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Segmentation and Tracking Framework for Video Object by Using Threshold Decision and Diffusion

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Abstract:
Video object segmentation and tracking are two essential building blocks of smart surveillance systems. However, there are several issues that need to be resolved. Threshold decision is a difficult problem for video object segmentation with a multibackground model.Addition to , some conditions make robust video object tracking difficult. These conditions include nonrigid object motion, target appearance variations due to changes in illumination, and background clutter. In this paper, a video object segmentation and tracking framework is proposed for smart cameras in visual surveillance networks with two major contributions. First, propose a robust threshold decision algorithm for video object segmentation with a multibackground model. Second, a new technic is proposed a video object tracking framework based on a particle filter with the likelihood function composed of diffusion distance for measuring color histogram similarity and motion clue from video object segmentation. The proposed framework can track nonrigid moving objects under drastic changes in illumination and background clutter. Experimental results show that the presented algorithms perform well for several challenging sequences, and the proposed methods are effective for the aforementioned issues.
Keywords— Diffusion distance (DD), particle filter, smart camera, surveillance, threshold decision, tracking.

I. INTRODUCTION

Content analysis in smart surveillance has become increasingly important, and emerging systems are being studied and deployed in real environments. In future surveillance networks, content analysis engines embedded in smart cameras will play an important role . In embedded content analysis algorithms, video object segmentation and tracking get the most attention as they are critical building blocks for other smart surveillance functions. Several video object segmentation algorithms have been proposed under various environmental assumptions. In several simple and efficient video object segmentation algorithms are proposed. However, the proposed algorithms cannot address dynamic backgrounds because only one background layer is employed in their background model. However, in multilayered, complex background models are employed to address dynamic backgrounds; the large memory requirements of these models result in implementation bottlenecks, especially in embedded systems, such as smart cameras. Performance comparisons of most existing video object segmentation algorithms are conducted with artificial datasets that indicate that algorithms with multilayer background models multimodels outperform those with single background models unimodels . Vosters proposed a more complex algorithm, consisting of an eigenbackground and statistical illumination model, which can address sudden changes in illumination; however, this algorithm is too complex to be integrated into existing smart camera platforms.

A threshold decision algorithm for deciding appropriate threshold values is also very important since the segmentation results deeply rely on the threshold value. In proposed a threshold decision method for single background models; however, it still cannot successfully and robustly determine the threshold values for conditions with dynamic background. For video object tracking, the data association of segmentation blobs is highly dependent on the quality of segmentation results. Gradient descent-based methods search for the most likely object candidate regions with gradient descent optimization techniques. However, they suffer from local minima problems, and it is difficult for them to address objects that have large motions. In the Kalman filter is employed to predict object motion and track objects however, it may fail for objects that have random motions.

Particle filter is a more robust methodology for object tracking, and it can address large and random motions more effectively; however, the features employed for object modeling and the distance measurements used to decide the weights of the particles, which are essential for making these algorithms effective, have to be appropriately selected and designed. For object modeling, color, gradient, edge, texture, and motion are usually the features employed. However, several defects may appear when these features are used as the object model.

A.Video Object Segmentation With Multibackground

The segmentation method is based on an online multilayer background modeling technique called multibackground registration, whose block diagram. The key concept in this algorithm is the fact that it models the background with *N* layers of background images instead of a single background layer. For each pixel position, the corresponding pixel in each layer of the background image represents one possible background pixel value. In the background model is established and maintained in the MBReg and background update and release blocks. In the MBReg block, each input pixel of the current frame is the pixel position and *t* is the time index, is compared with the corresponding background pixels in the multibackground image where and a matching flag, match is recorded.

II. RELATED WORK

The video object segmentation algorithm introduced in the following section is based on the previous work in which a multibackground registration scheme was proposed to model complex and dynamic backgrounds. To make it fully automatic for variant conditions.

A.Video Object Segmentation

For many segmentation tasks, the image can contain objects with completely different shapes or an object that exhibits shape variability, such as the side view of a walking person. In such situations, the prior shape energy must make use of a set of prior templates or the multiple instances of a single object. The latter case is normally addressed by formulating the shape energy based on a statistical shape space.

B Proposed Threshold

There are several threshold values in the proposed MBReg-based video object segmentation algorithm. They include Inempirical study, it was discovered that these thresholds can be set globally for all the positions and background layers without degrading the quality of the generated object masks. That is, the indices *i*, *j*, and *k* can be removed from these thresholds. In addition, among these thresholds are used to control the update speed of the background model. The parameters are not sensitive in the proposed algorithm and can thus be set as constants or adjusted according to the requirements of different scenarios. However, the thresholds are critical parameters that are highly correlated with the camera noise and should thus be temporally adjusted in order to address changes in illumination. In this proposed a threshold decision method for the single background registration-based video segmentation algorithm. However, this algorithm cannot successfully and robustly determine the thresholds for conditions inwe propose an improved threshold decision algorithm for video object segmentation algorithm with multiple backgrounds. In addition to the ability to address dynamic backgrounds, the threshold decision algorithm required must have several desirable characteristics. First, it must be able to determine the optimal thresholds without any user input. Second, since background subtraction-based video object segmentation may cause an error propagation problem while updating the per-pixel background model, a threshold determination algorithm that is based on a different mechanism is required here. Furthermore, the quantization effect of digital systems also has to be taken into consideration. To meet these requirements, to proposed the threshold decision.

III.PROPOSED METHOD

The algorithm is based on the assumption that the camera noise is in the zero-mean Gaussian distribution, and the camera noise is the only factor affecting the optimal thresholds. The proposed algorithm consists of three sections: Gaussianity test, noise level estimation, and threshold decision. Note that this proposed threshold decision algorithm is based on a mechanism that is different from that of the per-pixel background subtraction algorithm..

A.Gaussianity Test:

Before measuring the parameters this section, the memory requirements of the proposed method MBReg and that of previous works are compared the memory requirements for modeling each pixel. The kernel-based background model requires 3 B for each sample and would require 900 B if 300 samples are required for each pixel position. The mixture-of-Gaussian MoG background model is a well-known method for foreground object segmentation . It requires five floating-point numbers for each pixel to store

RGB means, a variance, and a weight parameter. It would require 200 B for 10 Gaussians, and 80 B for four Gaussians.
In the codebook model five floating-point numbers and four 16-bit integers are required for each codeword. It is claimed that four codewords are needed on average, which results in a total of 112 B. That is, 102 b are required for a single layer, and 51 B for four layers. Note that the performance of approach with four background.

B Memory Reduction in Background Modeling

The codebook model with four codewords. Moreover, since the threshold values are set as global parameters for all positions and layers, the required memory size is further reduced to 27 B for each four-layer pixel. Compared with the MoG model with 4 Gaussians, a reduction rate of 66% is achieved with proposed multibackground model. The advantage is quite significant.

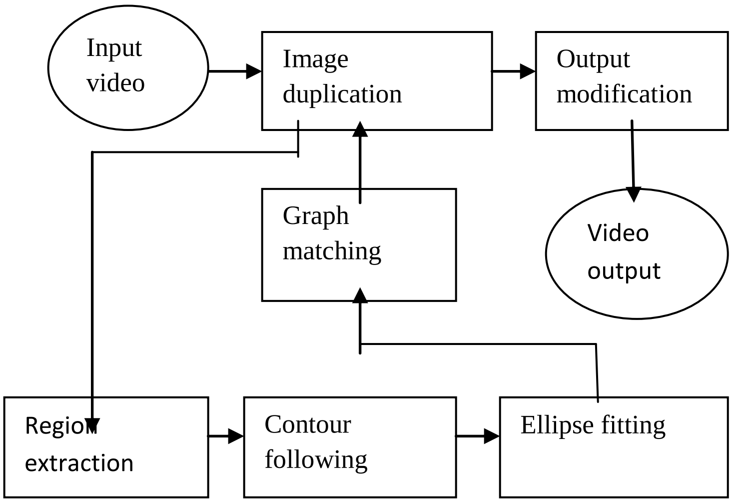


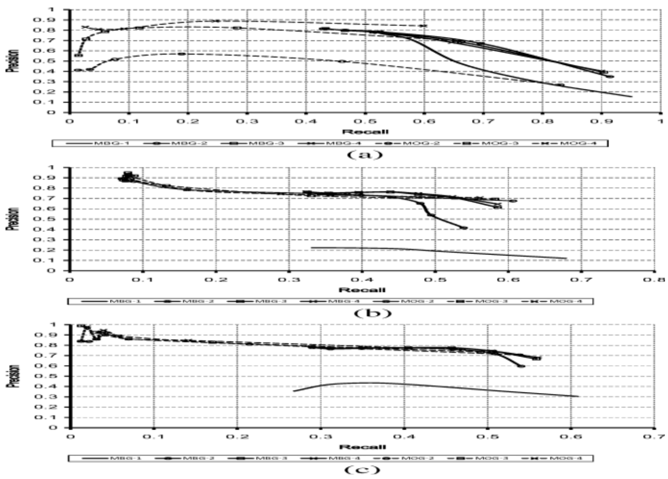
Fig 1.Proposed System

The tracker with 3-D color histogram and BhD first column almost lost track at while the tracker with 1-D color histogram and BhD second column lost track. This indicates that a tracker with BhD tends to lose tracking under these kinds of lighting condition changes. On the other hand, with cross-bin distance, such as EMD and DD, the trackers fourth column and third column can adapt to lighting condition changes and track the target correctly. Note that the target model learning scheme is similar to those employed in particle filter frameworks with color histogram as target representation. It can be seen that the trackers w ith EMD and DD outperform those with BhD. In there are acute changes in illumination. With BhD, the trackers lose tracking along the object trajectory. Even for EMD, there is tracking loss. The only tracker that tracked the target without any track loss was the tracker with 1-D histogram and DD.

The quantitative results of these three sequences and another two sequences the performances of these four trackers are evaluated by dividing the number of frames with correct trackers by the total number of frames having the object in ground truth. It was observed that the tracker with 3-D color histogram and BhD lost tracking for two sequences, while the tracker with 1-D color histogram and BhD lost tracking for three sequences. Meanwhile, the tracker with 1-D color histogram and EMD lost tracking for only one sequence, while the tracker with 1-D color histogram and DD successfully tracked all five sequences. In the error distance between tracked object center and the center in ground truth is shown. It shows that the tracker with the minimal error distance is either the tracker with DD or the tracker with EMD. From the above results, can conclude that DD is a better distance metric than the bin-to-bin histogram distance i.e., the BhD under changes in illumination. The tracker with DD for color histogram matching can track objects with nonrigid motion robustly under drastic changes in illumination. In addition to changes in illumination, the tracker may drift due to background clutter. In the background clutter problem is solved by including motion clue from video object segmentation. In there is a background clutter problem because the color histogram in the background region is too similar to that of the target.This shows a simple but efficient method to solve the background clutter problem.

IV. EXPERIMENTAL RESULTS

The algorithm was also qualitatively compared with other related tracking algorithms. The methods propose in and are based on blob matching and Kalman filter. Their performances are highly dependent on the quality of the segmentation results where proposed object segmentation
method can also be applied. The performance of the Kalman filter is not as good as that of particle filter, especially when
tracking objects with irregular motions.



The framework can accurately track a single object; however, for other issues in object tracking, such as occlusion and foreground clutter, the integration of more mechanisms into the object tracking framework may be required. background conditions without any user input. In addition, it is based on a mechanism that is different from perpixel background subtraction so as to prevent possible error propagations. Analysis results showed that the segmentation algorithm is memory efficient, and that the memory reduction rate is at least 66% when compared with previous works. For video object tracking, with the information from video object segmentation, the tracker is robust to background clutters. By using DD for color histogram matching, a nonrigid moving object can be robustly tracked even under drastic changes in illumination. From a computational point of view, DD is also ideal as it is most suitable for parallel implementation and hardware realization.

V.CONCLUSION

A new method for video object segmentation and video object tracking framework for smart cameras in visual surveillance networks was proposed with two key contributions: threshold decision for multibackground video object segmentation algorithms and DD for measuring color histogram distance. With the proposed threshold decision algorithm, the thresholds for segmentation can be robustly determined for dynamic background conditions without any user input. In addition, it is based on a mechanism that is different from perpixel background subtraction so as to prevent possible error propagations. Analysis results showed that the segmentation algorithm is memory efficient, and that the memory reduction rate is at least 66% when compared with previous works. For video object tracking, with the information from video object segmentation, the tracker is robust to background clutters. By using DD for color histogram matching, a nonrigid moving object can be robustly tracked even under drastic changes in illumination. From a computational point of view, DD is also ideal as it is most suitable for parallel implementation and hardware realization

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