

# A Fuzzy Integral Method for Shadow Detection of Moving Object<sup>★</sup>

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## Abstract

Moving cast shadow detection is important yet difficult problem in video analysis and applications. A novel shadow detection method is presented, which base on the fuzzy measure and fuzzy integral theory. This method integrates the extended Local Binary Pattern texture feature and color feature by using the choquet integral, where color similarity, texture similarity and feature importance degree are measured respectively between pixels in current and background images. The Experimental results on different video sequences show that the proposed method owns much higher performance of shadow detection than other methods.

*Keywords:* Shadow Detection; Fuzzy Measure; Choquet Integral

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## 1 Main Text

Moving object detection is the first stage in many video processing applications such as video surveillance, traffic monitoring and human detection. However, the shadow casted by the moving object is also detected. The shadow makes it difficult to detect the exact shape of object and to recognize the object. Therefore, the accurate detection of a moving object and the acquisition of its exact shape by eliminating shadows have a great effect on the performance of subsequent steps such as tracking, recognition, classification, and activity analysis.

Moving cast shadows are caused by the occlusion of light sources, points under shadows have lower brightness but similar color, texture, gradient or edge compared to their reference background points. Many methods to detect and remove the shadow use these properties.

C. Stauffer et al. [1] propose that the recent history of pixel intensity is modeled by a mixture of Gaussians, and the Gaussian mixture is adaptively updated for each site to deal with dynamics in background processes. In [2], the author uses brightness and chromaticity by estimating the cast

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shadow direction of each pixel from the recent images. Yang Wang [3] presents a new method for shadow detection. based on pixel intensity information, a conditional random field shadow detection model was constructed, spatial and temporal dependencies in traffic scenes are formulated under a probabilistic discriminative framework. M Shoaib et al. [4] suggest a novel scheme for real time detection of cast shadows using contour like structures of objects, which are obtained by gradient-based background subtraction. In [5], the method is proposed to detect a shadow by using edge information information. In [6], this paper discriminates between the shadow and the moving object by cascading three estimators which use the properties of chromaticity, brightness, and local intensity ratio. Li Guang-lun et al.[7] uses intensity, chromaticity and reflectance ratio to detection moving cast shadows.

In above methods, although different features are combined, in fact they are still used separately. So, a good fusion of several measuring features can strengthen the pixels classification as shadow or foreground. In a general way, the Choquet and Sugeno integrals[8] have been successfully applied widely in classification problems, in decision making and also in data modeling to aggregate different measures. In this paper, we propose to use the Choquet integral to aggregate color and texture features for shadow detection. Framework of the proposed method is shown as Fig. 1.

In this paper, we define a similarity measure between pixels in current and background images. In this case, pixels corresponding to shadow should be similar in the two images while pixels corresponding to foreground should not be similar. In order to embody the importance degree of the feature in the detection of shadow, the feature importance measure of the pixel can be computed from the training examples. The similarity measures and importance measure are computed for each feature which is then aggregated by the Choquet integral. The shadow/foreground classification is finally made by threshold the Choquet integral's result.

The organization of this paper is as follows. In Section 2, we introduce the color similarity measure, texture similarity measure and feature importance measure adopted. Section 3 defines the fuzzy integrals, and the proposed method for the shadow detection is involved. Finally, the last section compares our method with other methods using three test videos sequences.

## 2 Features Similarity and Importance Measures

Shadow detection is based on a comparison between current and background images. In this case, pixels corresponding to shadow should be similar in the two images while pixels corresponding to foreground should not be similar. The computing of the similarity measures can be done using the color and texture features. Meanwhile, the importance degree of different features is different, towards the final classification. So we propose in the following subsections to compute feature importance measure too.

### 2.1 Color Similarity Measure

We describe here the color similarity measure in a general way, i.e. the color feature may be any color space with three components noted  $I_1, I_2$  and  $I_3$ . Then, the color similarity measure  $S_i^C(x, y)$  at the pixel  $(x, y)$  is computed as in:

$$S_i^C(x, y) = 1 - \frac{|I_i^C(x, y) - I_i^B(x, y)|}{255} \quad (1)$$

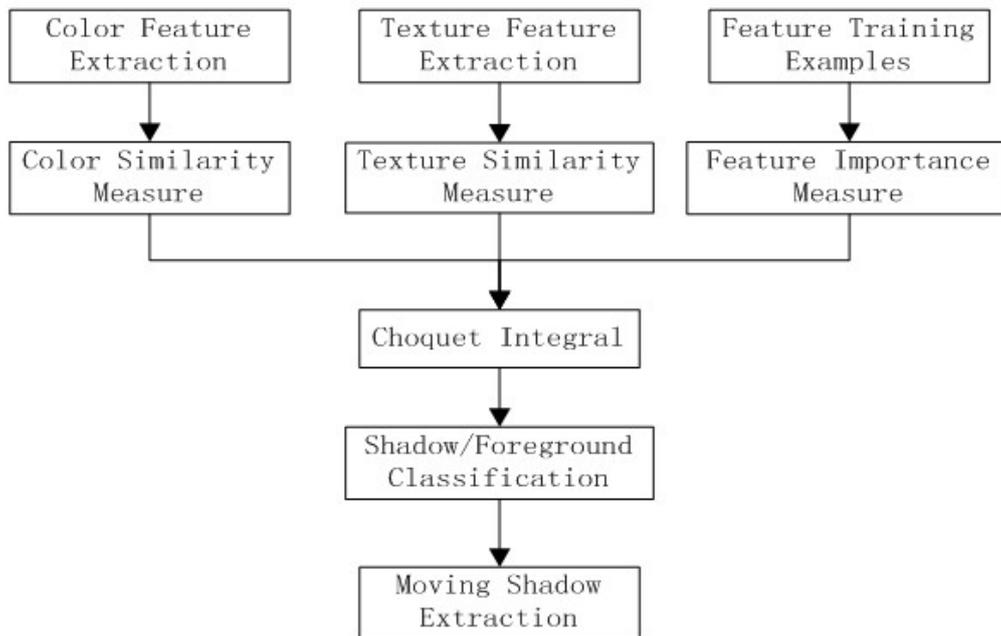


Fig. 1: Framework of the proposed method

where  $i \in \{1, 2, 3\}$  is one of the three color features,  $I^C(x, y)$  and  $I^B(x, y)$  represent respectively the current and the background images. Note that  $S_i^C(x, y)$  is between 0 and 1. Furthermore,  $S_i^C(x, y)$  is close to one if  $I_i^C(x, y)$  and  $I_i^B(x, y)$  are very similar.

## 2.2 Texture Similarity Measure

The texture features named the local gradient orientation binary patterns [9] developed from LBP, It encodes higher order pixel-wise information than LBP and preserves the monotonic gray-level transformation invariant property of LBP.

The operator labels the pixels of an image block by thresholding the neighbourhood of each pixel with the center gradient orientation angle and considering the result as a binary number:

$$LGOBP(x, y) = \sum_{i=0}^{N-1} s(l(g_i) - l(g))2^i \quad (2)$$

where  $l(g)$  corresponds to the gradient orientation angle of the center pixel  $(x, y)$  and  $l(g_i)$  to the gradient orientation angles of the  $N$  neighbourhood pixels. The function is defined as follows:

$$s(l(g_i) - l(g)) = \begin{cases} 1 & \text{if } l(g_i) = l(g) \\ 0 & \text{if } l(g_i) \neq l(g) \end{cases} \quad (3)$$

where for each pixel  $g$ , let  $\varphi(\nabla_g)$  denotes its gradient orientation angle. We partition the gradient orientation space uniformly into four subspaces. Pixels with gradient orientations fall in the same subspace are considered as with the same gradient orientations. More precisely, each pixel is given one of the four labels according to its gradient orientation. Then for each pixel  $g$ , its label  $l(g)$  is

determined by equation:

$$l(g) = \begin{cases} 1, & \text{if } \varphi(\nabla_g) \in [0, \frac{\pi}{2}) \\ 2, & \text{if } \varphi(\nabla_g) \in [\frac{\pi}{2}, \pi) \\ 3, & \text{if } \varphi(\nabla_g) \in [\pi, \frac{3\pi}{2}) \\ 4, & \text{if } \varphi(\nabla_g) \in [\frac{3\pi}{2}, 2\pi) \end{cases} \quad (4)$$

Fig. 2(b) shows the resulting binary numbers assigned to each neighboring pixel by using Equation 3. LGOBP encodes the second order pixel-wise information as the gradient orientations of each pixel already contain the first order pixel-wise interaction properties, while LBP only considers the first order information as it thresholds the neighboring pixels by only comparing their intensities to the intensity of the center pixel. LGOBP is also monotonic gray-level transformation invariant because although the gradient magnitude of each pixel changes according to monotonic gray-level transformation, their gradient orientations remain the same.

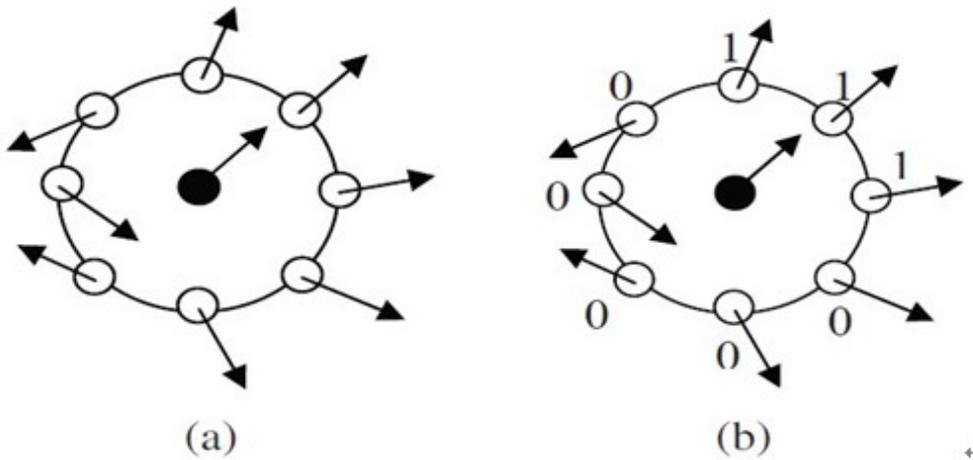


Fig. 2: (a) Arrows are representing the gradient orientations of different pixels; (b) Binary numbers are assigned to each neighboring pixel by applying Equation 3.

The original LBP operator worked with the  $3 \times 3$  neighbourhood of a pixel. Then, the texture similarity measure  $S^T(x, y)$  at the pixel  $(x, y)$  is computed as follows:

$$S^T(x, y) = 1 - \frac{|T_{LGOBP}^C(x, y) - T_{LGOBP}^B(x, y)|}{255} \quad (5)$$

where  $T_{LGOBP}^B(x, y)$  and  $T_{LGOBP}^C(x, y)$  are respectively the texture LGOBP of pixel  $(x, y)$  in the background and current images. Note that  $S^T(x, y)$  is between 0 and 1. Furthermore,  $S^T(x, y)$  is close to one if  $T_{LGOBP}^B(x, y)$  and  $T_{LGOBP}^C(x, y)$  are very similar.

### 2.3 Feature Importance Measure

Now we take into account the importance degree of the feature in the detection of shadow. Let  $\{(v_i^j, c_i^j)\}_{j=1}^n$  be set of training examples for pixel  $(x, y)$ , where  $v_i^j$  is the similarity measure value,  $c_i^j \in \{0, 1\}$  is the class label that is foreground or shadow and  $i \in \{1, 2, 3, 4\}$  is one of the four similarity measures  $\{S_1^C, S_2^C, S_3^C, S^T\}$ , which are computed as explained in section 2.1 and 2.2.

We discard the smaller similarity measure values of the set  $\{(v_i^j, c_i^j)\}_{j=1}^n$  by equation:

$$\text{if } v_i^k < T_1 \text{ then } \{(v_i^j, c_i^j)\}_{j=1}^n - \{(v_i^k, c_i^k)\} \tag{6}$$

where  $T_1$  is a constant threshold. Then a simplified set of training examples  $A_i = \{(v_i^j, c_i^j)\}_{j=1}^m$  is constructed, the feature importance measure at the pixel (x,y) is computed as follows:

$$S_i^I(x, y) = |A_i| \times Entropy(\{c_i^j\}_{j=1}^m) \tag{7}$$

where the entropy of the set of binary values  $\{c_i^j\}_{j=1}^m$  with the mean value  $c \in [0, 1]$  is defined in a standard way:

$$Entropy(\{c_i^j\}_{j=1}^m) = -c \log c - (1 - c) \log(1 - c) \tag{8}$$

### 3 Aggregation of Multiple Measures by Choquet Integral

Shadow can be detected by the fusion of multiple measures with a Choquet integral. We first compute the feature importance measure using a set of training examples. And then We use the well-known Gaussian Mixture Model (GMM) described in [10] to detect the moving pixels, including objects pixels as well as the shadow pixels. For each pixel of the differential image, color and texture similarity measures are computed from the background and the current frame. We defined the set of criteria  $X \in \{x_1, x_2, x_3, x_4\}$  with,  $(x_1, x_2, x_3)$ =three components color features and  $x_4$ =texture feature obtained by the LGOBP. For each  $x_i$ , let  $\mu(x_i)$  be the importance that takes the feature  $x_i$  in the decision of the shadow detection process. The fuzzy functions  $h(x_i)$  are defined in so that,  $\mu(x_1) = S_1^I(x, y)$ ,  $\mu(x_2) = S_2^I(x, y)$ ,  $\mu(x_3) = S_3^I(x, y)$ ,  $\mu(x_4) = S_4^I(x, y)$ ,  $h(x_1) = S_1^C(x, y)$ ,  $h(x_2) = S_2^C(x, y)$ ,  $h(x_3) = S_3^C(x, y)$  and  $h(x_4) = S^T(x, y)$ . Then, the Choquet integral of h with respect to  $\mu$  is computed as follows:

$$C_\mu = \sum_{i=0}^4 h(x_{\sigma(i)}) (\mu(A_{\sigma(i)}) - \mu(A_{\sigma(i+1)})) \tag{9}$$

where  $\sigma$  is a permutation of the indices such that  $h_{\sigma(1)} \leq h_{\sigma(2)} \leq h_{\sigma(3)} \leq h_{\sigma(4)}$  and  $A_{\sigma(i)} = \{\sigma(i), \dots, \sigma(4)\}$ .

To compute the fuzzy measure of the union of any two disjoint sets whose fuzzy measures are given, we use an operational version proposed by Sugeno [11] which called  $\lambda$ -fuzzy measure. Then,  $\mu(A_{\sigma(i)})$  can be computed as follows:

$$\mu(A_{\sigma(i)}) = \left[ \prod_{x_i \in A_{\sigma(i)}} (1 + \lambda \mu(x_i)) \right] / \lambda, \quad \lambda \neq 0 \tag{10}$$

where the value of  $\lambda$  can be found from the equation:

$$\lambda + 1 = \prod_{i=1}^4 (1 + \lambda \mu(x_i)) \tag{11}$$

The pixel (x,y) at position is considered as shadow if its Choquet integral value is more than a certain constant threshold  $T_2$  as follows:

$$\text{if } C_\mu(x, y) \geq T_2 \text{ then } (x, y) \text{ is shadow} \tag{12}$$

## 4 Experiments

In order to analyze the robustness and effectiveness of the proposed method, the three test video sequences (Highway I, Highway II and Guangyuan expressway) are adopted. The experimental results are shown in Fig. 1. In the shadow detection results, the moving object pixels are white, and shadow pixels are red. As shown in Fig. 3, moving cast shadows can be efficiently detected by the proposed method.

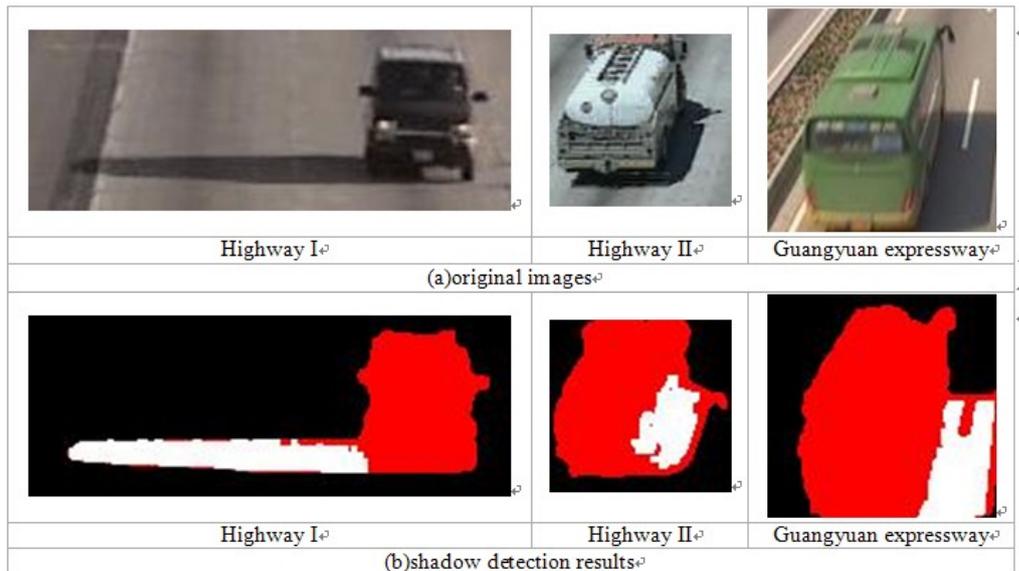


Fig. 3: Detection results in different scenes

Fig. 4 shows the detection results by some classical methods and the proposed method for the video sequences of Highway I.

To compare the performance of the proposed shadow detection with other methods, we applied these methods to the above three test video sequences by calculating the shadow detection rate and shadow discrimination rate, which are the performance metrics presented in the benchmark paper[12]. The shadow detection rate  $\eta$  and shadow discrimination rate  $\xi$  are defined as follows:

$$\eta = \frac{TP_s}{(TP_s + FN_s)} \quad \text{and} \quad \xi = \frac{TP_f}{TP_f + FN_f} \quad (13)$$

where  $TP_s$  and  $TP_f$  are the number of pixels which are determined correctly as shadow pixels and object pixels, in order.  $FN_s$  is the number of errors in which a shadow pixel is defined as an object pixel as a shadow pixel. In general,  $\eta$  is reduced with increasing  $\xi$ , and  $\eta$  is reduced with increasing  $\eta$ ; thus,  $\eta$  and  $\xi$  are a reciprocal relationship.

Table 1 shows a comparison between the proposed method and other methods in terms of shadow detecting performance.

Results were evaluated qualitatively, by visual inspection, and also quantitatively, by comparing the results with other competitive approaches using quantitative parameters. According to the above qualitative results and quantitative results, We can see that the proposed method outperforms other methods, and has better performance.



Fig. 4: Shadow detection results of different methods

## 5 Conclusion

In this paper, we have presented a novel fuzzy shadow model for detecting shadow from video sequences. A good fusion of several measuring features can strengthen the pixels classification as shadow or foreground, so this paper uses Choquet integral for fusing color features and texture features. In order to preserve invariant property of light illumination, the extended LBP is used, which encodes higher order pixel-wise information compare to the conventional LBP as it takes gradient orientations of the neighboring pixels into consideration which contain rich directional information. Three components color features can be any of color spaces(i.e. Ohta, HSV, YCrCb etc), we choose HSI color space[16]. The experiments on three test video sequences show that this method is robust and simple to implement. Further research consists in fusing other features and learning the fuzzy measures.

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Table 1: Comparison of the proposed method with other methods

Method	$\eta(\%)$	$\xi(\%)$
DNM[13]	67.94	68.57
MFFBSS[14]	70.20	75.14
GMSM[15]	75.43	73.67
KBL[2]	74.10	79.70
ASE[6]	78.74	80.07
Proposed method	81.98	84.97