Detection of Moving Cast Shadow Using Pixel and Texture

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Abstract: In this paper, a new methodology for moving cast shadow detection for visual surveillance applications, efficient localization, shadow suppression, extraction of only moving foreground objects has been presented. For moving foreground object detection and segmentation, adaptive Background subtraction algorithm is presented and then using pixel based shadow detection method potential shadow pixels using the photometric characteristics of pixels has been explained. Then by employing block based shadow detection using textural characteristics has been presented, because shadow region exhibits the same textual characteristics as that of background model. Final result of shadow detection and suppression is further enhanced by employing post processing operations. This paper presented an efficient algorithm for shadow detection in such a way that, it should be unaffected by environment type, complex background, or illumination variation. Experimentation has been carried out to validate the algorithm's performance on standard metrics for both indoor and outdoor video sequences and same is reported in this paper

Key words: Background subtraction , cast shadow, n-connectivity, texture, chromaticity.

1. Introduction

The detection of moving objects from a video is regarded as a one of the crucial steps in many video processing and computer vision applications. Fig. 1 demonstrates the working architecture of smart video surveillance system.

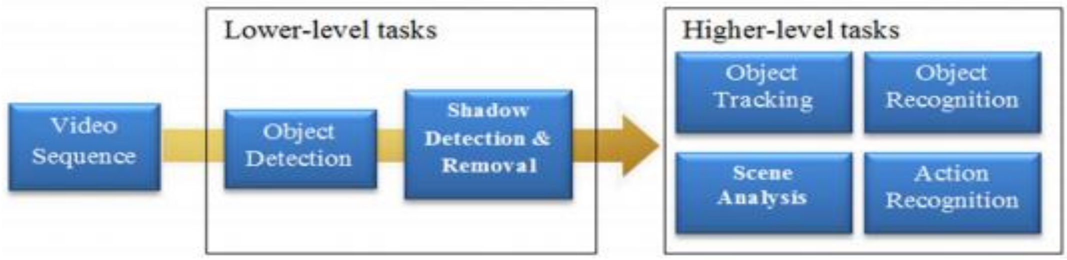

Fig. 1. Architecture of smart video surveillance system.

One major challenge one may encounter in detecting and extracting moving objects is that shadows are attached to moving objects in a video. During moving object segmentation step, distinguishing moving objects from shadows becomes very important task, because when shadows attached to moving objects, which create many complications such as, segmentation, modifications in objects shape, and losing of important texture information of background. Hence, shadow detection and suppression from actual moving object plays a pivotal role in getting the performance of computer vision applications. The detection of a shadow is a very important step, as valid actual moving foreground object may leads to misperception during successive phases of different computer vision applications such as object recognition, tracking, and segmentation etc., [1], [2]. There will be a false connectivity between foreground binary object and shadow which is explained in detail in the next section. Because of above said issues detection of cast moving shadows from the video is a very challenging research area.

A shadow is nothing but which appears when light from a source blocked by objects. Shadows can be divided into two classes, I) self-shadows and II) cast shadows. A self-shadow is on object's part itself not by direct source of light. A cast shadow generated by blockage of light by object and shadow will be on the surface. Further, Cast shadows can be sub-divided into umbra and penumbra shadows. In case of umbra, direct light is completely blocked and the in case of cast shadow direct light is partially blocked [3]. These are general information about the shadow, in next section this paper will brief about the related work researchers has conducted in the same field.

2. Related Work

One major challenge one may encounter in detecting and extracting moving objects is that shadows are attached to moving objects in a video. During moving object segmentation step, distinguishing moving objects from shadows becomes very important task, because when shadows attached to moving objects, which create many complications such as, segmentation, modifications in objects shape, and losing of important texture information of background. Hence, shadow detection and suppression from actual moving object plays a pivotal role in getting the performance of computer vision. The detection of a shadow is a very important step, as valid actual moving foreground object may leads to misperception during successive phases of different computer vision applications such as object recognition, tracking, and segmentation etc., [1], [2]. When shadow pixels are misclassified as part of a foreground object, leads to the formation of false objects as demonstrated in Fig. 2.

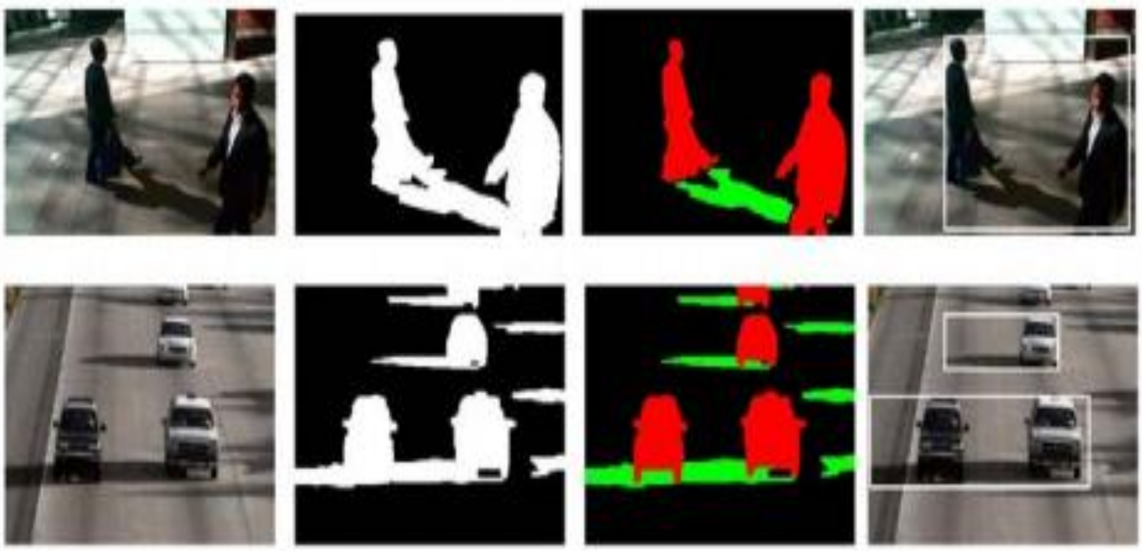

Fig. 2. Demonstration of misclassification of objects pixels with shadow a) original images with shadow b) binary mask with shadow, c) with shadow detected b) mis- classification because of shadow.

There is efficient research work has been carried out in the field of shadow detection. This section describes some of the important research contribution made by researchers to shadow detection area. Shadow detection approach is classified as statistical and deterministic approach as given in figure 3 [4].

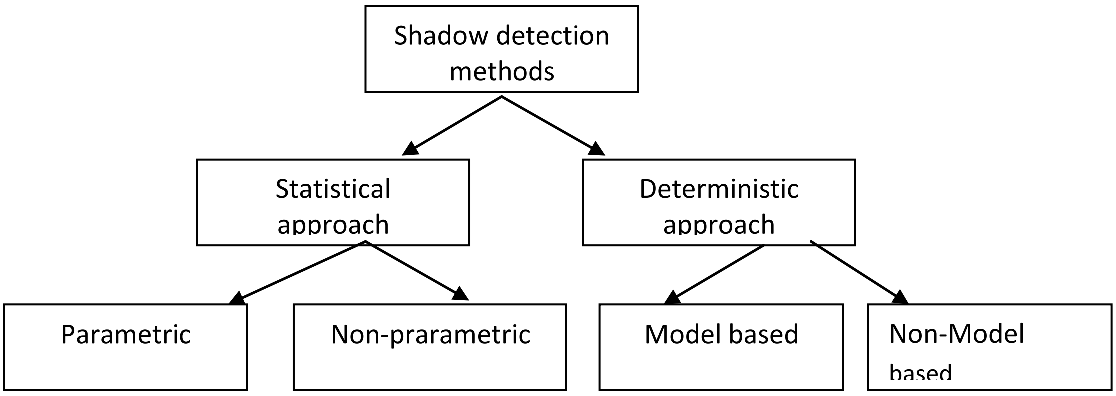

Fig. 3. Taxonomy of shadow detection approaches.

Non-model based approach of deterministic results in better output for a general purpose moving cast shadow detection which uses Hue Saturation Intensity (HIS) color space. In feature extraction for detecting shadow there are many domains spectral, spatial and temporal. Each domain is categorized into many approaches which are reckoned as a better taxonomy [5]. Under spectral class intensity, chromaticity, and physical properties are features and under spectral geometry and texture properties are important features to be used for modeling shadow. These are popular common shadow detection algorithms: Chromaticity approach [6], geometry approach [7], physical properties approach [8], small region (SR) texture-based approach [9] and large region (LR) texture-based approach [10].

Chromaticity based approach assumes that shadow regions are darker than background region in HIS color space. In geometry based approach there is an assumption that each blob objects is combination of object and shadow and it make a distinction. Physical based approach tries to build an appearance model of shadow pixels. All these above said methods are single pixel based shadow detection approaches. These methods suffer from spatial information between pixels and are computationally expensive. Next section describes some block or region based approaches to detect shadow.

SR texture-based approach extracts block/region-level correlation between regions while LR texture-based approach considers a method which distinguishes a blob area with shadow and background. All existing approaches consider single property, even which may achieve a good result in special scene but suffers when background and shadow is similar in video sequence. The proposed method extracts chromaticity for pixel based method and texture information for block based approach in order to adapt to various types of video scenes.

3. Proposed Methodology

This section presented a new approach of moving shadow detection and suppression. This method of shadow detection first makes use of background modeling using Local Binary Pattern (LBP) feature and ANN, inspired by Kohonen [11], then pixel based shadow candidates are extracted and later blocks of foreground mask is evaluated using texture feature for final shadow pixel classification.

3.1. Background Model and Foreground Extraction

This section describes and background model and foreground extraction using ANN and LBP as feature. Following is the algorithm for the same [12].

Background Model with foreground extraction:

1. 2-D Background model using LBP feature.
2. for each node
    a. j has weight vector Wj.
3. for each pixel
    a. build neural map which consists of nine weight vectors.
4. the LBP features are given input to all input nodes
5. for ech input vector, the neuron c with minimum Euclidian distance is selected.
6. background model is updated if no foreground pixel is found otherwise don't update
7. stop until all the frames in video sequence.

Fig. 4. Background subtraction algorithm.

3.2. Pixel Based Shadow Suppression

The shadow suppression approach adopted in this method which uses pixel intensity is borrowed from the literature [13] which has proved that method discussed in that paper is accurate and. The basic idea in detecting shadow is that a cast shadow makes the background darker. There is significant illumination variations especially in shadowed area, but only a small color variation will be there. If an object in the scene results in shadow pixel pt of It frame belongs to the shadow, then that pixel has been darkened by a shadow, i.e., if there exists at least one weight vector ci belonging to the model C = (c1, c2, c3, …, cn2)of pt such that

$$\left(\gamma \le \frac{p_t^V}{c_i^V} \le \beta\right) \cap \left(p_t^s - c_i^S \le \tau_S\right) \cap \left(\left|p_t^H - c_i^H\right| \le \tau_H\right) \tag{1}$$

where p_t^H, p_t^s and p_t^V represents the hue, saturation, and value respectively of pixel pt.

3.3. Block Based Shadow Extraction

This method block based shadow detection is based on fractal dimension estimation. There are different types of fractal dimension estimation in literature, the proposed method uses the method presented in [15] with some modifications and adjustments. This method leads to accurate estimation and lower execution complexity compare to other methods.

$$f_\varepsilon(i,j) = \max_{k=1,2,\dots,P_\varepsilon} \{f(i + i_{ek}, j + j_{\in k} + \beta\varepsilon\} \tag{2}$$

where $ft(i, j)$is the image intensity value in (i, j)location, $P_\varepsilon$is the number of structuring element (SE), β is constant which determines the shape of the S, and ∈ is the scale.

$$f_\varepsilon(i,j) = \max_{k=1,2,\dots,P_\varepsilon} \{f(i + i_{ek}, j + j_{\in k}\}$$

As β ∈ is independent of k, (2) can be rewritten as

$$f_\varepsilon(i,j) = max_{k=1,2,\dots,P_\varepsilon}\{f(i + i_{ek}, j + \beta\varepsilon\} \tag{3}$$

The local nature measure in a window of size W×W is defined as:

$$\mu_\in(i,j) = \frac{|f_{\in(i,j)} - f(i,j)|}{\sum_{i,j\in W}|f_{\in(i,j)} - f(i,j)|} \tag{4}$$

The measure of order q can be calculated as:

$$I(q,\epsilon) \equiv \alpha \sum_{i,j\in W} \mu_\varepsilon(i,j)^q \tag{5}$$

where

$$\alpha = \sum_{i,j \in W} \frac{|f_{\in(i,j)} - f(i,j)|}{\varepsilon} \tag{6}$$

Now, fractal dimension that is assigned to the central pixel of the window, is calculated by finding the slope of the line that is constructed using { ln(1/ ε),ln(I(q,ε)) } points.

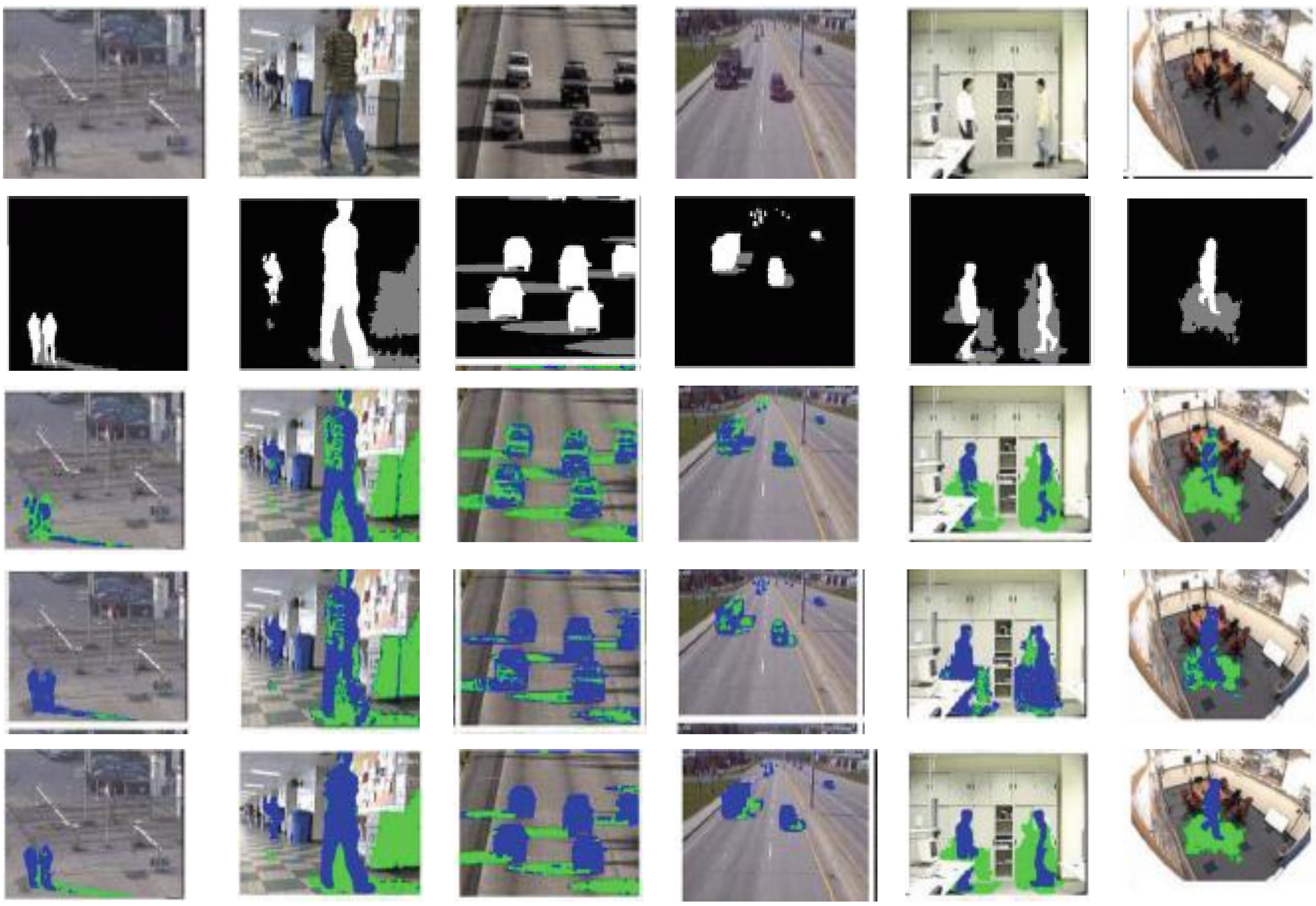

Fig. 5. The qualitative results of shadow detection. The green regions are the shadows and the blue regions are the foreground objects, (a) Campus; (b) Hall way; (c) Highway1; (d) Highway3; (e) Lab; (f) Room. 1st Row: current frame, 2nd Row: Ground Truth; 3rd Row: Chromaticity; 4th Row: SR Texture; 5th Row: Proposed Method.

3.4. Shadow Classification

Shadow regions do not change the background texture seriously as moving object regions do. This means that the fractal dimension of a background point in a window does not change seriously when shadow occurs in it. Another obvious fact is that when shadow occurs in a scene, the intensity of the related background region becomes darker. Based on the above assumption discrimination between foreground and shadow has been classified. Following is the expression for deciding whether the region is foreground or shadow.

$$\mathrm{PT}(i,j) = \begin{cases} 1 & f_t(i,j) > f_b(i,j) \text{ or } \left(\frac{\mathrm{FD}_{\max}(i,j)}{\mathrm{FD}_{\min}(i,j)}\right) > \tau_f \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where FDmax(i, j) = max(FDt(i, j), FDb (i, j))

FDmin(i, j) = min (FDt(i, j), FDb(i, j))

where $f_t(i, j)$ and $f_b(i, j)$are the foreground and background intensity values in (i, j) and τ_f is the fractal dimension threshold. Experiments have shown that a value between 1.02 and 1.2 is the best choice.

4. Results and Discussion

Six video sequences from Li dataset have been used as part of experimentation with the presented and state-of-the art methods. The results are compared for performance evaluation with pixel and chromaticity based [6], SR Texture based [17]. The shadow detection results obtained from proposed method and other state-of-art methods were demonstrated in further sections.

All the shadow detection methods including proposed, pixel-chromaticity and Texture based algorithms are implemented using MATLAB. Table 1 summarized the recall values obtained by all the methods including proposed method. The results values of recall metric obtained by proposed method outperforms all state-of-art techniques as demonstrated in Table 1.

Table 1. Recall Measure of Three Methods

Methods	Campus	Hallway	Highway1	Highway3	Lab	Room
Chromaticity	0.53	0.935	0.761	0.450	0.994	0.966
SR Texture	0.553	0.960	0.169	0.057	0.815	0.933
Proposed	0.735	0.956	0.685	0.419	0.910	0.941

The comparison of the F1 measure for all six video sequences of Li dataset has been demonstrated as graph Fig. 11. The F1 measure is a very good performance index which takes care of both recall and precision.

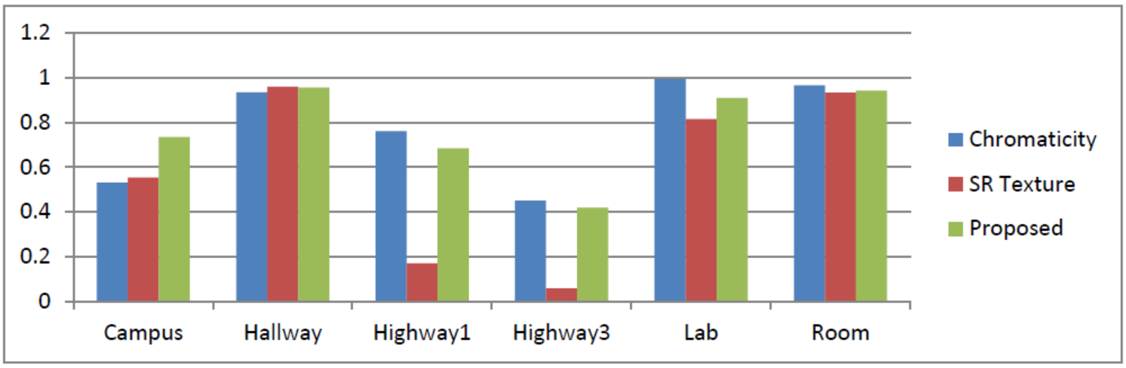

Fig. 6. F-Measure performance evaluation for different types of video sequence.

5. Conclusion

This research work is contribution of hybrid approach based on pixel and block based method to detect and suppress moving cast shadow from video sequence. This research work first uses pixel based method to extract candidate shadow pixel, which is accurate but results in more misclassification of shadow pixels and using texture region based approach, which is less accurate than pixel based but results in less amount of misclassification is proposed. Performance of the proposed method with all existing state-of-art techniques is reported. Analysis shows that proposed method is very robust and outperforms many existing algorithms for complex video sequences.

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