Moving Edge Segment Matching for the Detection of Moving Object

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Abstract. We propose a segment based moving edge detection algorithm by building association from multi-frames of the scene. A statistical background model is used to segregate the moving segments that utilize shape and position information. Edge specific knowledge depending upon background environment is computed and thresholds are determined automatically. Statistical background model gives flexibility for matching background edges. Building association within the moving segments of multi-frame enhances the detection procedure by suppressing noisy detection of flickering segments that occurs frequently due to noise, illumination variation and reflectance in the scene. The representation of edge as edge segment allows us to incorporate this knowledge about the background environment. Experiments with noisy images under varying illumination changing situation demonstrates the robustness of the proposed method in comparison with existing edge pixel based moving object detection methods.

Keywords: Edge Segment, Moving Object Detection, Multi-frame based Edge matching, Statistical Background Model.

1 Introduction

The detection of moving object has been studied extensively due to the increasing demand in vision based applications like robotics, security, data compression, activity recognition system etc. Due to the simplicity of the detection procedure, background subtraction method for the detection of moving object has gained popularity. Here, current image is subtracted form the background image with a threshold. The automatic selection of this threshold value is very hard due to the nature of the application. Detecting moving object becomes more challenging where there are motion variations in the background. Moreover, a sudden noise spike or change in illumination or reflectance from other objects can have dramatic effect over the detection performance of a system. A comprehensive literature review on various moving object detection techniques can be found in [12] and [9]. There are two types of moving object detection approaches: the region based approach and the feature based approach. In the region based approach every pixel in the background is modeled. This is very sensitive since the intensity feature is very prone to illumination change. On the other hand, feature

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based methods like edge, contour, curvature, corner, etc. tries to improve performance by utilizing feature strength, since features are less sensitive to illumination changing situation [12]. Among other feature based methods, edge based methods are popular since edge is more robust in the illumination change. Existing edge based moving object detection methods use edge differencing [11]. Kim and Hwang's method [10] uses edge pixel differencing algorithm using a static background. Thus the method gives scattered noise and cannot handle dynamic background. Dailey's method [5] computes background independent moving object by utilizing sequence image. But the method makes exact matching between edge pixels in consecutive frames. Thus the method brings out noise moreover it fails to detect slowly moving objects. Traditional edge based approaches also suffer from edge flickering. Edges flickers due to illumination variation, random noise, and reflectance from other objects. These flickering edge segments are not true moving edges. To cope with this difficulties, authors [13], tries to eliminate irrelevant edges by only selecting boundary edges. To solve edge inconsistency problems and to find object contour, authors used a multi-level canny edge map which is computationally very expensive. Even if they use multi-level canny edge map, to find a closed contour they needs to access image pixels directly, which is very noise sensitive. Edge segment based approach introduced by Hossain et al. [8], uses same chamfer [3] distance based matching method for both foreground and background edge segment. Since the characteristics of background edge segment are different from foreground edge segment, it is not suitable to use a common distance threshold for them. Moreover, their method cannot handle flickering edges that comes randomly due to the illumination reflectance of the other objects in the scene. We follow the approach proposed by Hossain et al. [8], but we have a separate evaluation technique for matching background edge and moving object edge. We use a statistical background model for matching every background edge segment separately as the motion variation of every background segment is not the same. Moreover, to overcome the problem of random flickering edges from the detected moving edges, we have used multi-frame based segment matching approach.

In the proposed method, edges from video frames are extracted using canny edge detector [4] and then we represent these edges as a structure of edge segments [1]. Here, a group of edge pixels form an edge segment and are processed together. An statistical background model adapts the motion variation of the background. Edge matching in multi-frame handles random flickering edges that evolve from the illumination reflectance of different objects by building associations within frames.

2 The Multi-frame Based Moving Edge Detection

The proposed method includes detection and verification of moving edge segments using a statistical background model for every input frame followed by building association within frames by matching detected moving edge segments.

For the detection of moving edge segments from a single frame, the system maintains two reference edge lists and a moving edge list. Static Background

Edge List (SBEL) is the first reference edge list that is generated by accumulating a number of training background edge image frames followed by thinning. Temporary Background Edge List (TBEL) is the other reference edge list. SBEL is a static list that is not updated but TBEL is updated at every frame. Moving Edge List (MEL) is made from the moving edges detected at current frame. Each edge segment in these lists has position, size and shape information. Moreover, TBEL edge segments have weight value with them.

Once moving edges are determined using a single input frame I_t, for every moving segment in that frame, we search for a matched correspondence with frame I_{t-1}. If the corresponding moving segment match is found within a distance threshold τ_d, the segment is placed in the output moving edge segment list for the frame I_t. The reason for this multi-frame match is straight forward; background model can eliminate background edges and edges from a stopped moving object from the scene but background model cannot handle flickering edges that comes occasionally by the illumination reflectance from background object or moving object. If an edge segment is true moving edge segment, it is more likely to come in consecutive frames where the flickering edges will not. The proposed moving edge detection method is given in Fig. 1.

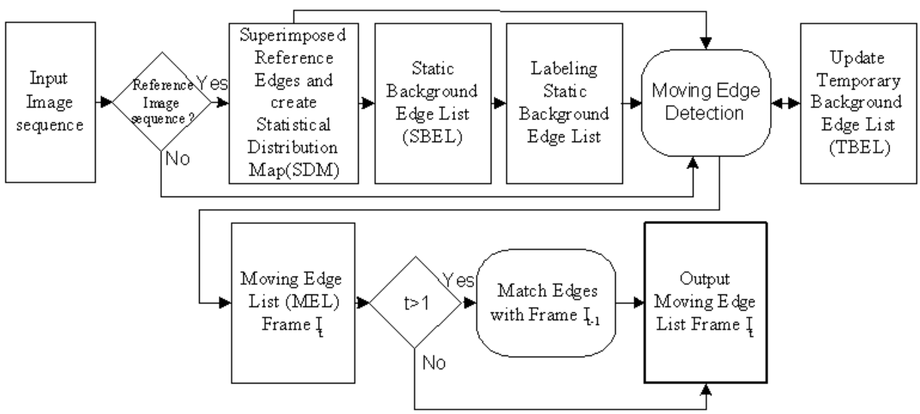
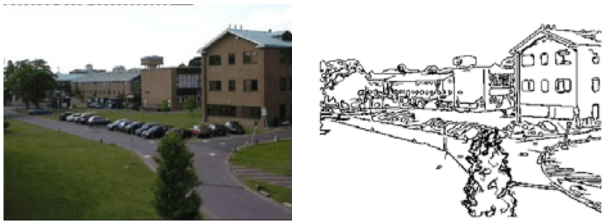


Fig. 1. The proposed moving edge detection method

2.1 The Statistical Background Model

Edges change their size and position within frames due to illumination change and noise. The amount of variation for different edge segment is different. Without considering this variation from the background, true moving edges cannot be detected.

Fig. 2 states the requirement to use statistical background model. Fig. 2(b) is made from the superimposition of twenty five reference edge lists. It is obvious that edges change their position and thus the edges in the superimposed edge image have thick lines. This thickness of the line is different for different background edge segment. Thus, in our proposed method, we treat every background



(a) (b)

Fig. 2. (a) A sample reference background frame. (B) Edges from 25 superimposed background reference edge images.

segment individually. Using the statistical frequency accumulation information for each segment, we can restrict the search boundary that can also enhance the accuracy of matching as well as the speed.

The static background edge list (SBEL). Edges from training frames are extracted and we superimpose first N reference edge images using Eq. 1 and create accumulated reference edge image (AREI).

$$AREI^{(E,N)} = \sum_{p=1}^{N} \sum_{q=1}^{z} e_{p,q} \tag{1}$$

Here, $E = \{e\}$ is the edge map of an image, N is the total number of frames used, z is the number of edge segments on the p^{th} training image. After the accumulation, a smoothing operation is performed over the AREI. To make AREI independent of training sequence, we threshold AREI with $\tau\%$ of N. Here, we emperically found that $\tau = 30\%$ gives good result. Thus after thresholding, we produce Statistical Distribution Map (SDM) for the background. We create SBEL from the SDM by thinning SDM and extracting thin edge segments from the mid positions for every thick line. We then create edge segment labeling map for the extracted SBEL edge segment using SDM as shown in Fig. 3(d). The labeling map represents the search boundary for a candidate background edge segment during matching. We also have edge specific threshold for every SBEL

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

Fig. 3. Distance Map used in Hossain et al. method and the proposed method. (a) A sample reference frame. (b) CDM made from 50 training frames. (c) SDM made from 50 training frames. (d) Edge segment labeling map over the SDM.

segment by calculating the average accumulation score of each SBEL segment over the SDM.

Background edge segment matching. The background edge segment utilizes background edge segments statistic. Thus, background edge with high motion variation statistic will be matched with wider region and vice versa. For a given sample edge segment l, to determine whether it is a background edge, we compute average accumulation score SD by averaging the superimposed pixel positions over the SDM by using Eq. 2.

$$SD[l] = [\frac{1}{k}\sum_{i=1}^{k} SDM(l_i)] \tag{2}$$

Here, k is the number of edge point in the sample edge segment l, $SDM(l_i)$ is the edge point accumulation value in the background for sample edge point position l_i. From the labeled image of SBEL, we can find the candidate background segment directly. If no candidate background segment is found then the segment is a candidate moving edge segment. Otherwise, if the computed SD value is different from the corresponding background segment's average accumulation score by $T\%$, then the segment is also candidate moving edge segment. Otherwise, it is a background edge segment.

2.2 Multi-frame Based Moving Edge Matching

The problem at hand is to build partial segment matching between the candidate moving segments found at frame I_t and frame I_{t-1}. If moving segments from a moving object are detected correctly, there should be similarities between the detected moving edges in successive frames. As we have shown segments change their position within frames but the shape changes slowly. So if a moving segment has a significant portion of partial match in some consecutive frames, we can assume the segment as a true moving segment. A segment that does not show this shape consistency is surely a flickering edge that is generated due to illumination variation or reflectance from other object and hence we should discard these segments from the list of true moving segments. There are a number of curve matching solution that considers matching curve under affine transformation [2], the registration of 2D and 3D point set [7], distance based similarity measure based on multidimensional Hausdorff distance [18], all these methods give whole to whole curve matching solution with similarity measures. But our problem statement lies on the matching of whole to part matching problem with an index of the starting point of the match. [14] and [17] provides solution for whole to part matching problems but there method computes curvature points to reduce dimensionality. i.e. there method is suitable for those aligning problems where the problem statement needs to consider sharing and scaling as well. Also there methods are expensive to use in real time applications. Since we are matching moving edges in two consecutive frames, we can simplify our assumption that the matching curves can have some translation, small rotation, and overall partial shape similarity. With this assumption, we need to match the edges considering partial shape match with translation and rotation only. The simple algorithm proposed in [15] best matches our interest. In their method two segments template segment and candidate segment are represented in slope angle-arclength space, or $\theta - a$ space by partitioning into segments of fixed arc-length a_0. In our case between a pair of segments to be matched, we assign the longer segment as candidate segment and shorter one as template segment. Matching is performed in $\theta - a$ space. During matching the template segment is moved along the a axis so that its centre is aligned with the centre of the candidate segment to which it is to be compared. The template segment is then shifted in the θ direction so that the mean θ value of the template segment has the same mean θ value as the image segment. This θ shift measures the average slope angle difference between them. The inverse of sum of the squares of these differences is used to measure the similarity between them. Finally, the location of the highest difference position along the a axis over the candidate segment is the position from where the two edge segments got match. For the details about the segment matching method please see [15].

2.3 Moving Edge Verification

Moving edges needs to be verified so that a stopped moving object is not detected as a moving object in future frames. A chamfer distance map is used to verify moving edge segments. A chamfer-3/4 distance map (CDM) [3] for the TBEL is created using Eq. 3.

$$CDM(i,j)^{(E)} = \min_{e \epsilon E} \|(i,j) - e| \tag{3}$$

Here, $E = \{e\}$ is the edge map of an image, i and j corresponds to row and column positions along the distance map. The distance value CD for any edge segment l can be computed using Eq. 4.

$$CD[l] = \frac{1}{3}\sqrt{\frac{1}{k}\sum_{i=1}^{K} CDM(l_i)^2} \tag{4}$$

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

To verify a moving edge segment, we create CDM for the high weighted segments from TBEL. Now the sample edge segment is placed over the CDM and distance value CD is calculated using equation Eq. 4. If CD is less than some threshold T_{CD}, then the segment is a non moving segment otherwise it is a moving segment.

2.4 Updating the TBEL

TBEL is constructed by adding the edges from MEL. If a moving edge is found in the same position in the next frame, the weight of that segment in TBEL is increased otherwise it is decreased. An edge segment will be dropped from TBEL if its weight reaches to zero.

3 Results and Analysis

Several experiments has been performed both in indoor and outdoor scene including parking lot, road scene, corridor. These images have background motion, illumination change, reflectance and noise. Our proposed method successfully detects almost all of the moving objects for the scene.

Fig. 4 shows the strength of our proposed method for varying illumination condition with noise. Fig. 4(a) shows a sample input frame No.890 of a street scene sequence. Four moving objects are (three people and a mini bus) present at the scene. Kim and Hwang [10] detects a lot of scattered edge pixels as shown in Fig. 4(b). The detection result for the Dailey and Cathey Method [5] is shown in Fig.4(c). Hossain et al. method [8] can control camera movement in a limited scale but in their method the selection of a lower threshold results in matching mostly rigid background edges where as higher threshold increases false matching of moving edge as background edge. Moving object detection in our method utilizes movement statistic of every background edge segment effectively. Moreover, to eliminate flickering edges the proposed method tracks edge to edge matching record from multi-frame, thereby building association within moving edge

(a) (b) (c)

(d) (e)

Fig. 4. (a) A sample input image frame No.890. (b) Detected moving edge image using Kim and Hwang's method (c) Moving edge using Dailey and Cathey's method (d) Detected moving edge segments proposed by Hossain at al. (e) Moving edge segments in the proposed method.

(a) (b) (c)

Fig. 5. (a) A sample image frame No.707. (b) Detected moving edge segments using the method proposed by Hossain et al. (c) Detected output moving edge segments using our proposed method.

segments. The detection output of our proposed method is given in fig. 4(e). Fig. 5 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, due to illumination reflectance and noise, brings out flickering edge as moving edge that is found in Fig. 5(b). Our method, fig. 5(c), uses multi-frame edge segment matching, thus only true moving edge segments will have a good match. As a result, our detection output is more accurate and thus can significantly improve the performance of video surveillance based applications.

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 is based on two criteria: Precision and Recall and is defined in Eq. 5 and 6. Precision measures the accuracy of detecting moving edges while Recall computes the effectiveness of the extracted actual moving edge segments. The experimental result is shown in Table. 1.

$$Precision = \frac{Extracted\ moving\ edge\ pixels}{Total\ extracted\ edge\ pixels} \tag{5}$$

$$Recall = \frac{Extracted\ moving\ edge\ pixels}{Total\ actual\ moving\ edge\ pixels} \tag{6}$$

Table 1. Performance of the proposed moving edge detector

Dataset	Environment	Frames	Precision	Recall
1	outdoor	500	94%	88%
2	outdoor	400	98%	90%
3	indoor	500	93%	84%

For segmenting the moving objects, an efficient watershed based segmentation algorithm [16] can be used, where the region of interest (ROI) can be obtained by utilizing method [6].

4 Conclusion

This paper illustrates the suitability of using multi-frame based moving object detection method along with the statistical background model using segment based structure for the detection of moving object. Here, we utilized an efficient partial edge segment matching algorithm for inter-frame segment matching, a statistical background model for background edge segment matching and chamfer distance based matching for verifying moving edge segments from the scene. Our proposed method can eliminate flickering edges that comes occasionally. The example figures described in this paper clearly justifies the advantages of using statistical background model along with multi-frame based matching, which is highly efficient under illumination variation, reflection condition and background edge location changing situation. In our future work, we will incorporate edge contrast information with edge's side color distribution map for the matching and tracking of more sophisticated video surveillance based applications like intrusion detection, activity recognition etc.

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