Moving Cast Shadow Detection Based on Fusion of Local Binary Pattern and Gabor Features

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***Abstract*—Detecting moving objects in the video sequences is an important issue for visual surveillance. It is needed to detect the moving cast shadow to describe the moving objects correctly. In this paper, a proposed method for shadow detection based on the texture similarity between the segmented moving objects and the corresponding regions in the background image is presented. The proposed method generates texture similarity maps based on Local Binary Pattern (LBP) and Gabor features. The feature maps are fused based on Principal Component Analysis (PCA) to generate an integrated texture similarity map to classify shadow pixels. HSV color model is then exploited for validation of the shadow pixels and reduce the misclassifications of both shadow and moving objects pixels. Finally, morphological operations are used as a post-processing step to determine the final shadow regions. Experiments show that the proposed method is effective in the shadow detection process and provides high-performance rates.**

Keywords— Moving shadow detection; Gabor filters ; Local Binary Pattern(LBP); Principal Component Analysis(PCA) .

I. INTRODUCTION

Extracting moving objects in a video sequence is an important task for applications in several fields, such as video surveillance, traffic monitoring, human action recognition, smart room tracking, counting applications, and patients monitoring. The presence of cast shadows changes the shape and the size of the moving objects and thus causes false classification between background and foreground objects and decreases the robustness of many computer vision algorithms. Shadow detection methods aim to localize the shadow regions to separate and remove them from the foreground objects for reliable and accurate object detection.

In literature, a number of shadow detection methods taxonomies have been presented. Prati et al. [1] organized the various algorithms in two categories: deterministic methods and statistical methods. Deterministic methods have an on/off decision process that classify the moving object pixels into shadow and foreground pixels. Deterministic methods are subdivided into model-based and non-model based methods. Statistical methods depend on probability estimation for the classification process. Statistical shadow detection methods are subdivided into parametric methods in case of the presence of a posterior probability for the classification and nonparametric in case of defining the thresholds of classification systematically.

Recently, Russell et al. [2] divided the existing methods into object shape-property methods and shadow-property methods. Object shape-property methods need a prior knowledge of the scenes and objects to model the shadow. Although object shape-property methods achieve acceptable results, but the high complexity and time consuming of these methods are the main problems. Shadow-property methods are subdivided into light-direction methods and image-feature methods. Light-direction methods rely on the geometric features such as the location and direction of the light source and the location that shadow cast in the background. On the other side, image-feature based methods rely on extracting the features from images such as colors, edges, and texture regardless of the scene type, object type or other geometric features.

In most applications, obtaining prior knowledge about moving objects is a difficult matter. Thus, the tendency to extract distinctive features for scenes and moving objects has become an urgent necessity. Therefore, most of the existing methods tend to exploit the features to identify the shadow regions. As the shadow is considered a local change in illumination, it is important to use illumination invariant features for the shadow detection. In other words, using features that doesn't influenced by the existence of a shadow.

Methods that depend on chromaticity features put an assumption that the shadow region pixels are darker than the corresponding background pixels but preserving the same chromaticity as the background pixels. Cucchiara et al. [3] chose the color information in HSV color model for shadow detection to enhance moving object extraction. Sun et al. [4] utilized HSI color model to extract the bright object pixels in foreground regions. Then, the theory of photometric color invariants in c1c2c3 color model is exploited to distinguish the dark and colorful object pixels from shadow pixels. Dai et al. [5] derived a method based on multiple feature (intensity, color, and texture) fusion. Then, a feature map by a linear combination of these features is extracted to detect shadow pixels.

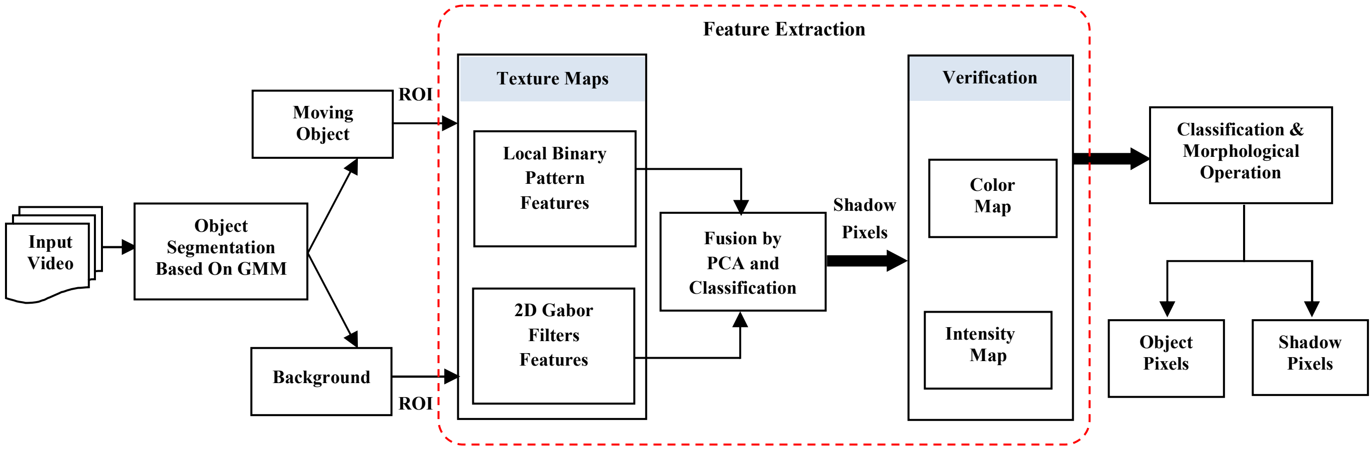


Fig. 1. Overview of the proposed method

The misclassification between the object and its shadow (if the moving object and shadow have the same color or if the object is darker than the shadow) is the drawback of chromaticity based methods. Xiao et al. [6] indicated that using edge information can overcome such limitation. The method solved the limitations of other chromaticity based methods but it fails to detect thin shadows where edges aren't clear or when the shadow regions are remote from the camera.

The texture based methods assume the similarity between the shadow region and the texture of the corresponding background region. Leone et al. [7] proposed a shadow detection method that describes the textures as redundant patches of Gabor functions. On the other side, Zhang et al. [8] employ the local binary pattern (LBP) to describe the texture information for shadow detection. Hamad et al. [9] use the entropy as a texture descriptor with the color information to detect the shadow regions. Xie et al. [10] proposed the regional gradient direction histogram to describe the texture features, which then used with color features to extract shadow pixels. All of the above methods exploit only one texture feature which cause these methods suffer from the drawbacks such as the lack of clarity of shadow regions texture under different illumination conditions. This is because the structural texture of the shadow isn't clear under high illumination conditions.

In this paper, a proposed shadow detection method based on two texture features LBP and Gabor features in addition to the utilization of the color information for the validation of shadow pixels. First, two texture feature maps have been captured for moving object region and the corresponding region in the background image based on two descriptors which are robust against illumination changes: LBP features and Gabor features. Thus, the proposed method overcomes the limitation of the texture structure that is not clear under different illumination conditions. The Gabor filtering and LBP complement each other in texture analysis, where LBP captures small and fine details while Gabor filters describe the appearance information over a wide range of scales and orientations. Then, to preserve all relevant information contained in the texture maps, the Principal Component Analysis (PCA) algorithm is exploited. PCA fuses the LBP and Gabor features that produce an integrated texture similarity map to extract shadow pixels. Finally, the HSV color model is used for the validation of shadow pixels. Post-processing operations are performed to get the refined shadow regions. Experiments and results show that the proposed method exhibits high performance in the shadow detection process and achieves high detection rates.

The remaining parts of this paper are organized as follows: Section 2 explains in details the proposed shadow detection method. Section 3 analyzes the experiments and provides the performance evaluation. Finally, conclusions are given in Section 4.

II. PROPOSED METHOD

In this section, the local texture descriptors LBP and 2D Gabor filter are used along with HSV color model for shadow detection. Fig. 1 shows the overview of the proposed method. First, the moving objects are obtained using Gaussian Mixture Model (GMM). Then, the features of the detected moving object and the corresponding region in the background image is extracted. This step includes generating similarity texture map based on LBP and similarity texture map based on 2D Gabor filters and performing a fusion by PCA for the Gabor and LBP maps which generates an integral texture map. This texture map is classified to extract shadow pixels. Finally, the validation process of these pixels based on HSV color model is performed and followed by post-processing operation to get the final shadow pixels.

A. Moving Object Detection

Before starting to detect the shadow regions, the moving objects in the video sequence should be detected and localized. The shadow is detected as a part of the moving object. There are several background subtraction techniques used for object segmentation and background modeling. In this work, the well known Gaussian Mixture Model that proposed by Stauffer et al. [11] is used to extract moving objects in the RGB color model.

To adapt to the changes in the background, GMM models the intensity of each pixel as a mixture of adaptive Gaussians. At each iteration, a simple heuristic process used to evaluate Gaussians to define which ones are maximum likely to correspond to the background. Pixels that don’t match with the background Gaussians are classified as a foreground object. Finally, foreground pixels are grouped using connected component analysis.

After obtaining the foreground image and the estimated background image, these images are exploited in the shadow detection process. An example of the moving object detection using GMM is shown in Fig.2. The first row shows the current frame, the estimated background. The second row shows the binary foreground mask including shadow, the segmented objects. The last row explores the region of interest (ROI) in the current frame and the corresponding region in the background image.

B. Feature Extraction

Assume that $I(x, y)$, $B(x, y)$ and $M(x, y)$ are the values of a pixel intensity in the current frame, the background image, and the binary mask of moving objects at coordinates (x, y), respectively.

1) Texture Similarity Map Based On LBP

The original LBP operator introduced by Ojala et al. [12] is used to capture texture information which characterized by its robustness against illumination changes and its computational simplicity. LPB describes the image pixels by thresholding the neighbors of each pixel and considers the output as a binary number. Then, LPB encodes the texture information as a histogram. As images have rich textures in the grayscale rather than binary images, both the regions of interest (ROI) in the current frame and in the corresponding background image are converted to grayscale. Then, for each center pixel in (x_c , y_c) with gray value (g_c) and the intensity value of neighbors (g_n), the mathematical LBP descriptor for a pixel (x_c , y_c) is computed as follows:

$$LBP_{P,R} = \sum_{n=0}^{P-1} f\left(g_n - g_c\right) 2^n \quad , f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{1}$$

where P is the number of neighbor pixels and R is the radius of a circle that should be small to increase the correlation between pixels. Subsequently, the texture in the current frame and the corresponding background is represented by the histogram of 2^P bins for these pattern numbers.

The histogram backprojection proposed by Swain et al. [13] is used to find the similarity between the patterns of pixels in the current frame and the corresponding background image. Histogram backprojection gives the location of the texture patterns that belong to the moving object and the corresponding region in the background image. It creates an image has the same size as that of the input image. Each pixel in the resulting image corresponds to the probability that this pixel belongs to the background image. High probability means high similarity between object and background.

Assume that h_I and h_B are the normalized two LBP histograms with respect to the current frame I and background B, respectively. The histogram ratio is calculated by taking the background histogram h_B as a target over the collage image histogram h_I . A histogram ratio R_h defined as:

$$R_h = min\left[\frac{h_B}{h_I}, 1\right] \tag{2}$$

This histogram ratio R_h is then back projected on to the original collage image $I(x, y)$ (i.e. each pixel is replaced with the value of the corresponding index of the histogram ratio).The resulting back projected image

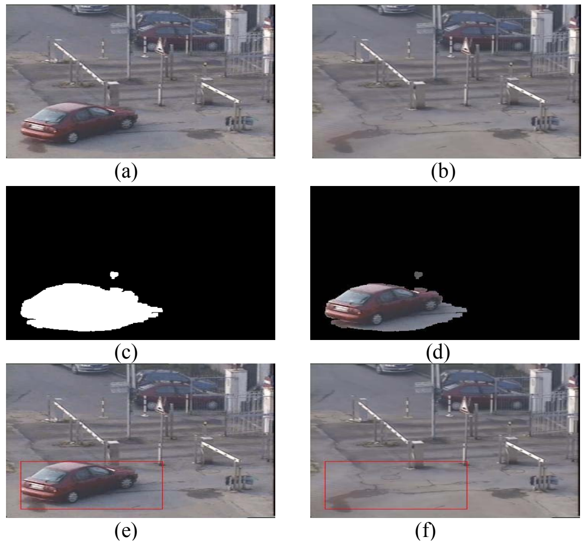


Fig. 2. Example of moving object detection using GMM. (a) Current Frame, (b) Background, (c) Foreground mask, (d) Segmented object, (e) ROI in current frame, (f) ROI in background

(LBP_{map}) shows the similarity coefficients betwwen the moving object and the corresponding region in the background image. This image (LBP_{map}) is then later used as an LBP texture similarity map besides Gabor features in the detection of shadow regions.

2) Texture Similarity Map Based On 2D Gabor Filters

Gabor filter is a band-pass linear filter that represents the frequency and orientation as similar to the human visual system [14]. It is suitable for texture representation where it measures the spatial arrangement of the intensities by analyzing whether there is any specific frequency content in the image in a specific orientation in a local region around the point or region of analysis. It is characterized by robustness against illumination changes like the shadow. 2D Gabor filter in spatial domain is a Gaussian kernel function modulated by a sinusoidal plane wave. This Gaussian kernel function is a Bi-dimensional Gaussian function centered at origin $(0,0)$ with a scale variance S modulated by a complex sinusoid with phase P and polar frequency as magnitude (F) and direction (W) described by the following equation as shown by Movellan. [15]:

$$g(x,y,S,F,W,P) = K\, G(x,y,s) * S(x,y,F,W,P) - DC(F,S,P)\,, \tag{3}$$

$$\begin{cases} G(x,y,s) = e^{(-\pi S^2(x^2+y^2))}\,, \\ S(x,y,F,W,P) = e^{(j2\pi F(x\cos W + y\sin W + P))}, \\ DC(F,S,P) = e^{(-\pi(\frac{F}{S})^2 + jP)} \end{cases} \tag{4}$$

The shape of shadow doesn't change when the object changes its orientation, therefore, one Gabor filter is enough to adopt with $P=0$ and for convenience, the Gabor features are selected with $k=1$, $W=0$, $F=0.5$, and $S=0.8$.

To analyze the texture frequencies of the current frame and the corresponding background image, first, the ROI image for both is converted to the gray level and divided into 8x8 distinct blocks. The Gabor filter representation of each block is the convolution of the block with the Gabor kernel (g) as defined by eq. (3). Since the phase information of Gabor transform is time-varying, the magnitude information is taken as Gabor features. Let *I(x, y)* be a gray level distribution image, the convolution output of image *(I)* and a Gabor kernel (g) is defined as follows:

$$gabor(x,y) = |\, I(x,y) * g(x,y) \,| \ . \qquad (5)$$

Assume that $gabor_{I(x,y)}$ and $gabor_{B(x,y)}$ are the Gabor magnitude features with respect to the current frame *I* and background *B*, respectively. To define the similarity between the Gabor texture features of current frame and background image the similarity ratio of $gabor_{I(x,y)}$ over $gabor_{B(x,y)}$ is computed as:

$$Gabor_{map} = \frac{gabor_{I(x,y)}}{gabor_{B(x,y)}} \ . \qquad (6)$$

The high ratio denotes a high similarity between textures. The $(Gabor_{map})$ is then used as Gabor texture similarity map for shadow detection.

3) Feature Fusion using PCA for Shadow Detection

Now two texture feature maps ($\mathrm{LBP_{map}}$ and $\mathrm{Gabor_{map}}$) are calculated. Instead of specifying whether the pixel belongs to the shadow in each map individually, the two maps are fused using Principal Component Analysis (PCA) image fusion algorithm to generate an integrated map which is classified for shadow detection. According to Metwalli et al. [16], PCA is a mathematical process which transforms a number of correlated variables into a number of uncorrelated variables called principal components. The illustration of PCA based image fusion algorithm is shown in Fig. 3. [17]. the input images are arranged in two column vectors and their empirical means are subtracted. The resulting vector has a dimension of *m*x2, where *m* is length of the each image vector. The following step is to compute the covariance matrix. Then, the eigenvalues and eigenvectors of the covariance matrix are calculated and the eigenvectors corresponding to the larger eigenvalues are obtained. The normalized components *C1* and *C2* are computed from the obtained eigenvector. The fused map is computed as follows:

$$Fused_{map}(x,y) = C1.\,LBP_{map}(x,y) + C2.\,Gabor_{map}(x,y) \qquad (7)$$

The fused map consists of the moving object pixels in addition to shadow pixels. Therefore, the classification decision is made by the following formula:

$$Sh(x,y) = \begin{cases} 1 & if \ \ Fused_{map}(x,y) \geq \ T \\ 0 & \qquad otherwise \end{cases} \qquad (8)$$

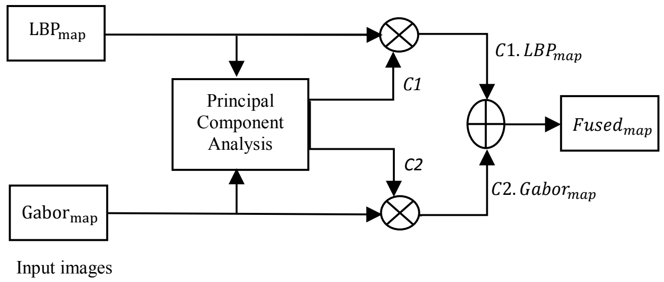


Fig. 3. Illustration of PCA image fusion

where *Sh(x,y)* is the binary mask of the cast shadow. If *Sh(x,y)* =1, this means that the pixel is labeled as shadow, otherwise the pixel belongs to the moving object. T is a constant threshold that is determined empirically , $T \in \{0\ ,1\}$.

Fig.4 shows the shadow detection results derived from different scenes based on the classification of the fused map. As shown in the figure, there are some misclassification pixels in the moving object mask and in the shadow mask. Therefore, a verification step using HSV color model followed by post-processing operation are necessity going to refine these misclassifications pixels.

4) Verification Based On HSV Model and Post-processing

As shown in Fig.4, the fusion of LBP with Gabor features provides the shadow regions effectively, but there are still some misclassifications pixels in both shadow and object masks. Therefore, the color information is exploited to verify the shadow pixels and exclude moving object pixels. According to Cucchiara et al. [3], the HSV color model is similar to human vision to colors. Also, it provides a good separation of the chromaticity from the intensity. The chromaticity of cast shadow region and the corresponding region in the background image are similar but shadow region intensity is lower than the background region intensity. Therefore, the pixel is confirmed to be a shadow if it satisfies the following classification decision in eq. (9). First, the ROI in current frame and in the background image are converted into HSV color model. Then, for all detected pixels in *Sh(x,y)* the pixel is verified a shadow pixel if:

$$shadow(x,y) = \begin{cases} 1\ ,\ if\ \alpha \leq \frac{V_{I(x,y)}}{V_{B(x,y)}} \leq \beta\ ,\cap \\ \quad |H_{I(x,y)} - H_{B(x,y)}| \leq t_h\ ,\cap \\ \quad |S_{I(x,y)} - S_{B(x,y)}\ | \leq t_s \\ 0\ , \qquad\qquad otherwise \end{cases} \qquad (9)$$

Where *H, S, V* denotes the hue, saturation and value components of the current frame $I(x,y)$ and the corresponding background $B(x,y)$. α, β, t_h and t_s are thresholds that selected empirically according to experiments. The difference

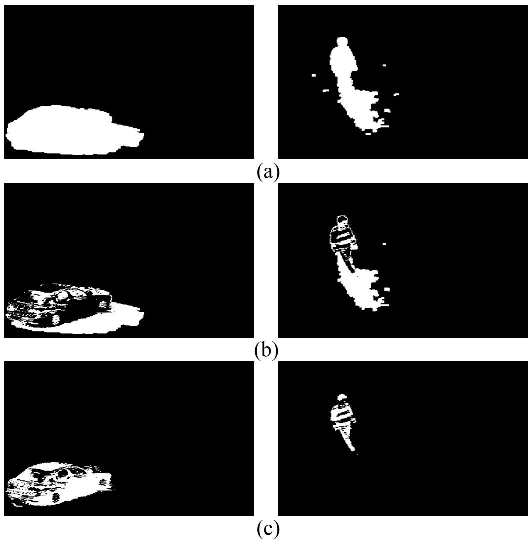
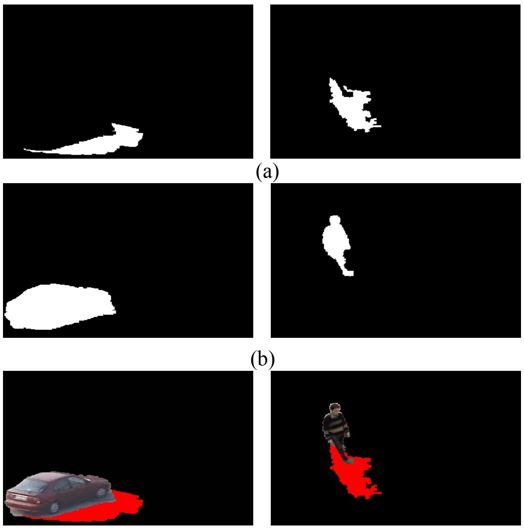


Fig. 4. The result of detection based on fusion map. (a) The moving foreground mask, (b) The binary mask of moving shadow pixels, (c) The binary mask of moving object pixels



(c)

Fig. 5. The result of shadow verification based on HSV and post-processing steps. (a) The masks of shadow pixels, (b) The masks of moving object pixels , (c) The segmented object with the detected shadow pixels

between cast shadow and background in hue and saturation is very small, therefore, t_h and t_s are small values, in this paper the values of thresholds t_h and t_s are set to 0.4 and 0.2, respectively. α and β are the thresholds of intensity ratio where α prevents to identify the near black objects as shadow and β determines the maximum effect for the darkness of shadow on the background. Generally, α and β are set to 0 and 1, respectively. $shadow(x,y)$ is the binary mask of shadow pixels. To get the moving object mask, the shadow pixels are subtracted from the binary mask $M(x,y)$ of the whole object:

$$object(x,y) = M(x,y) - shadow(x,y) \qquad (10)$$

Finally post-processing step is performed to the output images of shadow detection step in order to remove small blobs which are defined incorrectly in the shadow regions and moving objects. In this paper, the morphological reconstruction introduced by Landabaso et al. [18] is followed to reconstruct the moving objects and get the refined shadow regions. Fig.5 shows the results after shadow verification based on HSV and post-processing.

III. Experiments and Results

In this section, the performance of the proposed method is evaluated by using various real well-known dataset videos (captured using a static camera). The evaluation is performed in terms of quantitative and qualitative analysis. The results of the proposed method are compared with several cast shadow detection methods. Table.1 shows the details about the used dataset for the evaluation as the ground truths are available. The proposed method is implemented on PC with Intel core-i5, 2.5 GH using Matlab R2013a.

TABLE 1. The details of used dataset videos

Dataset	**Hallway**	**Room**	**Highway1**
Environment	Indoor	Indoor	Outdoor
Video frames	4320	718	702
Video size	320×240	320×240	320×240
Shadow effect	Light	Medium	Heavy
Objects type	Humans	Humans	Vehicles

A. Quantitive Evaluation

To evaluate the accuracy and the performance of the proposed method, two metrics which proposed by Prati et al. [1] are used: the shadow detection rate η and the shadow discrimination rate ζ, also the average detection rate μ is computed for the evaluation. These metrics are computed as:

$$\eta = \frac{TP_{sh}}{TP_{sh}+FN_{sh}} \quad , \quad \zeta = \frac{TP_{obj}}{TP_{obj}+FN_{obj}} \quad , \quad \mu = \frac{\eta+\zeta}{2} \qquad (11)$$

Where TP is the number of true positive pixels which classified correctly as a shadow or object, FN is the number of false negative pixels which misclassified as a foreground object or shadow.

The proposed method is compared quantitatively with various existing traditional and recent methods including, detection based on deterministic nonmodel (DNM) introduced in [3], detection using invariant color features(ICF) proposed in [19], detection using combined color models(CCM) in [4], detection based on multiple features fusion(MFF) in [5] and detection based on stationary wavelet transform(SWT) proposed in [20].

The quantitive metric μ (average detection rate) is computed on the selected dataset videos in Table.1. Fig.6 shows the comparison results of average detection rate with the various methods. The comparison declares that the proposed method outperforms other existing methods and achieves best results.

B. Qualitative Evaluation

In order to confirm the efficiency of the proposed method, the visual comparison results have attached in Fig. 7 where the moving object pixels marked in white and the moving shadow pixels in red colors. As shown in Fig. 7 (a) is the current frames selected from the dataset videos attached in Table.1. Fig. 7 (b) is the ground truths and from Fig. 7 (c) to (g) are the detection results of various methods and the last row (h) is the result of the proposed method.

As shown in Fig. 7, DNM has the worst detection performance in both indoor and outdoor datasets, followed by ICF and CCM, especially in highway dataset. MFF and SWT perform good detection, but the proposed method still outperforms them in both indoor and outdoor scenes.

From the previous analysis, it is concluded that the proposed method provides high performance in comparison with the various existing method in terms of quantitive and qualitative evaluation. The proposed method depends on two features (LPB ana Gabor) that emphasize image fine details and describe the appearance information. Also, the exploitation of color information decreases the misclassifications of shadow and moving object pixels.

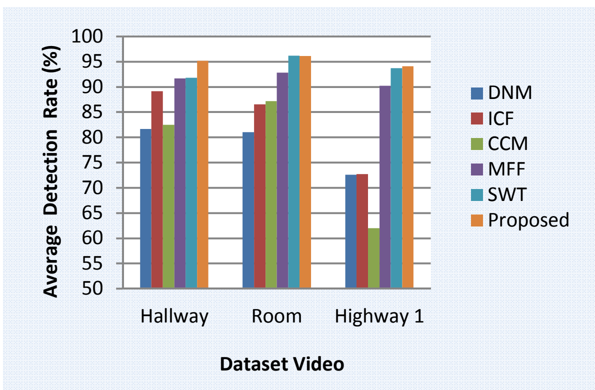


Fig. 6. The average detection rate comparison

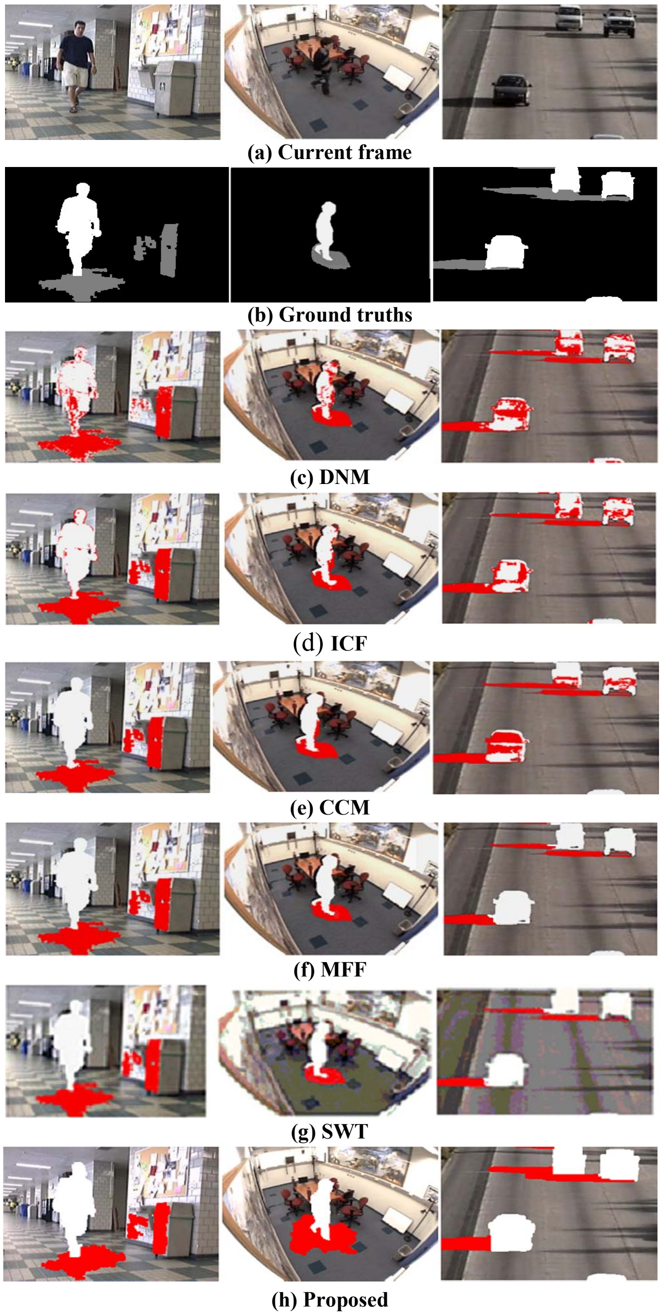


Fig. 7. The visualized comparison outcomes

IV. CONCLUSION

In this paper, a robust and accurate moving cast shadow detection method is introduced based on the fusion of Gabor and LBP feature sets. A verification step based on the HSV model is performed to decrease misclassifications of both shadow and moving object pixels. The features fusion using PCA keeps and provides fine features for shadow detection. The quantitive and qualitative evaluation declared that the proposed method achieved high performance and outperforms several existing methods. The threshold parameters in this work are empirically set. The values of these thresholds affect the performance of the proposed method; therefore a statistical modeling will be incorporated to determine values of these thresholds.

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