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ST-MRF BASED VIDEO OBJECT DETECTION AND TRACKING IN VIDEO SURVILLANCE

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Abstract: Object tracking is an interesting and needed technique for many real time applications. But it is a challenging one, because of the presence of challenging sequences with unexpected motion, drastic illumination change, large position variation, occlusion, spoilt background and also the camera shake. This paper presents a new method of video object tracking by using the algorithms Spatio-Temporal Markov random field (ST-MRF) in video surveillance, which overcome the above mentioned problems and provide a better tracking process. This method is also capable of tracking multiple objects in video sequence even in the presence of an object collaborations and occlusions that achieves better results with real time performance. The proposed method is tested on a number of standard sequences, and the results demonstrate its advantages over some of the recent state-of-the-art methods.

Keywords: *Video object tracking, Spatio-temporal Markov-Random field, motion detection, video surveillance, objects tracking.*

1. INTRODUCTION

Video-based object tracking in static or in dynamic scenes is one of the challenging problems with vast variety of applications. Tracking moving objects by analyzing video sequences is one of the active research topics in the field of computer vision. This paper mainly focuses on performing review on tracking moving objects in video scenes in both pixel-domain and compressed-domain with detailed descriptions of tracking strategies.In this compressed realm MRF tracking using spatial and time information is proposed and the same method can be used even for other older video format is presented. MRF[1] method mainly uses information such as space, temporal dependence information to track object in subsequent frame, coding each block of frame, motion vector of individual frame etc. for accurate tracking [2]. It is one of the simplest methods and supplies reliable and robust results, if the colors in the background differ significantly from those in the target object. Finally, Gaussian Mixture Model (GMM) [3] method based on background modeling method to extracting moving objects and for trajectory prediction is discussed. Survey of tracking methodologies in both pixel and compressed domain for object recognition and tracking includes ST-MRF. Experimental result has been evaluated for different video sequences with different conditions such as noise illumination changes, shadow, scale change in the objects etc. estimate the performance of these algorithms. Pixel domain and compressed domain are the few major groups of approaches to track moving objects in a video sequence. Pixel domain will provide high accuracy.

It needs higher computational complexity.

This approach uses the data from compressed video bit stream like block coding modes vectors, motion compressed prediction residual or its transform coefficients etc.

A.OBJECT DETECTION

Every tracking method requires an object detection mechanism either in every frame or when the object first appears in the video. A common approach for object detection is to use information in a single frame. However, some object detection methods make use of the temporal information computed from a sequence of frames to reduce the number of insincere detections. For object detection, there is several common object detection methods described in [4]. Performance of an automated visual surveillance system considerably depends on its ability to detect moving objects in the observed environment. A subsequent action, such as tracking, analyzing the motion or identifying objects, requires an accurate extraction of the foreground objects, making moving object detection a crucial part of the system.

Mainly object detection method consists of two main steps. The first step is a preprocessing step including gray scaling, smoothing, and reducing image resolution and so on. The second step is filtering to remove the image noise contained in the object.

B.OBJECT TRACKING

Object tracking is nothing but the process of extracting an object of interest from a video scene and continuous track of its motion, orientation and occlusion. It follows the segmenting step which is same as recognition step in image processing. First main step of information extraction is deletion of moving objects from video streams. Three approaches are there for object tracking. One is feature based approach, which extracts the characteristics like points, line segments. Differential methods of approach are mainly based on optical flow computation. The third approach uses the correlation to read the image displacements. Based on the domain of the problem any of these approaches its selected.

II OUTLINE OF THE PROPOESD METHODS

A.PREPROCESSING

Tracking algorithm makes use of two types of information from the compressed bit stream: MVs and block coding mode (partition) information. In this method texture data does not require to be decoded. Four basic MB modes are defined in the above mentioned bit stream: 16 × 16, 16 × 8, 8 × 16, and 8 × 8, here the 8 × 8 mode can be again split into 8 × 4, 4 × 8, and 4 × 4 modes. Being 4×4 is the smallest coding mode (partition) in AVC, so as to have a uniformly sampled MV field, this method map all MVs to 4 × 4 blocks. This is simple in inter-coded blocks, as well as SKIP blocks where the MV is simply set to zero.

B.ST-MRF BASED TRACKING

In MRF (Markov Random Field) tracking using spatial and temporal dimension tracking [5] of pre-recorded video is done. Initially, preprocessing of the video is done to remove noise by using Gaussian filter. GM [6] estimation is prepared to estimate the camera movement and GM compensation is done to remove GM which includes intra-coded block processing. After preprocessing tracking is performed using MRF method which uses spatial and time information.

MRF [7] make use of markov property to track rigid object by using compactness behavior of the moving object which will not get dispersed in frame sequence. A block diagram of MRF Tracking method using spatial and temporal information is shown in Figure 1. In proposed MRF [8-9] based method compact space information for tracking moving rigid object in frame sequence, MV temporal continuity information is used find movement similarity between blocks in the frame in use by the objects. Video is taken as input and converted into frame; next frame is divided into 4X4 blocks. Blocks are labeled based on presence of object such as non-object and object blocks as 0 and 1 respectively.

Suppose the block labeling is done for frame ‘x’ and previous frame ‘x-1’ then tracking between the frame is done using motion information which is denoted by:

$$fx=(mx, bx)$$

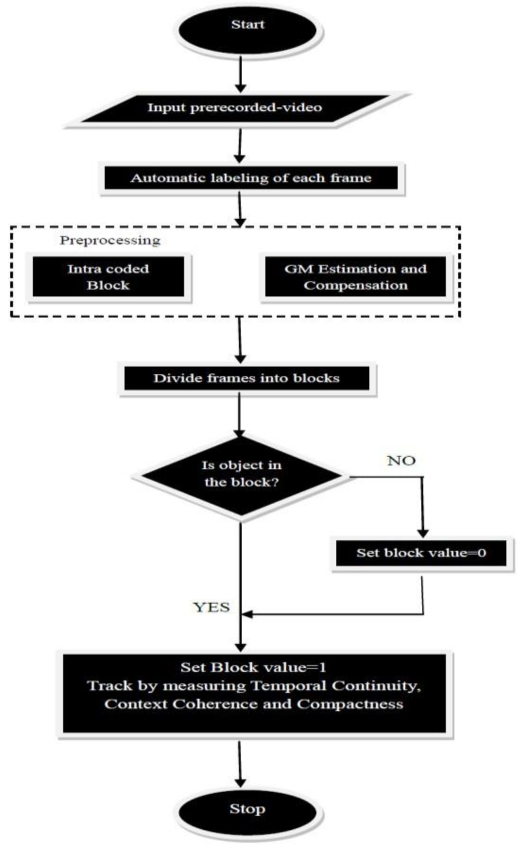

Figure 1: Flow chart of ST-MRF tracking Module

where mx denotes MV for inter calculation between previous and current frame and bx(t) denotes block coding mode where t=(x,y) represent block position in the frame. Labeling is done using MAP (Maximum A Posteriori) criterion where block is selected with maximum posterior probability:

$$P\,(wx \mid wx\text{-}1,\, fx)$$

Temporal continuity and spatial continuity is measured between previous frame labeling and candidate current frame labeling ψ which is the powerful cue for object tracking and represents compactness of rigid moving object.

C. ST-MRF Optimization

The characteristics of a moving rigid object are relative similarity of motion within the region occupied by the object, spatial compactness i.e. not dispersed in different parts of the frame, and a continuous motion trajectory. Though the motion of flexible objects is not so characteristic it is in principle that these objects can be treated in a divide and conquer manner as a group of smaller sufficiently rigid objects. So this ST-MRF model is based on rigid object motion characteristics. The frame should be divided into smaller blocks (i.e. 4×4). Object blocks can be labeled 1 and non-object blocks can be labeled as 0. In past two algorithms Stochastic Relaxation (SR) and ICM were used. SR has some advantage in accuracy compared to ICM, but at a higher computational cost [10]. At first, the label of each block is initialized by projecting the previous frame labeling ω $t-1$ into the current frame. Then each block is relabeled with the label (0 or 1) that leads to the largest reduction in the energy function. Relabeling procedure is done until no further energy reduction is achieved. Normally, six iterations are needed to reach the local minimum. This is worth mentioning that because results are dependent on the initial labeling.

III. EXPECTED RESULT

Proposed algorithm is implemented in MATLAB and tested on various video sequences. Different sequences, that represent typical situations critical for video surveillance systems because of its capacity in simulating various tracking conditions, including illumination changes, position variations, occlusions, and distraction. A number of standard test sequences were used to evaluate the performance of our proposed approach. Sequences were in the YUV 4:2:0 format, at two resolutions, CIF (352 × 288 pixels) and SIF (352 × 240 pixels), all at the frame rate of 30 fps. We found that the average performance does not change much if some of these parameter values are changed, especially the parameters that represent the effect of camera motion on energy function, and only affect a few frames. The below figures illustrates a few intermediate results from the tracking process for a sample frame from *Coastguard*. As seen from Figure 2, the MV field around the target (small boat) is somewhat erratic, due to fast camera motion in this part of the sequence. The proposed ST-MRF-based tracking algorithm computes the energy function for the chosen MRF model, which is shown in figure 3. Here, the darker the value, the smaller the energy, hence the higher the posterior probability. Therefore, despite the erratic MV field, the target seems to be localized reasonably well. Figure 4 shows the detected target region after the tracking process has been completed.

Figure 2: Object detection during ST-MRF-based tracking: *Coastguard* overlaid by scaled MV field after GMC.

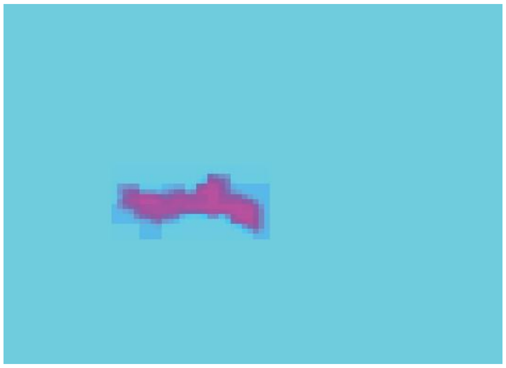

Figure 3: MRF energy value—the darker the color, the higher the energy.

Figure 4: Tracking results by the proposed method.

IV CONCLUSION

In this paper, we have presented a novel approach to track a moving object using MRF. The only data from the compressed stream used in the proposed method are the motion vectors and block coding modes. As a result, the proposed method has a fairly low processing time, yet still provides high accuracy. After the preprocessing stage, which consists of intra-coded block motion approximation and global motion compensation, we employ Spatio-Temporal Markov Random Field model to detect and track a moving target. Using this model, an estimate of the labeling of the current frame is formed based on the previous frame labeling and current motion information. The results of experimental evaluations on ground truth video demonstrate superior functionality and accuracy of our approach against other state of the- art compressed-domain segmentation/tracking approaches.

Although our algorithm works well even with fixed parameter values, possibly better performance may be obtained by adaptive tuning, although this would in general increase the complexity.

REFERENCES

[1]. Sayed Hossein Khatoonabadi and Ivan V. Baji´c, "Video Object Tracking in the Compressed Domain Using Spatio-Temporal Markov Random Fields", IEEE transactions on image processing.

[2] Alper Yilmaz, Omar Javed, and Mubarak Shah. Object tracking: A survey. *Acm Computing Surveys.*

[3].M. G. Arvanitidou, A. Glantz, A. Krutz, T. Sikora, M. Mrak, and A. Kondoz, Global motion estimation using variable block sizes and its application to object segmentation, in Proc. IEEE Workshop Image Anal.

[4]. Yun Ji Zhao , Hai Long Pei "Model Update Particle Filter for Multiple Objects Detection and Tracking", Intelligence Information Processing and Trusted Computing (IPTC).

[5]. Z. Liu, Y. Lu, and Z. Zhang, "Real-time spatiotemporal segmentation of video objects in the H.264 compressed domain," *J. Visual Commun.* .

[6]. Y.-M. Chen, I. V. Bajic, and P. Saeedi, "Moving region segmentation from compressed video using global motion estimation and Markov random felds," IEEE Trans. Multimedia, vol. 13.

[7]. R. Huang, V. Pavlovic, and D. N. Metaxas, "A new spatio-temporal MRF framework for video-based object segmentation", in Proc. MLVMA Conjunct. Eur. Conf. Comput. Vis., 2008, pp.

[8]. Y.-M. Chen, I. V. Bajic, and P. Saeedi, "Moving region segmentation from compressed video using global motion estimation and Markov random fields", IEEE Trans. Multimedia, vol. 13, no. 3, pp. 421431, Jun. 2011.

[9] Y.-M. Chen and I. V. Bajic, “A joint approach to global motion estimation and motion segmentation from a coarsely sampled motion vector field”, IEEE Trans. Circuits Syst. Video Technol., vol. 21, no. 9, pp. 13161328, Sep. 2011

[10]. H. Grabner, M. Grabner, and H. Bisch of, “Real-time tracking via online boosting,” In British Machine Vision Conference, pp. 47-56 , 2006. 1, 2,5 ,6,7.