Moving Cast Shadow Elimination Based on Luminance and Texture Features for Traffic Flow

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***Abstract*—A new algorithm namely moving cast shadow elimination based on luminance and texture features (MSELT) to detect moving shadows of vehicles is investigated in this paper. Different from traditional methods only performed in color space, we combine the luminance in the CIE Luv color space and texture feature to determine shadows. The proposed algorithm based on Gaussian Mixture Model (GMM) uses the luminance weight in the CIE Luv color space to model background, do texture analysis and detect shadows. Texture analysis is performed by evaluating the gradients in the foreground with the observation that shadow regions present smooth texture characteristics. The experimental results show that this method outperforms results obtained with color space information alone, particularly in detection of vehicles which present similar luminance characteristics with shadows.**

***Index Terms*—Gaussian Mixture Model, moving cast shadow detection, CIE Luv color space, texture analysis**

I. Introduction

The vision-based approach becomes popular in ITS owing to its easy fixing, low expense and high flexibility. A main challenging problem in the design of ITS is to extract accurate real-time information of the traffic flow. However, problems arise due to unexpected shadows because moving cast shadows would cause errors in localization, segmentation, measurements, tracking and classification in vehicle detection.

To solve problems caused by moving cast shadows, Cucchiara [1] proposed the algorithm on the basis of assumptions that shadows reduce surface brightness and saturation while maintaining chromaticity properties in the HSV color space. Xiahou [2] used the luminance weight in the CIE Luv color space to model background and detect shadows. Problem of these methods is that object points might be misjudged if they present similar color space features with shadows. Leone [3] took advantage of the same textural characteristics between a shadow region and its corresponding background to determine shadows. However, better performance means more parameters and complicated calculation. Shoaib [4] detected cast shadows using contour obtained by gradient-based background subtraction but this method is not applied for outdoor environment. Liu [5] combined color feature in the HSV color space with textural characteristics to judge a shadow region.

Gaussian Mixture Background Model is widely used in video surveillance field. Stauffer [6] used a mixture of Gaussian to model each pixel and an on-line approximation to update the model. Both parameters and components of the GMM are constantly adapted for each pixel in [7]. Nicolas [8] used the GMM to build statistical models describing moving cast shadows and judge a new pixel whether satisfied these models. But too many parameters make the algorithm very complicated and parameters learning constant also causes serious effect to algorithm. The proposed algorithm MSELT improves algorithm used in [2] by augmenting texture analysis. We combine the luminance in the CIE Luv color space and texture feature to determine shadows. Results show that our method can effectively solve the problem that regions with similar luminance characteristics with shadows of vehicles might be misjudged to be shadows.

II. MOVING CAST SHADOW ELIMINATION ALGORITHM

There are six steps in the proposed algorithm MSELT: image pre-processing, shadow elimination based on luminance weight in the CIE Luv color space (SEBL), shadow elimination based on texture analysis (SEBT), Gaussian Mixture background Model, shadow elimination and vehicle detection.

A. SEBL Description

The CIE Luv color space has advantages of good model consistency and accuracy [2]. Benedek [9] classified the color spaces according to two different components as luminance and chrominance component. In the CIE Luv color space, the L represents luminance and u, v represent chrominance component, and thus Benedek [9] named it mixed space. In [2][9] authors demonstrated that in the CIE Luv color space, distribution of shadow point and moving object point were more centralized than the RGB and HSV color space, and the distinguishing ability of the shadow and object was better. For the consideration that the distribution of shadow is fit to Gaussian distribution , we adopt the L weight to detect moving cast shadows [2].

Let $C(i,j)(1 \leq i \leq M, 1 \leq j \leq N)$ is the pixel of the current image while $B(i,j)$ is the pixel of the same location

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in background image, we define μ and σ as follows:

$$\begin{cases} \mu = \dfrac{1}{M \times N} \displaystyle\sum_{i=1}^{M} \sum_{j=1}^{N} (\dfrac{C(i,j)}{B(i,j)}) \\ \sigma = \sqrt{\dfrac{1}{M \times (N-1)} \displaystyle\sum_{i=1}^{M} \sum_{j=1}^{N} (\dfrac{C(i,j)}{B(i,j)} - \mu)^2} \end{cases} \tag{1}$$

we determine shadow and object according to:

$$\begin{cases} |(\dfrac{C(i,j)}{B(i,j)} - \mu| < \lambda\sigma, C(i,j) \in shadow \\ |(\dfrac{C(i,j)}{B(i,j)} - \mu| \geq \lambda\sigma, C(i,j) \in object \end{cases} \tag{2}$$

The transformation from the RGB color space to CIE XYZ color space is presented in (3), and(4) expresses transformation from CIE XYZ color space to the L weight in CIE Luv color space. The Y_n in equation is chromaticity coordinate of the used light source.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412 & 0.358 & 0.180 \\ 0.213 & 0.715 & 0.072 \\ 0.019 & 0.119 & 0.950 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3}$$

$$\begin{cases} L = 116 \times (Y/Y_n)^{1/3}, & if \;\; Y/Y_n > 0.008856 \\ L = 903.3 \times Y/Y_n, & if \;\; Y/Y_n \leq 0.008856 \end{cases} \tag{4}$$

B. SEBT Description

In the proposed algorithm MSELT, gradient is chosen to implement texture analysis. The foreground regions always contain much textural information and the difference between moving cast shadows and moving objects is : shadows keep the texture characteristics of the corresponding background but objects would change them intensively. Gradient can exactly describe the textural information and it is easy to calculate.

Fig.1 shows the 4 gradient operators used in our experiment, and they can express gradient features of the horizontal, vertical and diagonal direction.

0	**0**	**0**	**-1**	**0**	**+1**	**-1**	**0**
+1	**-1**	**0**	**+1**	**-1**	**0**	**0**	**+1**

Fig. 1. Gradient operator

Fig. 2 shows the location of the four pixels in each gradient operator.

(x-1,y-1)	**(x,y-1)**
(x-1,y)	**(x,y)**

Fig. 2. Location of each gradient operator

Gradient calculation is performed on the foreground image. The gradient in location (x,y) is:

$$G(x,y) = \sum_{i=1}^{4} |g_i(x,y)| \tag{5}$$

In our experiment, shadow point is determined as follows

$$\begin{cases} shadow, \;\; if \;\; G(x,y) \leq 6 \\ vehicle, \;\; else \end{cases} \tag{6}$$

C. Shadow Elimination and Vehicle Detection

Information alone is that some points in vehicle might be misjudged to be shadow points. It would cause errors in segmentation such as one car is divided to several parts.

In our proposed algorithm, after doing shadow elimination with SEBL and SEBT respectively, OR operation is performed on the results to keep the integrality of the moving objects.

III. MSELT DESCRIPTION

1) Image pre-processing: smooth the original images with Gaussian filter. The smoothing template chosen in our experiment is 3×3 , and the smoothing scale is 1.

2) Color space transformation: transform the RGB color space to the CIE Luv color space according to (3) and (4).

3) GMM of the background: the proposal algorithm MSELT uses the L weight in the CIE Luv color space to model background within GMM. The recent time period $(1, \cdots, t)$ of each pixel $(X_1, \cdots, X_t)$ is modeled by a mixture of K Gaussian distributions. The probability of observing the current pixel is:

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} \eta(X_t, \eta_{i,t}, \sigma_{i,t}^2 I) \tag{7}$$

where K is the number of distributions, $\omega_{i,t}$ is an estimate of the weight (what portion of the data is accounted for by this Gaussian) of the i^{th} Gaussian distribution in the mixture at time t, $\mu_{i,t}$ is the estimate of mean value and $\sigma_{i,t}^2$ is the estimate of variance that describe the Gaussian components at time t. The covariance matrices are assumed to be diagonal and the identity matrix I has proper dimensions [3][7].

A new pixel X_t at time t is checked against the existing K Gaussian distributions. A match is defined if the Mahalanobis distance from the component is less than 2.5 standard deviations.

If the new pixel X_t matches the i^{th} Gaussian distribution, the K Gaussian distributions are updated according to the matching results as follows:

The updating equations of the i^{th} distribution that matches the new pixel are :

$$\begin{cases} \omega_{i,t} = (1-\alpha)\omega_{i,t-1} + \alpha \\ \mu_{i,t} = (1-\rho)\mu_{i,t-1} + \rho X_t \\ \sigma_{i,t}^2 = (1-\rho)\sigma_{i,t-1}^2 + \rho(X_t - \mu_{i,t})^T (X_t - \mu_{i,t}) \end{cases} \tag{8}$$

where α is learning rate and $\rho = \alpha/\omega$[7]. We set α 0.002 in our experiment.

Parameters for unmatched distributions are:

$$\begin{cases} \omega_{i,t} = (1-\alpha)\omega_{i,t-1} \\ \mu_{i,t} = \mu_{i,t-1} \\ \sigma^2_{i,t} = \sigma^2_{i,t-1} \end{cases} \tag{9}$$

Then the first B distributions are chosen to be the background model,

$$B = \arg\min_b \left(\sum_{k=1}^{b} \omega_k > T\right) \tag{10}$$

where T is a measure of the minimum portion of the data that can belong to the background. We set T 0.9 in our experiment.

4) Shadow detection in the CIE Luv color space: according to the proposed algorithm SEBL in section A the value λ is 2.5 in our experiment.

5) Texture analysis: according to the proposed algorithm SEBT in section B.

6) Shadow elimination and vehicle detection: according to the method proposed in section C.

IV. Results and Discussion

In order to demonstrate the performance of the proposal algorithm MSELT, a standard image sequence is tested on a 2GHz PC . The size of the image is 320×240 pixels and the frame rate is 30fps.

Fig. 3. Original images

Fig. 4. Results without shadow elimination

Fig. 5. Results of SEBL

The 60^{th} frame, 190^{th} frame and 1068^{th} frame are chosen in our experiment. Fig 3 shows the initial three frames. Segmentation results without shadow elimination are show in

Fig. 6. Results of SEBT

Fig. 7. Results after OR operation

Fig 4. Fig 5, 6 illustrates results of SEBL, SEBT respectively. Fig 7 is the final results after OR operation.

It can be seen that accurate vehicle detection could be difficult without shadow detection in Fig 4. The results show that some points of the vehicles are missed in Fig 5 and in Fig 6 parts of these points are detected. Comparing results obtained with color space information alone in Fig 5 with the final results obtained using our algorithm MSELT in Fig 7, we can observe here that the proposal algorithm MSELT could get better segmentation results and enhance accuracy in localization, measurements, tracking and classification of vehicle detection.

V. Conclusion

This paper presents a new algorithm MSELT for visionbased traffic flow detection. It only uses the luminance weight in the CIE Luv color space to model background and detect shadows for the consideration of low calculation complexity. Shadow regions are determined both by luminance and texture features to solve the problem that parts of vehicle points with similar luminance characteristics with shadows might be misjudged to be shadows. The experiment results have shown that our algorithm MSDLT has strong robustness in vehicle detection.

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