Statistical Background Modeling: An Edge Segment based Moving Object Detection Approach

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Abstract

We propose an edge segment based statistical background modeling algorithm and a moving edge detection framework for the detection of moving objects. We analyze the performance of the proposed segment based statistical background model with traditional pixel based, edge pixel based and edge segment based approaches. Existing edge based moving object detection algorithms fetches difficulty due to the change in background motion, object shape, illumination variation and noise. The proposed algorithm makes efficient use of statistical background model using the edge-segment structure. Experiments with natural image sequences show that our method can detect moving objects efficiently under the above mentioned environments.

1. Introduction

Detection of moving object is an important research topic for the past few decades covering prevalent applications in a variety of disciplines. A simplest but popular method for moving object detection is background subtraction. Here, moving objects are obtained by subtracting background reference image from current image followed by thresholding. Choosing optimum threshold value is application dependent and very difficult to achieve. Detecting moving object becomes more challenging where there are motion variations in the background. Background modeling is thus the core technique for background subtraction based methods. There are extensive surveys on moving object detection methods [14], [9]. To model background is time consuming and complex. Moreover, modeling every background pixel is difficult since intensity feature is very prone to illumination change. It also suffers from dynamisms of the environment [6]. Thus, some methods try to improve the performance of background modeling by utilizing spatial features like edge, corner, contour of the boundary, etc. [14] Edge is more robust than intensity in the illumination changing situation. Edge extraction can significantly reduces data access rate and discard less useful information by keeping important structural property of an image [17]. Thus, processing edge image is much faster than processing intensity image. These features attract many researchers to work with edge information for various application domain including object detection, tracking, change detection, recognition, etc. Existing boundary based moving object detection methods use edge differencing [12]. However, they treat every edge pixel individually. Most of the existing edge pixel based approaches suffer from random noise. Pixel by pixel matching of edge segments is not suitable for matching due to higher computational cost. Edge segments extracted from each frames does not always shows consistency within frames. Kim and Hwang detected moving objects from sequence images by using edge differencing method with a combination of three edge map [10]. Using edge pixel differencing method they compute current moving edges and temporary moving edges. Finally, moving edges are determined by applying logical OR operation between them. Their method does not update the background model. Thus, the method cannot handle dynamic background and results in higher false alarm. To solve the problem of handling dynamic background, Dailey et al. [4] computes moving object without using any background. In their method, two edge maps are extracted from the edge difference image of three consecutive frames. Finally, the moving edges are extracted by applying logical AND operation between the two edge maps. Here, the method makes exact matching between edge pixels from the two edge maps. Due to random noise or small camera movement, edge pixel position may change in consecutive frames. Therefore, exact edge matching is not sufficient to detect moving objects. The method also fails to detect slowly moving objects and thus cannot be used for real-time applications. Hossain et al. [8] utilizes edge segment structure while detecting moving objects. There algorithm is dependent upon some initial training frames for generating background model which should be solely ideal,

978-0-7695-4264-5/10 $26.00 © 2010 IEEE
DOI 10.1109/AVSS.2010.18

i.e., without any moving objects. In case of a surveillance area, a busy street or in a public place, it is very difficult to collect training background frames without any moving objects in it. For matching background edge segment as well as stopped moving object's edge segment (edge segments from a car that stops moving in the scene), they have used same chamfer distance [2] based matching method. Since every segment of the background does not usually have uniform motion variation, it is not suitable to use a common global distance threshold for matching them. There should be a different matching method to match background edge segment and to match moving edge segment for the robustness of moving edge detection. Our work is similar to the work proposed by Hossain et al. [8], but we emphasize segment matching problems differently. We use a statistical background model to handle each background segment separately as the motion information of every background segment is not the same. We applied edge specific threshold value for matching every background edge segment using a Statistical Distribution Map. Moreover, our method is not dependent upon the ideal training reference frames. We can generate background model even when there are moving objects present in the scene. Hence, our method overcomes the drawbacks of the method proposed by Hossain et al.

In our method, we extract edges from video frames using canny edge detector [3] and then represent them as a structure of edge segments using an efficiently designed edge class [1]. We do not process intensity values individually rather all the edge pixels of a segment are processed together. We employ statistical background model to adapt the motion variation of the background environment. The proposed method detects background edge segments using Statistical Distribution Map (SDM), and verifies moving edge segments using Chamfer Distance Map (CDM) [2]. To solve the problem of dynamic background, background model updating scheme is used to handle the change in background scene and illumination variation. Our method can tolerate camera jittering or calibration error in a limited scale. It takes less time to process since we do not need to search every edge pixel individually unlike the traditional methods. Thus, our method utilizes the robustness of edge segment structure and utilizes statistical background model to facilitate fast and flexible edge segment matching for the detection of moving object.

2. Background Modeling

Background modeling is used to adapt the change in the dynamic environment. It is very challenging for every background subtraction based method. Traditional method utilizes temporal differencing or optic flow based method. The temporal differencing method utilizes two or more consecutive frames to extract moving regions [11]. Optical flow uses the characteristics of flow vectors of the moving objects over time [13]. If the background contents are not visible for long time, all these methods will fail to generate accurate background model. These methods are vulnerable and prone to false detection, if the temporal changes are generated by noise or illumination change due to weather condition [7]. Considering the robustness, suitability and reduced data access rate, current research has focused on the benefit of edges structure in processing sequence images. But edges show shape and size variation within frames due to the changes in illumination and noise. Moreover, the variations for different edges are not the same. Without considering this variation from the environment, detectors output cannot be reliable. To solve this problem, we represent edge as segment, that allows us to incorporate knowledge to every edge segment about its motion, shape, position, and size variation. And thus, it helps us to model the environment using the statistics of all edge segments. Fig. 1 describes the necessity to incorporate statistical information for background modeling. As is shown in Fig. 1, edges in reference image change their position due to illumination variation, noise, reflectance and for the movement in the air. Fig. 1(a) shows a sample background reference image. Fig. 1(b) is composed of reference edge list extracted from a single reference image. Fig. 1(c) is made from the superimposition of twenty five reference edge lists. It is clear that edges change their position and thus the edges in the superimposed edge image have thick lines. This thickness of the line indicates the movement statistic for that corresponding reference edge segment. Again, from Fig. 1(d), which is made from 50 reference edge images, we see that the movement statistic for different reference edge segments is different. Thus, in our proposed method, we treat them differently, i.e., segments having small motion variation statistic will be matched with a high threshold, while a low threshold may be used for those having large motion variation (e.g. the branches of a tree).

3. Structure of the Proposed Method

The proposed method includes statistical background modeling, the verification of moving edge segments, and updating the temporary background model. The system maintains two background reference edge lists and a moving edge list. The first reference edge list is Static Background Edge List (SBEL), obtained by accumulating the training set of extracted background edge image followed by thinning. The other reference edge list is the Temporary Background Edge List (TBEL) that is updated at every frame. Moving Edge List (MEL) is composed of moving edges, detected at current frame. Each edge segment in the three lists has its position, motion, size, and shape variation information. Additionally, edge segments from TBEL and MEL has a weight value with them. TBEL is formed by including edge segments from MEL having higher weight

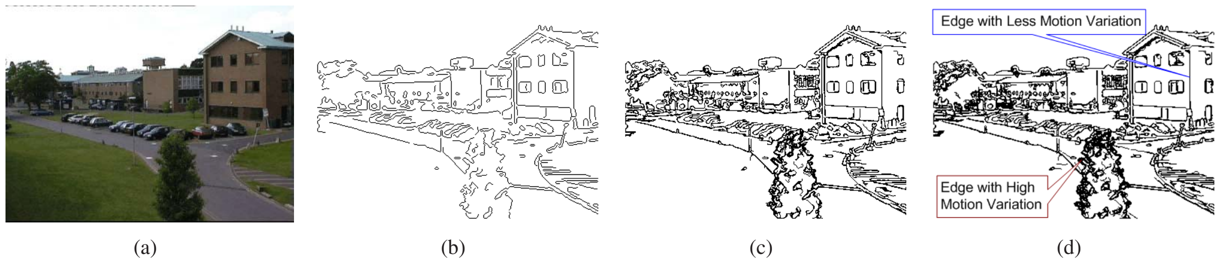

Figure 1. (a) A sample background reference image. (b) Edges from a single background reference image. (C) Edges from 25 superimposed background reference edge images. (d) Edges made from the accumulation of 50 superimposed background reference edge image.

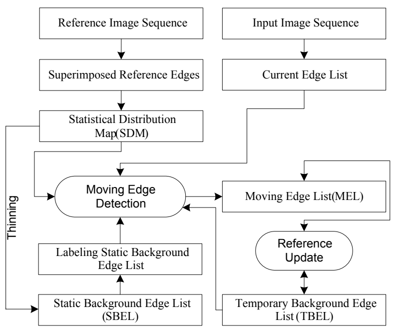

Figure 2. The framework of the proposed moving edge detection method.

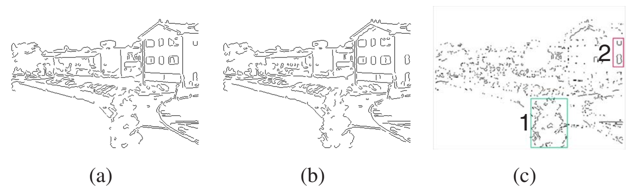

Figure 3. (a)-(b) Edge segments from two consecutive frames. (c) Difference of (a) and (b).

value. Therefore, moving edge segments staying in the same position for longer period of time is considered as temporary background edge. The framework of the proposed moving edge detection method is given in Fig. 2.

3.1. Edge Segment based Statistical Background Model

Accuracy of matching background edges in a video sequence suffers from position and shape variation in different frames due to illumination change, background movement, camera movement and noise. This variation differs from edge to edge even for the same scene. Fig. 3 illustrates the characteristics of background edges for consecutive frames. Fig. 3(a) and Fig. 3(b) shows two consecutive background edge image. Fig. 3(c) shows the edge difference image of those two images. From Fig. 3(c), the region labeled '1' contains the moving edges from a tree with noise and the region labeled '2' has illumination variation. Thus, in the edge difference image, we have more compact edge segments in those regions compared to the other regions. It is obvious from Fig. 3 that, we should model every background edge segment individually unlike traditional global common distance threshold based methods.

Edge segment based statistical background model can estimate background edge behavior by observing a number of reference frames and thus can keep the statistics of motion variations, shape, and segment size variation for every background edge segment. This statistic helps to improve background edge matching accuracy by setting edge specific threshold. To calculate and incorporate this knowledge of edge variation, we represent edges as segments by using an efficiently designed edge class.

3.1.1 Generation of Static Background Edge List (SBEL)

The proposed method is capable to generate background reference edge list with moving objects in the training frames for a limited scale. Initially, edges from the training frames are first extracted and then we accumulate first N reference edge images using Eq. 1 and create accumulated reference edge image (AREI).

$$AREI(i,j)^{(E,N)} = \sum_{p=1}^{N}\sum_{q=1}^{M_p} f((i,j),e_{p,q}) \qquad (1)$$

Here, $E = \{e\}$ is the edge map of an image, N is the total number of frames used to generate AREI, M_p is the total edge segments on the p^{th} training image and the function $f((i,j),e_{p,q}) = 2$ if point (i,j) is over the edge $e_{p,q}$, $f((i,j),e_{p,q}) = 1$ if point (i,j) is over one of the eight neighbors of $e_{p,q}$, and $f((i,j),e_{p,q}) = 0$, otherwise.

To reduce the effect of moving edges from AREI and to reduce contribution from fluctuating unstable edges, we threshold AREI with a constant and thus we produce Statistical Distribution Map (SDM) for the background. We create SBEL from this SDM by using a thinning algorithm over the SDM. Thus we extract thin edge segments from SDM through the mid position for every thick line. We then create edge segment labeling map for the extracted SBEL

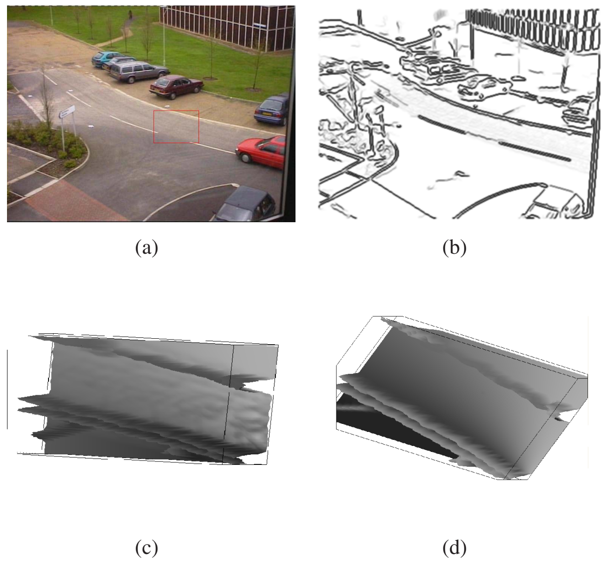

Figure 4. Background reference edge image accumulation from training images containing moving objects. (a) A sample background reference frame with moving objects. (b) Generated AREI. (c) 3D profile of AREI for the selected region in (a). (d) 3D profile of SDM for the same region.

edge segments using SDM as shown in Fig. 5(d). The labeling map thus represents the search boundary for that label corresponding edge segment during matching. We also set edge specific threshold for every SBEL segment by calculating the score of each SBEL segment over the SDM. $T\%$ of the score for every segment is set as the threshold value for that segment. Fig. 4 shows a sample reference frame with moving objects in it. We use a total of 50 reference frames and all these frames have some moving objects. AREI is shown in Fig. 4(b). Since we have more accumulation of background edge segments in AREI, background edges will create higher peak in the profile image of AREI which is found in Fig. 4(c). After thresholding AREI we create SDM, see Fig. 4(d), where it is clear that the SDM is not influenced by the edges of moving objects.

3.1.2 Flexible Background Edge Segment Matching

The background edge segment matching in our proposed method utilizes background edge segments statistic. Thus, background edges that has high motion variation statistic will be matched with wider region and background edges having less motion variation will be matched with small search region. Thus the proposed method utilizes edge specific flexibility during matching background edge segments that drastically reduces false alarm rate. Now for a given sample edge segment l, to determine whether it is a background edge, we compute distance SD by summing the superimposed pixel positions over the SDM for that segment by using Eq. 2.

$$SD[l] = \frac{1}{4N}[\frac{1}{k}\sum_{i=1}^{k} D(l_i)] \qquad (2)$$

Here, k is the number of edge point in the sample edge segment l, $D(l_i)$ is the i^{th} distance value over the SDM for the l^{th} edge segment and N is the total training image used to build the SDM.

From the labeled image of SBEL, we can find the corresponding background edge segment and its threshold directly. If no corresponding background segment is found then the segment is a moving edge segment. If the computed SD value is less than corresponding background segment threshold, then the segment is also moving edge segment. Otherwise, it is a background edge segment.

3.2. Moving Edge Verification

Detected moving edges from few previous frames with higher weight are used to generate temporary reference edge list so that a moving object whose edges are detected at the same position for many times (moving edges detected from a stopped moving car) will not be detected as a moving object in future frames. A chamfer-3/4 distance map (CDM) [2] and a temporary background edge list (TBEL) are used to verify these moving edge segments. The distance value CD for any edge segment l can be computed by using Eq. 3.

$$CD[l] = \frac{1}{3}\sqrt{\frac{1}{k}\sum_{i=1}^{k} D(l_i)^2} \qquad (3)$$

Here, k is the number of edge point in the sample edge segment l, $D(l_i)$ is the i^{th} distance value over the CDM for the l^{th} edge segment.

To verify a moving edge segment, we create CDM for the TBEL. Now the sample edge segment is placed over the CDM and distance value CD is calculated using equation Eq. 3. If CD is less than some threshold T_{CD}, then the segment is a non moving segment otherwise it is a moving segment.

3.3. Updating the Temporary Background Edge List

TBEL is constructed by including the edge segments from MEL. If an already registered edge segment in MEL is again found in the next frame at the same position, then the weight of that segment is incremented otherwise it is decremented. A moving edge segment from MEL will be added to TBEL if the segment weight exceeds threshold T_M. Thus the segment will not appear as moving edge from later frames. An edge segment is dropped from the MEL if

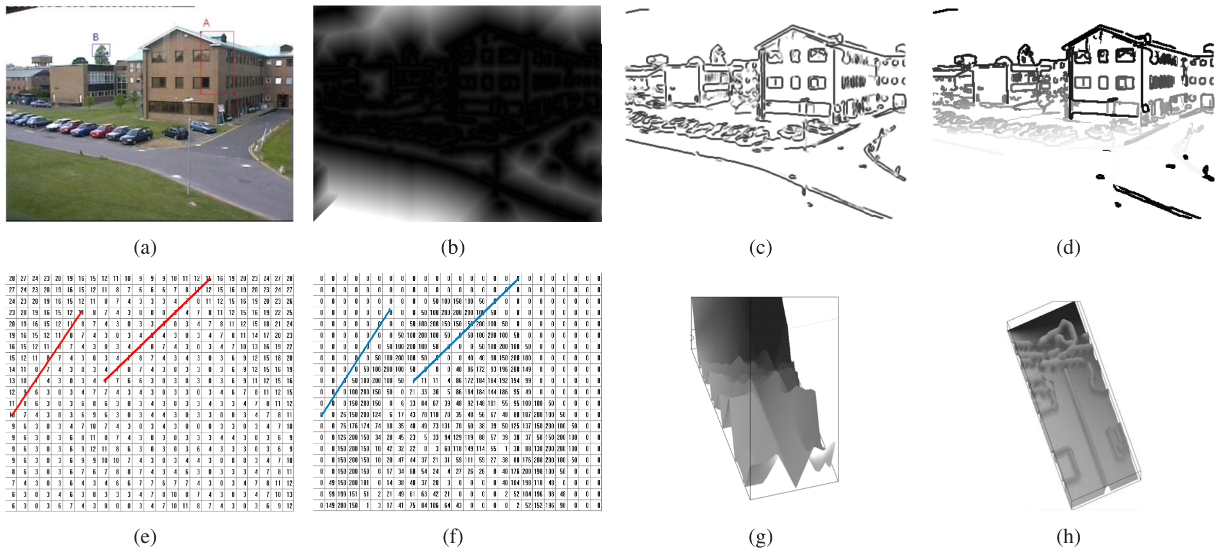

Figure 5. Distance Map used in Hossain et al. method and the proposed method. (a) A sample reference frame with two selected region labeled ‘A’ and ‘B’. (b) CDM made from 50 training reference frames. (c) SDM made from 50 training reference frames. (d) Labeling the SDM distance map of (c). (e) The Distance values of CDM in the selected region labeled ‘B’ in (a) and two superimposed line segment over the map. (f) Distance values of SDM in the same region labeled ‘B’ and two line segments in the same position as in (e). (g) CDM profile of the selected region labeled ‘A’ in (a). (h) SDM profile of the selected region labeled ‘A’ in (a).

its weight reaches to zero. Using the similar way, if a TBEL edge is not found in current input frame, the weight of the edge is decreased and is removed from the list, if the weight reaches zero.

4. Results and Analysis

We tested our method on several video sequences including corridor, parking lot, road scene and video sequences from PETS database which could be downloaded from $ftp://ftp.pets.rdg.ac.uk/pub/$. All images were of size 640×520 with background motion, illumination change and noise. The proposed system was able to detect almost all of the moving objects in the sequences. We used visual C++ and MTES [15], an image processing environment tool. Our system can process 10 frames per second. Fig. 5 demonstrates the performance of SDM over CDM. From the profile Fig. 5(g) we see uniform distance map for CDM. Thus every edge segment is matched using a common threshold. The profile Fig. 5(h) shows that every background segment has its own motion statistic. An edge segment that has high movement statistic will be matched with a wider search area and low threshold. Non moving edge segments will benefit from high threshold and narrow search region. Two synthetic edges are placed over the CDM and SDM in Fig. 5(e) and Fig. 5(f) respectively. In both of the map, the numeric value in every small cell indicates distance score an edge pixel will obtain if it passes over that point. In CDM, every entry vale ‘0’ indicates the segment to be matched with and over the SDM every value ‘200’ represents the exact position for the corresponding matched segment (since we have used 50 training reference images in this example). The matching score of the left most line over the CDM is 2.938, i.e., according to CDM the line is just three pixels apart from the reference background edge image. Thus the CDM will detect the above line as background edge. But in SDM the score of the same line is ‘0’. Thus, the proposed method accurately detects the line as a moving edge line. The red color in the Fig. 5(e) indicates false detection where the blue color in the Fig. 5(f) represents correct detection. Here we see that moving edges will be detected accurately while using SDM because of its statistical search boundary and automatic threshold selection. Fig. 6 shows the strength of our proposed method for changing illumination with background movement. Fig. 6(a) shows a sample input frame No. 41 of a street scene sequence. Two moving objects are (man and car) present at the scene. Due to illumination variation, Kim and Hwang [10] detects a lot of scattered edge pixels as shown in Fig. 6(b). The detection result for the Dailey and Cathey Method [4] is shown in Fig. 6(c). Dailey’s method is very sensitive to camera movement. Although in the given sequence there are no camera movement, Dailey’s method cannot give compact shape of the moving object. Instead it gives scattered pixels in the moving object region. Hossain et al. [8] can control camera movement in a limited scale but they uses chamfer distance map that uses a common threshold value for all the background segments. Selection of a lower threshold results in matching of edges with small movement variation. On

(a) (b) (c) (d) (e)

Figure 6. (a) A sample input image frame No. 41 (b) Detected moving edge image using the method proposed by Kim and Hwang (c) Moving Edge image using Dailey and Cathey's method (d) Detected moving edge segments proposed by Hossain et al. [8] (e) Moving edge segments using our proposed method.

(a) (b) (c)

Figure 7. (a) A sample image frame No. 412 (b) Detected moving edge segments using Hossain et al. method (c) Detected moving edge segments using our proposed method.

the other hand, higher threshold increases false matching of moving edge and background edge. Moving object detection in our method utilizes movement statistic of every background edge segment effectively. The detection output of our proposed method is given in Fig. 6(e). Fig. 7 shows another example where we compared our method with Hossain et al. method since both of the methods have utilized edge segment structure. Using Hossain et al. method, the waving tree branches are detected as moving edges and is found in Fig. 7(b) due to the use of a common distance threshold to match every background edge segment. Our method, Fig. 7(c), uses different threshold value and different search boundary for different background edge segments based on the statistic of that edge segment and thus can accurately detect waving tree edges correctly. The use of statistical knowledge of edge motion variation during background modeling can detect background edges accurately while keeping the foreground moving edges intact. As a result, our detection output is more accurate and thus can significantly improve the performance of video surveillance based applications. For segmenting the moving objects, we can use an efficient watershed based segmentation algorithm [16], where the region of interest (ROI) can be obtained by utilizing method [5]. To evaluate the performance of the proposed system quantitatively, we compare the detected moving edge segments with the ground truth that is obtained manually. The metric used for performance evaluation is based on two criteria: Precision and Recall and is defined in Eq. 4 and Eq. 5. Precision measures the accuracy of detecting moving edges while Recall computes the effectiveness of the extracted actual moving edge segments.

Dataset	Environment	Frames	Precision	Recall
1	outdoor	1000	92%	90%
2	outdoor	900	97%	93%
3	indoor	500	91%	85%

Table 1. Performance of the proposed moving edge detector.

The experimental result is shown in Table. 1.

$$Precision = \frac{Extracted\ moving\ edge\ pixels}{Total\ extracted\ edge\ pixels} \tag{4}$$

$$Recall = \frac{Extracted\ moving\ edge\ pixels}{Total\ actual\ moving\ edge\ pixels} \tag{5}$$

5. Conclusion

This paper illustrates the suitability of using statistical background model along with the edge segment based structure to detect moving objects for the video surveillance based applications. The strength of our approach lies in the ability to separate background edge segments from moving edge segments. To achieve this, we utilize statistical background model for background edge segment matching and chamfer distance based matching for verifying moving edge segments from the scene. Here, we focused mostly on background modeling problem. The example figures described in this paper clearly justifies the use of statistical background model, which is highly efficient under illumination variation condition and shape change situation. In our future work, we will incorporate multi frame based edge segment matching algorithm along with edge's side color distribution matching for the detection and tracking of moving edges for more sophisticated vision based applications like airport security, activity recognition, etc.

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