SHADOW DETECTION FOR MOVING HUMANS USING GRADIENT-BASED BACKGROUND SUBTRACTION

Muhammad Shoaib, Ralf Dragon, Jörn Ostermann

Institut für Informationsverarbeitung, Leibniz Universität Hannover
Shoaib@tnt.uni-hannover.de

ABSTRACT

Cast shadows cause serious problems in the functionality of vision-based applications, such as video surveillance, traffic monitoring and various other applications. Accurate detection and removal of cast shadows is a challenging task. Common shadow detection techniques normally use color information, which is not a reliable base in every scenario. This paper presents a novel scheme for real time detection of cast shadows using contour like structures of objects, which are obtained by gradient-based background subtraction. The scheme does not use any color information. Two basic rules are followed for shadow detection. The first rule is that shadows do not change the texture of the background. The second rule is a cast shadow lies outside the boundary of an object and has a relatively small common boundary with the object. Experimental results show the performance of the proposed scheme. Objective evaluation shows that the algorithm classifies 90 percent of the pixels of the objects and their shadow correctly.

Index Terms— Shadows, background subtraction, video surveillance.

1. INTRODUCTION

Applications, like automatic video surveillance, require accurate detection of moving objects from video sequences. Foreground object detection is normally done using techniques such as background subtraction, optical flow and temporal differencing [1]. Foreground object detection techniques are often affected by the shadows. The shadow causes serious problems in the segmentation and extraction of the objects. These problems include the merging of objects, classification of background as foreground, distortion of the objects shapes and missing objects. Since later processing stages, like object classification and tracking depend upon the accuracy of the object segmentation, it is very important to deal with shadows.

A number of shadow detection schemes have been reported in past literature [2]. Most of the real-time shadow detection techniques work at pixel level and use color information for shadow detection, whether it be directly or indirectly, wholly or partially. These techniques normally function by making certain assumptions about the shadow properties. Some common assumptions are: (i) a shadow darkens the background area on which it falls; (ii) a shadow only falls on the ground plane [11]; and (iii) a shadow changes luminance of an area significantly but does not impact color much. Color-based techniques often result in misclassification due to the incorrectness of these assumptions. The main reasons behind failure are; either foreground object possesses similar features as the shadow or assumed conditions do not hold in all scenarios. For example parts of the foreground object may also be darker than the background. Thus due to the failure of the assumptions, either shadow is not removed accurately or holes may result within the body of the detected object. Hence using only color information for shadow detection is unreliable. Recent literature shows a trend towards the use of texture information or region level processing for the shadow detection [3, 4, 5, 6]. In [10] authors have proposed shadow detection algorithm using color information and constraints from physical knowledge. Our paper also presents a shadow detection technique based on the texture information. Based on the output of Gaussian mixture model [7] and gradient-based background subtraction [9], we developed a morphological filter for removing shadows. The technique does not depend upon color information but the contour of the moving objects.

The rest of the paper is organized as follows. Section 2 gives the system overview of the proposed technique. Section 3 explains the design and methodology of the proposed technique. Section 4 provides some experimental results and the paper will be concluded in Section 5.

2. SYSTEM OVERVIEW

The proposed shadow detection algorithm requires two inputs. 1).Foreground objects as part of the changed area with respect to the background, present in the current frame. 2). Contours inside this changed area.

We have utilized the mixture of Gaussians method proposed in [7] for separating background and foreground, which is a slightly modified version of the background subtraction method presented by Stauffer and Grimson [8]. Using mixture of Gaussians, the recent history of each pixel is

maintained using k Gaussian distributions. K typically ranges from 3 to 5. Each distribution has its associated attributes like weight w_k, mean μ_k and variance σ_k.
For the detection of contours, we have utilized the gradient-based background subtraction presented in [9]. The work of [9] was developed for the detection of moving objects, not to be effected by quick illumination changes or relocation of background objects. The method cannot detect shadows. We use this method to detect contours in the foreground identified by the mixture of Gaussians described above.
The algorithm produces output in the form of contour like structures of the foreground objects. Sometimes the contour of an object may be partially filled (Fig 2.d). We shall refer to this contour like structure as contour in the rest of our paper.

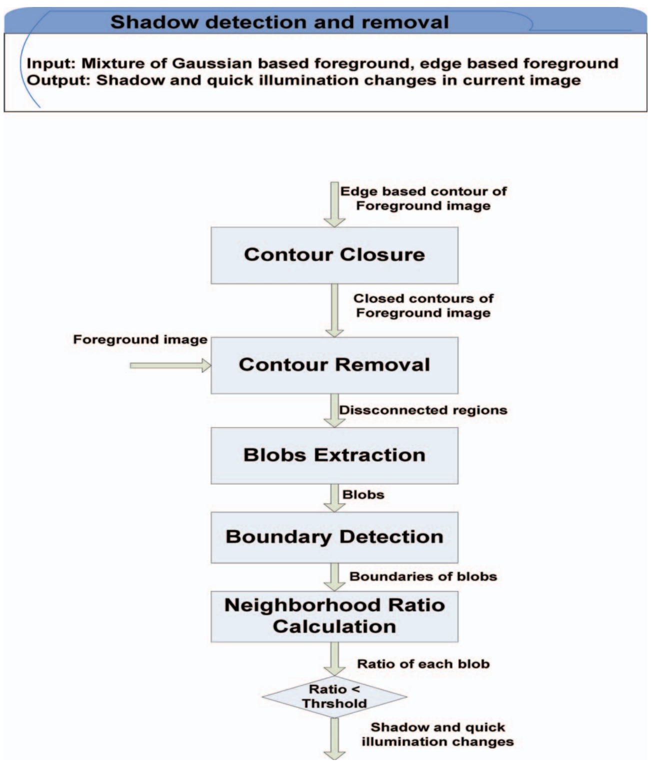

Figure 1: Flowchart for the proposed shadow detection algorithm

3. PROPOSED SHADOW DETECTION METHOD

In this section, we present our shadow detection algorithm. Gradient-based background subtraction results in at least partial contours of the moving objects [9]. Assuming that the texture is not changed by a shadow, shadow does not have any contour representation. On the other hand the mixture of Gaussians, results in the complete foreground objects but with shadow [7]. Both of the above outputs can be used together to give an acceptable foreground object without any shadow. The underlying principle behind the scheme is that anything lying outside of the object contour is a shadow. The algorithm determines the location of a shadow on the basis of its connectivity with the contour. Anything lying inside a closed object contour has more connectivity and common borders with it and is considered as a body part. Anything lying outside of this contour has relatively small connectivity and common borders with this contour and is detected as a shadow. Shadows being outside of the object contours have both internal and external boundaries. The internal boundary is adjacent to the object contour. Quick illumination changes do not result in changed areas, since they do not result in contours. The technique successfully removes the shadows and quick illumination changes in most cases. Figure 1 provides a flowchart of the proposed shadow detection algorithm; Figure 2 shows the internal processing results of the proposed algorithm. The algorithm is based on the following steps:

3.1. Contour closure

First short contour segments of less than 10 pixels are removed from the image obtained from gradient-based subtraction.
The boundary of the detected contours is not always completely closed, which may result in performance degradation of the algorithm. Hence, a fast blind contour closure is done. For every foreground pixel, the right and bottom pixels are checked for a foreground neighbor and if present the process moves to the next foreground pixel. If this is not the case then the search is continued in the similar direction, until a certain corresponding limit T_{vert} or T_{horz} is reached. If we found a foreground pixel within the limit, then the two foreground pixels are connected by changing the in between background pixels to foreground. Otherwise process moves to the next foreground pixel without making any changes. This fast procedure may result in extra filling with in the contour. This extra filling does not harm the shadow detection procedure since only the outside of the closed contour is of interest. (Fig. 2. e)

3.2. Contour removal

Gradient-based contours are then removed from the color-based foreground. The process results in a number of blobs identified by connected component analysis. These blobs may lie inside or outside the objects contours. (Fig. 2.f)

3.3. Boundary detection

The boundaries around each blob are calculated for further processing. (Fig 2.g)

3.4. Neighborhood Ratio calculation

For every blob, a neighborhood ratio is calculated. For each boundary pixel in a blob, its 8-neighbors are checked if they overlap with the object contour (Fig 2.e). If either of the 8-neighbors exists, a match count M_c is incremented.

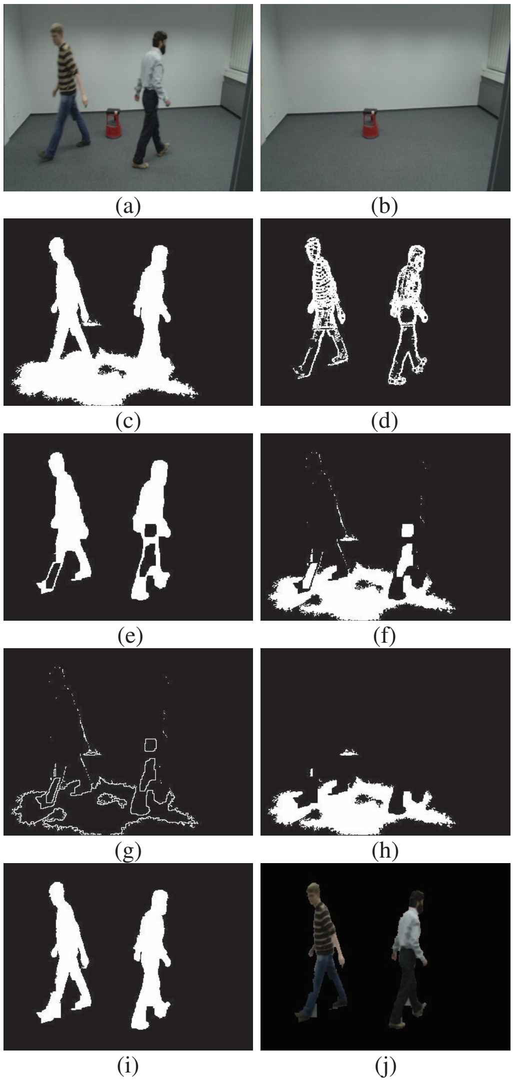

Figure 2: Illustration of the shadow removal process using sequence Office. (a) Current frame. (b) Background for the corresponding frame. (c) Foreground objects detected using mixture of Gaussians [7]. (d) Contour of foreground objects detected using gradient-based background subtraction [9]. (e) Contours of the objects after closure. (f) Parts of the foreground as candidate shadow. (g) Boundary of the candidate shadows. (h) Shadows after applying neighborhood ratio. (i) Binary masks of foreground objects after shadow removal. (j) Final foreground objects after shadow removal.

At the end of the process, the neighborhood Ratio, N_r, for a blob is calculated by dividing its match count, M_c, by its total number of boundary pixels, B_c.

$$N_r = \frac{M_c}{B_c} \tag{1}$$

If the neighborhood ratio, N_r, of a blob is less than a threshold, T_N, then the blob is considered a shadow region and is discarded from the color-based background subtraction result (Fig 2.h, 2.i). On the other hand, the quick illumination changes normally do not neighbor the edge based contour, and are automatically removed. Since the gradient-based background subtraction can deal with quick illumination changes, our algorithm maintains this property.

Finally an erosion operation is performed to smooth the boundaries of the objects.

4. EXPERIMENTAL RESULTS

The shadow detection mechanism has been tested for different indoor and outdoor scenarios. Assuming vertically elongated objects, (humans) the threshold T_{vert} is set to 12 and T_{horz} to 8. Threshold T_N for the neighborhood Ratio N_r is set to 0.6. T_N value 0.6 specifies that less than 60% of the shadow boundaries are connected to object contour. Figure 3 shows results to verify the quality of the shadow detection algorithm. The top row shows original frames from the test sequence Hall Monitor. The second row shows the detected foreground objects using mixture of Gaussians. The bottom row shows the foreground objects after shadow removal by the proposed algorithm. More results are available at [12].

In order to quantify the objective performance of the algorithm, we use metrics mentioned in [10]. The authors propose evaluation of shadow segmentation through the evaluation of video object segmentation. The objective evaluation is performed with respect to ground-truth segmentation. Two types of errors can be defined in each frame, n, of the sequence, namely false positives, $\varepsilon_p(n)$, and false negatives, $\varepsilon_n(n)$. False positives are pixels incorrectly detected as belonging to the object mask, while false negatives are undetected pixels, belonging to the object but not detected. If Card(C (n)) represents the number of pixels detected as object pixels at frame n, and Card (C_g (n)) the number of the pixels belonging to the ground-truth, then we compute the deviation from the reference segmentation as:

$$\varepsilon(n) = \begin{cases} 0 \ \ if \ \ Card(C(n)) = 0 \wedge Card(C_g(n)) = 0 \\ \dfrac{\varepsilon_n(n) + \varepsilon_p(n)}{Card(C(n)) + Card(C_g(n))} \quad otherwise \end{cases} \tag{2}$$

Where ε(n) is in [0, 1]. The spatial accuracy of the segmentation result is then quantified by:

$$\boldsymbol{v}(\mathbf{n}) = \mathbf{1} - \boldsymbol{\varepsilon}(\mathbf{n}) \tag{3}$$

That takes again values in [0, 1]. If v(n) = 1 then there is a perfect match. The accuracy of the algorithm has been tested for test sequence Hall Monitor for comparison. The mean value of spatial accuracy is observed to be 0.90 and it is valid for $0.5 < T_N <= 0.8$. [10] has a spatial accuracy of about 0.86 for the test sequence Hall Monitor. The spatial accuracy for test sequence Office is 0.92. The algorithm has been implemented in C++ and processes 20-30 frames a second for a frame size of 240x352 pixels. The algorithm has been tested on a 2.00 GHz Pentium 4 machine with memory size of 512 MB.

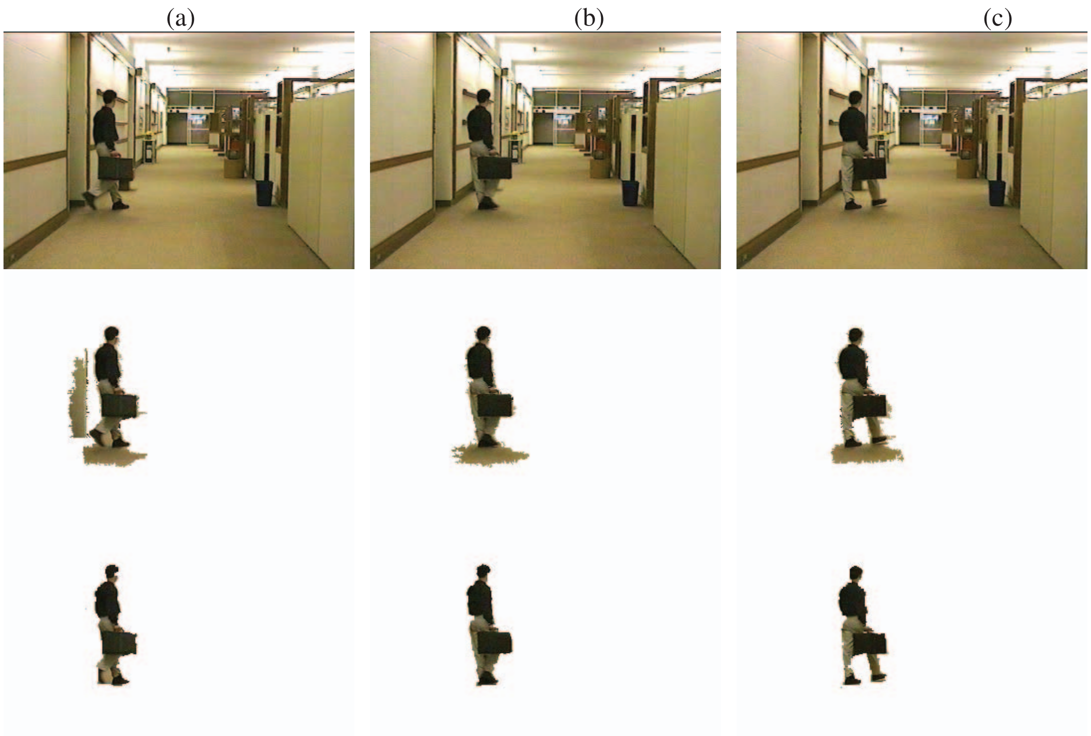

Figure 3: Results of proposal shadow detection and removal method. Top row: frames of the video sequence Hall Monitor. Second row: detected foreground objects with shadows. Bottom row: foreground objects after shadow removal.

5. CONCLUSION

In this paper, a new robust and reliable shadow detection and removal approach has been presented. The approach detects a shadow on the basis of its location, with respect to object contour and its neighborhood ratio with the object contour. Two basic rules are followed for shadow detection in the proposed method. The first rule is that Shadows do not change the texture of the background. The second rule is a cast shadow lies outside the boundary of an object and has a relatively small common boundary with the object. The approach classifies 90 percent of the pixels of objects and their shadows for generic indoor and outdoor scenarios without any manual adaptation correctly. The proposed shadow removal algorithm works in real time and can be used in or incorporated within video surveillance systems and other vision-based applications.

11. REFERENCES

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