \quad (3)$$

$$D^3_{2^{j-1}}(m,n)=\sum_{x,y}A^0_{2^j}(x,y)g(x-2m)g(y-2n) \quad (4)$$

Here h is the low-pass filter, g is the high-pass filter.

Because the scaling function and wavelet function is separable, each of the filtering process can be broken down into one dimensional filtering in lines and column directions. Seen from the angle of realization, the two dimensional image of the wavelet transform is a filtering and resample. First of all, along the lines of direction for the low-pass and high-pass filtering makes the image decomposed into two parts of approximation and details and sampling. Then along the column direction of the line computation of the results using the high-pass and low-pass filter for computing and sampling. The four outputs $A^0_{2^{j-1}}(m,n)$ are the approximate composition of the source image, $D^1_{2^{j-1}}(m,n)$ is the details of the vertical direction, $D^2_{2^{j-1}}(m,n)$ is the details of horizontal direction, and $D^3_{2^{j-1}}(m,n)$ is the details of diagonal direction. The image is decomposed into a low-frequency and three high frequency components.
Represented LL , LH , HL , HH and shown in Fig .1.

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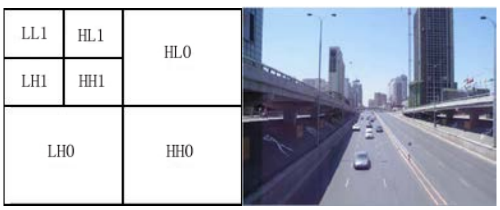
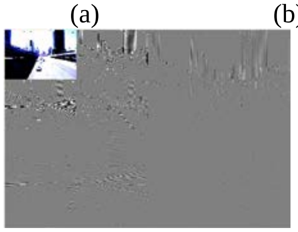
2.2 Multi-scale Decomposition of the image

In the vehicle Recognition， The camera is usually fixed above the road. When we use the algorithm to identify the vehicle it will be seen as the camera is fixed. In the existing algorithms, the use of background subtraction split of the background for the camera is installed in a fixed position. However, the key is how to get a clean background with strong robustness. So we need modeling for background. Firstly,we get real-time traffic image by the fixed camera. In order to construct a multi-scale feature vector, we first need to divide the image into sub-block. The specific approach is to make the image to divide the sub-image blocks and these sub-image blocks don't have the overlap section.



(a) (b)



(c)

Fig.1.(A)Three-Layer Wavelet Decomposition Diagram; (B) Original Image;(C) Results Of Wavelet Decomposition

Using Mallat decomposition sub-image and the decomposition of the image is represented as S_i. We get an 8 * 8 image block after the decomposition of multi-scale image. The decomposition number is 2, so the number of decomposed sub-images is 7 and those are represented by $S_0, S_1, S2, S_3, S_4, S_5, S_6$.The benefit of doing this is to reduce the interference of the discrete noise points in the subsequent processing.

2.3 Multi-scale Feature Vector

Through the above processing, we've got a multi-scale image based 8 * 8 image sub-block . Now, using these sub-images to build a multi-scale feature vector. First we need to calculate their average value and the variance to all sub-images. It's easy for us to find through research, Multi-scale decomposition of the sub-images HH_0 and LL_1 is the diagonal part of the original image of the high-frequency and approximate part. S_0 section contains little texture information of the vehicles, the change of the mean and variance in the time series of images is little. S_6 contains approximate information of the image. When the reflected light of the vehicle affects the brightness of camera images ,it will affect the recognition results. In other scales, vehicle information has been a very good performance, so we give up the two layers. The advantage is that we can reduce the impact of the sudden changes of light.

The image horizontal and the vertical detail will be separated in the different sub-image level. When the road surface has the vehicles through the sub-image's average value and the variance will change. We may realize from these changes to the pictorial information and use these as a basis to identify vehicles. We use the mean and variance features of the sub-image to build multi-scale feature vector $f = \{\mu_1, \sigma_1, \mu_{2,} \sigma_2 \cdots\cdots \mu_5, \sigma_5\}$.

2.4 Mixture Gauss Background Modeling based on Multi-scale Feature Vector

Because the transportation image is along with the time variation, therefore the sub-image's multi-scale feature vector is also along with the time variation. Using Gauss mixture model to describe the 3.2 multi-scale feature vectors. We establish the K Gauss mixture model for the value of the feature vector in time. F_i represents the value of the feature vector in the time i , $\{F_0, F_1, F_2 \cdots\cdots F_t\}$ represents the value from the beginning to the time t .The probability of F_t can be expressed as :

$$P(F_t) = \sum_{k=1}^{K} \omega_{k,t} \cdot \eta(F_t, \mu_{k,t}, \Sigma_{k,t}) \tag{5}$$

K is the number of Gauss distribution, $\omega_{k,t}$ is the time t k -th Gauss distribution of the weight, $\eta(F_t, \mu_{k,t}, \Sigma_{k,t})$ is the Gauss probability density function:

$$\eta(F_t, \mu_{k,t}, \Sigma_{k,t}) = \frac{1}{(2\pi)^{D/2} |\Sigma_{k,t}|^{1/2}} \times e^{\left\{-\frac{1}{2}(F_t - \mu_{k,t})^T \Sigma_{k,t}^{-1} (F_t - \mu_{k,t})\right\}} \tag{6}$$

D is the dimension of F_t, $\mu_{k,t}$ and $\Sigma_{k,t}$ are represented at time t , K-th the Gauss distribution

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mean and covariance. Assume that feature vector and the covariance matrix are independent of each other. Covariance matrix can be expressed as:

$$\Sigma_{k,t} = \sigma^2 \cdot I \tag{7}$$

The mean, variance and weight of the adaptive update are as follows:

$$\mu_{k,t+1} = (1-\rho)\cdot \mu_{k,t} + \rho \cdot F_{t+1} \tag{8}$$

$$\sigma_{k,t+1}^2 = (1-\rho)\cdot \sigma_{k,t}^2 + \rho \cdot (F_{t+1} - \mu_{k,t+1})^T \cdot (F_{t+1} - \mu_{k,t+1}) \tag{9}$$

$$\rho = \alpha \cdot \eta(F_{t+1} | \mu_{k,t}, \sigma_{k,t}) \tag{10}$$

2.5 Background update and vehicle detection

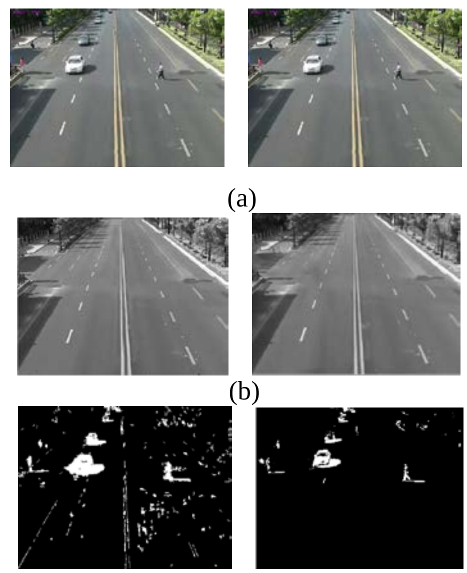
To judge whether the sub-block belongs to the background uses Gauss mixture model. If the judge of the result is sub-block belongs to the background image,then make the sub-image add to the background to update the background model. If the judge of the result is no, then the sub-image will be abandoned to fill in the background model. However, there is a problem, if it does not belong to the background image, does it mean that it belongs to the foreground image? The answer is no. Because the background modeling method we used is based on the 8 * 8 image block. Judgment is based on the image block. There is no way to directly used for the detection of the prospects can only be used for background modeling. However, in order to obtain the foreground image,we need to do further image segmentation which is based on background image. We take the background subtraction to obtain the foreground image

3. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the validity of the algorithm, test it at Intel E2410 PC machine, using VC++. Compared with the traditional Gauss mixture modeling method, the algorithm does not remove shadow algorithm for processing.

As it is shown on figure 2, the input image at 8863 frame, global brightness changes because light affects the whole image. If we use traditional Gauss mixture modeling method, we will produce many noise spots in the prospect. So segmentation is not satisfactory between foreground and background images. However, putting multi-scale approach into this Gauss mixture modeling, foreground and background images are segmented basically stable, and just a small amount of generated at the top of the image.

Both processing methods are completed without any morphological processing. Background image modeling using Gauss mixture modeling method, this algorithm turns the image into 8 * 8 sub-image block modeling. So it has avoided the possibility of the former algorithm based on the pixel model which misinterprets effectively. Judgment of the foreground image is more accurate. In the process of multi-scale of image, noise is separated into a separate image layer. This algorithm is well suited to a lot of suddenly appeared noise. And it can quickly rebuild a new background image when the whole image changes, to adapt to the interference when changes appear.



(a)

(b)

(c)

Fig.2.(A)Image At 8863 Frame;(B)Background Image;(C)F Foreground Image

Figue3 is the 10702nd image. It shows that because vehicle is reflective, the whole image's brightness is changed. There will be a large area of misjudgment phenomenon for foreground by the traditional Gauss mixture modeling. The effect of the multi-scale Gauss mixture modeling method based on image block is obviously better than it. Less noise on the image, because the multi-scale Gauss mixture modeling method based on image block can suppresses the noise spot and the interference by leaves shaking.

4. CONCLUSIONS

This paper presents a vehicle Recognition based multi-scale Gauss mixture background modeling. Comparing the test with the traditional Gauss mixture modeling, the algorithm can solve the problem of false alarm points in the traditional Gauss mixture modeling techniques. The algorithm

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for noise point has a good inhibition, when the image brightness changes.

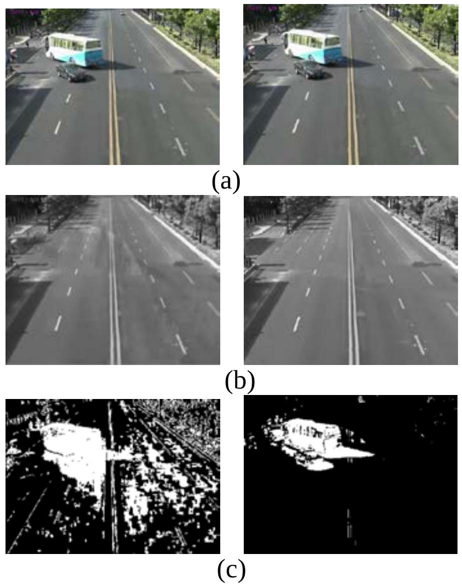

Fig.2.(A)Image At 8863 Frame ;(B)Background Image;(C)F Foreground Image

It makes up for the problem of producing a discrete noise point during the background modeling techniques which is based on single pixel. Image noise and vehicle features are separated through the multi-scale analysis. Describing the eigenvectors of multi-scale by multi-scale Gauss mixture modeling makes the vehicle identification more stable and reduces the noise interference on the vehicle identification. Also it can quickly adapt to changes by the impact of the light brightness changing when the background image changes.

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