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Research Article

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Intelligent traffic flow videos based on gauss mixture model

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ABSTRACT

In this paper, the algorithm of mixed Gauss background modeling is analyzed from two aspects of theory and application. Accurate and robust vehicle detection and the recognition still a challenging task in the field of intelligent transportation surveillance systems. This exhibits promising potential for implementations with real-world applications.

Key words: Intelligent traffic; video; Gauss mixture model

INTRODUCTION

A traffic surveillance camera system is an important part of an intelligent transportation system [1]. It mainly includes automatic monitoring digital cameras to take snapshots of passing vehicles and other moving objects, as is shown in Fig 1. The recorded images are high-resolution static images, which can provide valuable clues for police and other security departments, such as a vehicle plate number, the time it passed, its movement path and the driver's face, etc. In prior days, massive amounts of stored images were processed manually, but this required hard work and resulted in poor efficiency. With the rapid development of computer technology, the latest in automatic license plate recognition software is utilized at an increasing rate in the field with great success [2]. Unfortunately, sometimes we may not discover the license plate of a vehicle because of cloned license plates, missing license plates, or because the license plate can't be recognized. This is why automatic vehicle detection and recognition is becoming the imminent requirement for traffic surveillance applications [3]. This technology will save a lot of time and effort for users trying to identify blacklisted vehicles or who are searching for specific vehicles from a large surveillance image database [4][5].

Vehicle detection and recognition is a vital, yet challenging task since the vehicle image is distorted and affected by many factors. Firstly, the number of vehicle types is rising with new car model promoted regularly. And then there is also a great deal of similarities between some vehicle models. At last there are also significant differences among vehicle images due to differences of road environments, weather, illumination, and the cameras used. Nowadays, most of the published research mainly focuses on the classification of vehicles into broad categories, such as motorbike, cars, buses, or trucks , but this does not provide sufficient functionality to satisfy users' demands. Some researchers studied vehicle logo detection and recognition using frontal vehicle images to access the information that would reveal the vehicle's manufacturer. Recently, some researcher have recently adapt feature extraction and machine learning algorithms to classify vehicles into precise classes. V. Petrovic and T. Cootes described an investigation of feature representations and recognition, which is to create a rigid structure recognition framework for automatic identification of vehicle types with the recognition rates of over 93%. In recent years, computer vision and pattern recognition has made great progress in the development of image feature description and recognition, especially in the field of face recognition [16]. Face recognition continues to be an active, hot research point in image processing and computer vision research, which yields many useful and effective methods and algorithms. Compared to face recognition, vehicle recognition is very similar. For examples, each face consists of the same components, such as eyes, mouth, and nose, and each frontal vehicle consists of the same components, such as lights, bumper, and windscreens. Based on current, highly effective face recognition methods, the paper proposes an integrated vehicle detection and classification system.. However, this is not a valid technique when there are vehicles with non-symmetrical front license plates and the vehicle contour may not be accurate enough for some types of vehicles, particularly those that are either larger or smaller than the average. This paper proposes a robust vehicle detection scheme based on an AdaBoost algorithm. The basic idea is to extract the Haar-like features from vehicle samples and then use the AdaBoost algorithm to train classifiers for detection, which is distinct from previous research on vehicle detection for static images. The second part of this paper concentrates on vehicle recognition, which can also be called vehicle type classification. As vehicle images are subject to their environment and vehicles position can vary, a Gabor wavelet transform and a local binary pattern (LBP) operator are used to extract multi-scale and multi-orientation vehicle features; then, the principal components analysis (PCA) is used to reduce the feature vector dimensions; finally, an euclidean distance comparison algorithm is used to measure the similarity of vectors with lower dimensions in order to finalize the vehicle types.

2 Gauss mixture model overview

Gauss mixture model is the expansion of a single Gauss probability density function, through the density distribution function of a plurality of Gauss density function[1] weighted to form multi peak functions to smooth approximation of other shapes. A single D dimensional Gauss probability density function is g (x), such as the formula(1)

$$g\left(\vec{x}\right)=\frac{1}{(2\pi)^{D/2}\left|\Sigma\right|^{1/2}}\exp\left\{-\frac{1}{2}\left(\vec{x}-\vec{\mu}\right)^{T}\Sigma^{-1}\left(\vec{x}-\vec{\mu}\right)\right\}$$

(1)

In it , $\vec{\mu}$ is the mean vector; Σ is the covariance matrix which is usually simplified into a diagonal matrix: $\Sigma = \begin{bmatrix} \sigma^2 & & \\ & \ddots & \\ & & \sigma^2 \end{bmatrix}$,

The shape center, width and direction of Gauss probability density function are decided by this two parameters. The mathematical definition of GMM as shown in formula (2):

$$p\left(\vec{x}\right)=\sum_{i=1}^{M}\alpha_i\beta_i\left(\vec{x}\right) \qquad (2)$$

Where M is the mixing coefficient of Gauss mixture probability density, $\vec{x}$ represents a point in D - dimensional space, α_i weighted for each value of a Gauss function and must satisfy the condition of (3) representing, its value is bigger, the Gauss function is more dominant in all density distribution function.

$$\sum_{i=1}^{M}\alpha_i=1 \qquad (3)$$

Thus to know, $p\left(\vec{x}\right)$ is decided by α_i , μ_i , Σ_i ,i=1,2,…,M[1]

3 Gauss mixture background model

Stauffer and Grimson first proposed the based on Gauss mixture model in 1999, which is a very typical background modeling algorithm currently. Gauss mixture model according to each image sample values (the color values of pixels) into different probability models and updates the parameters of the Gauss distribution all real-time . Conduct of operations for the Gauss mixture model, it include Gauss distribution of weights, such as mean and covariance parameters. The pixel value distribution of the background converges to one or several Gauss distribution, clustering to achieve the background pixel values, thus the vehicle target emerged from video image.

3.1The model definition

The background modeling method based on Gauss mixture model, according to the pixel frame image color values, such as RGB, HSV color space values for modeling. In the Gauss mixture model, each frame of the image pixels, it is regarded as a random process system[2]:

$$\left\{X_1,....X_t\right\}=\left\{I(\mathrm{x}_0,\mathrm{y}_0,\mathrm{i});1\le i\le t\right\} \qquad (4)$$

Based on the formula, the color value of pixel $(\mathrm{x}_0,\mathrm{y}_0)$ in the moment of I is $I(\mathrm{x}_0,\mathrm{y}_0,\mathrm{i})$. For the $(\mathrm{x}_0,\mathrm{y}_0)$,it build a Gauss mixture model with hybrid coefficient K value.

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} \bullet \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \qquad (5)$$

In it, $\omega_{i,t}$ is the weight of Gauss distribution in the moment t, $\eta(X_t, \mu_{i,t}, \Sigma_{i,t})$ $\omega_{i,t}$ is the probability density function of Gauss distribution in the moment t. The mean is $\mu_{i,t}$,the covariance is $\Sigma_{i,t}$. $P(X_t)$, appear probability of pixel values which is observed in the moment t. The value of K is decided by the memory space requirements and operational capability of computer, its value is bigger, it needs more memory and the speed is slower. Generally, it is selected from 3 to 5.

For simple operation, we make K=3, and the blue, green, red tricolor channels are independent of each other, variance covariance is consistent. Namely, covariance matrix is diagonal, and $\Sigma_{i,t} = \sigma_i^2 I$ .When each frame color image of the video is into grayscale processing, formula (5) can be transformed as

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} \bullet \eta(X_t, \mu_{i,t}, \sigma_{i,t}) \qquad (6)$$

In it, $\sigma_i^2 I$ is the average variance of the Gauss model, η is the Gauss model, which is expressed as

$$\eta(X_t, \mu_{i,t}, \sigma_{i,t}) = \frac{1}{\sqrt{2\pi}\sigma_{i,t}} e^{-\frac{(X_t - \mu_{i,t})^2}{2}} \qquad (7)$$

3.2 Matching and updating of the model

Gauss mixed background modeling algorithm can do matching according to the current image pixel values and K Gauss distribution, if the matching successful , updates the model. If the pixel value in the image is 2.5 times variance range of Gauss distribution, that a successful match. No successful matching parts remain unchanged.

When the pixel value in the image are not match K Gauss distributions, then use the new Gauss distribution to replace the Gauss distribution ,which has minimum mean, the new distribution is the current pixel value. At the same time, we distribute a larger initial covariance and a smaller initial value for it. If there exists a Gauss distribution can joint distribution, we can do the following adjustments to the weights of the various distribution:

$$\omega_{i,t} = (1-\alpha)\omega_{i,t-1} + \alpha M_{i,t} \qquad (8)$$

In it, α is learning rate and its value is between 0 and 1.For the Gauss distribution which match the current pixel value, $M_{i,t}$ =1,or $M_{i,t}$ =0.Thus,we make the Gauss distribution weight increase, and the Gauss distribution weight decrease. For the new matching degree, we adjust the Gauss distribution parameters are as follows:

$$\mu_t = (1-\rho)\mu_{t-1} + \rho X_t \qquad (9)$$

$$\sigma^2 = (1-\rho)\sigma_{t-1}^2 + \rho(X_t - \mu_t)^T (X_t - \mu_t) \qquad (10)$$

In it, ρ is another learning rate, its value is $\rho = \alpha\eta(X_t | \mu_k, \sigma_k)$ 。

3.4 Background description

For traffic flow videos, the images in an arbitrary period of time need to choose a Gauss mixture model or a few Gauss distributions for background modeling.

According to the calculation steps of background modeling and updating described above, the Gauss distribution which has greater weight and smaller covariance updates constantly and is more likely to be the background pixel. Therefore, in order to clear the background model, for any pixel in the image of each frame, we according to the value of ω / σ, then , we make the K Gauss distribution based on order. The first B Gauss distributions which match the equation (12) is background value.

$$B=\arg\min_b\left(\sum_{k=1}^{b}\omega_k > T\right) \qquad (11)$$

T is the minimum proportion of the background model accounting for all values of the Gauss distribution. If the T value is smaller, the Gauss mixture model will degenerate into single Gauss distribution model; When the T value is slightly big, it can build a plurality of Gauss mixed distribution models for vehicles, walking groups and other complex dynamic background.

4 Experiment analyze

For the intelligent traffic, traffic flow video processing requirements of precision and real-time is very high, in order to perform the various traffic flow video contrast, this paper adopts three kinds of road conditions to test. The three kinds conditions are less traffic flow and no shadow、large vehicle flow and complex 、vehicle shadow. Through the simulation experiment, drawing as that part of the results (3), (4), (5) are shown:

Fig.1 Vehicle flow less and no shadow

Fig. 2 large vehicle flow and complex

CONCLUSION

the Gauss mixed background modeling has relative good effect on three conditions: (1) The algorithm has a good processing effect when the traffic is less and road situation is simple, but the algorithm is complex, the operation time is long. When can achieve the same in background extraction effect, it’s longer than the average method and simple algorithm. Therefore, this kind of video should be used in other algorithm of high real-time performance. (2)On the contrary, for the condition of large vehicle flow and complex, compared with other background extraction, this algorithm effect is better. But in actual processing, it required operation space is large and the computing time is slow, we need to improve the method to match the requirement of real-time.

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$$\alpha_l^{new} = \frac{1}{N}\sum_{\mathrm{i}=1}^{N} p(\mathrm{l} \mid \mathrm{x}_i, \Theta^g)$$

$$\mu_l^{new} = \frac{\sum_{i=1}^{N} x_i p(\mathrm{l} \mid \mathrm{x}_i, \Theta^g)}{\sum_{\mathrm{i}=1}^{N} p(\mathrm{l} \mid \mathrm{x}_i, \Theta^g)}$$

$$\Sigma_l^{new} = \frac{\sum_{i=1}^{N} p(\mathrm{l} \mid \mathrm{x}_i, \Theta^g)(\mathrm{x}_i - \mu_l^{new})(\mathrm{x}_i - \mu_i^{new})^T}{\sum_{\mathrm{i}=1}^{N} p(\mathrm{l} \mid \mathrm{x}_i, \Theta^g)}$$