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Extraction of Dense Representation of the Motion Segmentation

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Abstract—In this paper presents object oriented segmentation in a video sequence. In this project, it is aimed for a unified approach to segment video frames without over-segmentation. The existing method is to segment the videos that are formed by the coherent motion of frames and the proposed method is to make the segmentation possible for all motion models. The input video is converted in to frames. The tracking process of object depends on sample points in a scene or particles. The particles are clustered in spatio-temporal space as the object in the sequence changes with respect to time. To segment the object, the particles terminating in adjacent frame are extended in to current frame and they are linked, it finds the long range motion in a sequence. The linked particles are optimized, pruned to reduce false occlusions finally new particles are added to estimate the particle trajectory. The trajectories which intend to coherent motion need to be segmented by ensemble clustering of particles, then the obtained clusters are validated and filtered to reduce the outliers then dense segmentation extraction is done to determine the pixel assigned to each moving object, finally the object is segmented.

Index Terms— Ensemble clustering, Motion segmentation, Occlusion, Trajectory, Pruning, Spatial –temporal segmentation, Spatial proximity

1 INTRODUCTION

Motion segmentation is an important preprocessing step in many computer vision and video processing tasks, such as surveillance, object tracking, video coding, information retrieval, and video analysis. These applications motivated the development of several 2-D motion segmentation techniques (x,y), 3-D motion segmentation technique (x,y,z) and spatio-temporal motion segmentation (x,y,t), where each frame of a video sequence is split into regions that move coherently.

Video segmentation is very important to application areas such as human-computer interaction; object based video compression, and multi-object tracking. To differentiate independently moving objects composing the scene, one of the key issues in the design of these vision systems is the strategy to extract and couple temporal (or motion) information and spatial (or intensity) information in the segmentation process. Motion information is one fundamental element used for segmentation of video sequences. A moving object is characterized by coherent motion over its support region. The scene can be segmented into a set of regions, such that pixel movements within each region are consistent with a motion model (or a parametric transformation). Examples of motion models are the translational model (two parameters), the affine model (six parameters), and the perspective model (eight parameters)

Furthermore, spatial constraints could be imposed on the segmented region where the motion is assumed to be smooth or follow a parametric transformation. Moreover, layered approaches have been proposed to represent multiple moving objects in the scene with a collection of layers. Typically, the expectation maximization (EM) algorithm is employed to learn the multiple layers in the image sequence.

On the other hand, intensity segmentation provides important hints of object boundaries. Methods that combine intensity segmentation with motion information have been proposed. A set of regions with small intensity variation is given by intensity (over)segmentation of the current frame. Usually, a region adjacency graph or a partition tree can be used to represent the regions in the scene.

Dengsheng Zhang and Guojun Lu, [3] tells that object in a video segmentation framework is related to the concept of region homogeneity, and different applications require different region homogeneity criteria. In video coding, segmentation is frequently used to explore the data redundancy in time. In this he tells that the object in the region that retains in its characteristics (e.g., color or texture) along the sequence can be considered homogeneous and redundant. Thus, even if the object region moves along the temporal sequence, the region representation remains the same, i.e., redundant, within the object motion boundaries.

P. Sand and S. Teller,[2] provides a new approach for estimation of long range motion patterns using feature tracking or optical flow. Feature tracking follows a sparse set of image points over many frames, whereas optical flow estimates a dense motion field from one frame to the next. Our author combines these two approaches to produce motion estimates that are both long-range and moderately dense. M. Gelgon, P. Bouthemy, and J.-P. Le Cadre[5](2005) tells about combining several partial information about an object The object is tracked over the whole image sequence, by combining partial object segmentations previously computed in different parts of the sequence. This is done by modeling the motion and geometry of the objects, and these models are combined assuming smooth trajectories, and are used to eliminate ambiguities caused by occlusions and incorrect detections.

Early work on segmentation tries to segment images into mov-

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ing objects using local measurements. Potter [Potter75] uses velocity as a cue to segmentation. The work is based on the assumption that all parts of an object have the same velocity when they are moving. Potter's approach to motion extraction was based on the measurement of the movement of edges.

2 Proposed Method

The structure of coherent motion segmentation approach can be divided in three main parts:

1. Estimation of Particle Trajectories
2. Segmentation of Particle Trajectories
3. Dense Segmentation Extraction.

The first block deals with the selection and tracking set of points in the scene.This stage takes input original video frames as input, and returns set of particles and their respective trajectories as the output. During the estimation of particle trajectories, the particles whose correspondent point locations in the scene suffer occlusion are eliminated, and new particles are created in regions that become newly visible along the video sequence.

The second block deals with the segmentation of particle trajectories, so that particles moving coherently are grouped together. This stage takes the particles trajectories computed in the first stage as input and returns labels for all the particles as the output, representing the motion segmenta-tion of frame regions according to the particle trajectories. The third and final block of the proposed motion segmentation method is the dense segmentation extraction. This stage takes as input the original video frames, the segmentation labels returned by the second stage, as well as the particle positions returned by the first stage, and returns as the output the corresponding segmentation labels for each pixel of each frame of the video sequence. This is equivalent to the segmentation of a spatio-temporal volume in several tunnels. It is done by creating implicit functions for each particle, based on motion and spatial position. This representation of motion segmentation through tunnels can be employed to obtain efficient motion predictions for video coding applications.

3 Estimation Of Particle Trajectories

In this, the estimation of particle trajectories does not require any temporal smoothness constraints. Second, the particle sampling density is adaptive, in the sense that regions with more details are sampled with more particles. Thus, higher motion segmentation precision can be obtained. Third, motion information can be inferred from neighbouring particles, reducing the effect of the aperture problem in homogeneous regions, where there is not enough motion information. These properties suggest that this particle video approach potentially can estimate long-range coherent motion patterns. A particle is created in a frame pixel when a maximum proximity criterion. As soon as a particle is created, it is tracked along subsequent frames, until the point it represents becomes occluded. The method for estimating particle trajectories used in this work can be divided in five steps: propagation, linking, optimization, pruning, adding.

1.1 Particle Pruning

In this objective function that is minimized to fine-tune the location of particles particles is employed as a measure of particle location reliability in the particle pruning stage. This objective function is composed by three terms, namely Ep[c],Ef,Ed.

$$Ep[c](p,t) = \sum([I[c](xp(t), yp(t), t) - I[c](xp(t0p), yp(top), top)])$$

First term represents projection error of particle p in a frame of the sequence First term represents projection error of particle p in a frame of the sequence.

$$Ef(p,t) = \sum([u(xp(t-1), yp(t-1), (t-1) - (xp(t) - xp(t-1))]$$

Second term represents the difference between the actual displacement of the particle p in frane at time t and estimate based on the local optimal flow displacement.If a particle becomes occluded or leaves the visible field, this particle is eliminated and it is no longer considered in the tracking process.

4 Segmentation Of Particle Trajectories

The representation of motion in videos based on particle trajectories is flexible, allowing the identification of object motion without global motion constraint handling occlusions. For example, it may happen that a pair of particles in coherent motion along the video sequence does not coexist in the same video frame, because of their different lifetimes. Moreover, it is difficult to avoid the incidence of erroneous motion patterns, which may occur due to the noise. Only particles that appear simultaneously in at least two consecutive frames can be compared directly in terms of their motion. In this clustering algorithm is applied to each set of particles that coexist in the video sequence and these subset are combined to form larger particles.

4.1 Ensemble clustering of particles

In order to group particles that are in coherent motion along the video sequence, we first identify the subsets of particles that present similar motion in neighbouring frames.

P= p1,p2,…….p3.These are the whole set of particles in a video sequence.

ep(t,t+l) be the displacement vector of particle p between frames time t and t+l

$$ep(t, t+1) = xp(t+1) - yp(t+1) - yp(t)$$

Displacement vectors between adjacent frames up to three units are found l=1.These three clustering are used in each frame to reinforce the tendency of particles with similar motion patterns to group together, reducing the influence of outliers and inconsistencies in individual clustering in the final partition. The mean shift method is employed to obtain the clusters.

4.2 Particle meta-clustering validation

The particle tracking errors may occur, resulting in incorrect particle-to-meta-cluster assignments. To detect these inconsistencies after the ensemble clustering stage, a cluster validation step is performed by analyzing trajectories in the context of particles grouped together. This is particularly important when particles are assigned to one object but migrate to another object during the tracking process, because of occlusion.

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$-Wv \le= \forall Vx,, \exists vy <= Wy, \forall Yx + \forall yy \in Z$

Wv represents window size. The context of a particle moving coherently with its neighboring particles often does not change from one frame to another.. The projection error of a point in a window at [-Wv,Wv] sub-pixel level, that specifies the context of particle p, given the motion of the particle between frame at time t and frame at time t-ρv, can be computed as . In order to detect context changes, the mean Wof the -best matches are computed.

4.3 Spatial Filtering

The last stage in the classification process is the particle spatial filtering. The goal of spatial filtering is to eliminate outliers and groups of adjacent particles that are not significant. To represent the particles spatial adjacency, the Delaunay triangulation DT(t)is computed based on the particle positions in (xp(t) yp(t)) each frame at time t Two particles are considered adjacent if they share an edge in the triangulation DT(t). The association between adjacent particles is represented by assigning binary weights to the edges of ; that is, an edge receives "1" if it connects two particles belonging to the same meta-cluster, or it receives "0" if connects particles belonging to different meta-clusters. The components are assigned to the meta-cluster that shares more edges with weight 0.

5 Dense Segmentation Extraction

In many computer vision and image processing tasks, and in many video coding problems, it is necessary to extract a dense representation of motion segmentation. It means that we must determine which pixels are assigned to each moving object. At this stage, each pixel is assigned to the most similar particle meta-cluster. To perform this task, we compare pixels with sets of particles in terms of motion and spatial proximity using implicit functions.

Let P=P1,P2,……..Pnpv be the whole set of particles of the video, and the set of labels that indicates for each particle, to which meta-cluster the particle is associated with. So, to each particle in a frame at time , represented by its spatial coordinates , is assigned a multivariate gaussian kernel σSσM

Where upt=xpt-xpt-1 and vpt=ypt-ypt-1. represent the displacement of particle in frame at time to which meta-cluster the particle is associated with. So, to each particle in a frame at time t, represented by its spatial coordinates , is assigned a multivariate gaussian kernel $\sigma_S\sigma_M$

Where upt=xpt-xpt-1 and vpt=ypt-ypt-1. represent the displacement of particle in frame at time.

6 Experimental Results

6.1 Video to Frames

The input videos of eight seconds time duration are converted in to 48 frames. Here the frames of cars moving in the track.

(a) (b) (c)

Fig.1.Video into Frames (a) shows Frame 1, (b) shows Frame 2 , (c) shows Frame 3.

6.2 Clustering of frames

Clustering of particles are performed with displacement motion vectors taken from pairs of frames. As we know that clustering is a way to separate groups of objects and it treats each object as having a location in space. The frames of the video sequence are given, in which the frame 1 has a movement of object that is a car. In frames have the move-ment of car, so that the clustering process has been simply done by tracking a movement object as the car particularly.

(a) (b) (c)

Fig.2.Clustering of Frames.(a) shows Frame 1,(b) shows Frame 2 (c) shows Frame 3.

6.3 Optical Flows

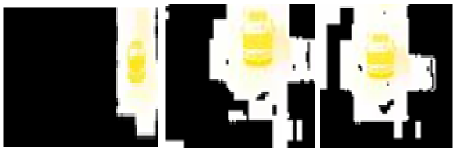
The optical flow estimation technique to estimate the motion vectors are in each frames of the video sequence. The optical flows of the video through the frames are given below, in which the optical flow is to determine the changes in brightness of frames and to determine how to track it. The frames are also shown us the detail about the optical flow process, in which the background of video in all the frames does no changes, but the moving objects or cars are changes contiuously.

(a) (b) (c)

Fig.3.Optical Flows.(a) shows Frame 1,(b) shows Frame 2 (c) shows Frame 3.

6.4 Segmentation

The car which is racing in the track is segmented as shown below. which is identified in yellow color. As per the frames, moving car is particalurly segmented for the region of car. The segmented frames are represented to notify the segmented region called moving objects as car. The process has been done with the help of determining the image properties of the particular region. The segmentation process has been used by taking the image properties like contrast, brightness and colours. The moving car having the change in properties of video frames, so that it can bsegmented from the background image. In the segmentation process, an object can be easily detected in an image if the object has sufficient contrast from the background.



(a) (b) (c)

Fig.4.Segmentation (a) shows Frame 1,(b) shows Frame 2 (c) shows Frame 3.

6.5 Segmentation of Existing method

Motion-based segmentation involves the partitioning of images in a video sequence into segments of coherent motion. The segmented frames are given as below, in which the frames are illustrates us that in motion segmentation the segmentation process takes places in both the background and foreground details of the video frames. It normally based on the image properties like contrast, brightness and colours, so that the video frames are segmented based on it.

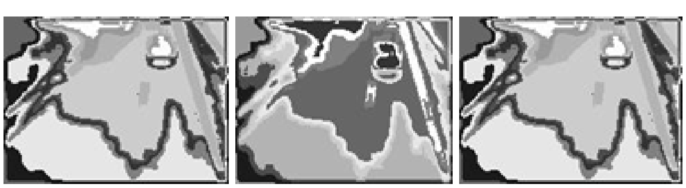
(a) (b) (c)

Fig.5.Motion Segmentation of Existing method .(a) shows Frame 1,(b)shows Frame2 (c) shows Frame 3.

In frames, the segmentation has been processed on the background as roadway and also on the moving car. The contrast variation in the different objects shows us the varying brightness of the image.

6.6 Dense Segmentation Extraction

The segmented frames of the video sequence are done by the process of the spatio-temporal segmentation as a proposed technique. Video segmentation can be formulated as tracking regions across the frames, such that the resulting tracks are locally smooth. The frames are given as below, in which the frames provide us the accuracy details of the image by observing the clear traffic marks and in case of frames also provide us the precise image segmenting detail of moving car and its background. It enclosed with the tracking details of the moving objects and it ensures that the segmented images provide the smooth details as compared to the other existed method. This can be done in spatial temporal segmentation by the means of the tracking region across the frames.



(a) (b) (c)

Fig.6 .Dense Segmentation Extraction. (a) shows Frame 1, (b) shows Frame 2 (c) shows Frame 3.

It ensures that the proposed method has the advantages of accuracy of the segmented video frame than the existed method segmented video This is equivalent to the segmentation of a spatio-temporal volume in several tunnels. It is done by creating implicit functions for each particle, based on motion and spatial position. This representation of motion segmentation through tunnels can be employed to obtain efficient motion predictions for video coding applications. frame.

7 Conclusion

It estimates all the particles in the frames to estimate the particle trajectories and the optical flow is tracked between the particles and the objects which are moving in the sequence are segmented. This is called as segmentation of particle trajectories. The extraction of a dense representation of motion segmentation to do the image processing tasks, the task is to compare pixels with sets of particles in terms of motion and spatial proximity using implicit functions. The tracking process for spatio-temporal segmentation provides us to produce accurate segmentation in the continuous frames.

References

[1] S. Luciano Silva and S. Jacob Scharcanski,, Senior Member, IEEE " Video Segmentation Based on Motion Coherence of Particles in a Video Sequence," IEEE Trans. On Image Process.,vol.19, no.4, pp.1036-1049, April 2010H.

[2] R. Nicole, P. Sand and S. Teller, "Particle video: Long-range motion estimation using point trajectories," Comput. Vis. Pattern Recognit., vol. 2&3.4, pp.2195–2202, 2006.

[3] Dengsheng Zhang and Guojun Lu "Segmentation of Moving Objects in Image Sequence: A Review" in Gippsland School of Computing and Information Technology Monash University, Churchill, Vic 3842,

[4] H.Sekkati and A. Mitiche, "Joint optical flow estimation, segmentation and 3D interpretation with level sets," Comput. VisImage Understand., pp. 89–100, Aug. 2006.

[5] M.Gelgon,P.Bouthemy, and J.-P.Le Cadre,"Recovery of the trajectories of multiple moving objects in an image sequence with a PMHTapproach, Int. J. Comput. Vis., vol 23, no. 1, pp. 19–31, 2005.

[6] A.Mitiche, R.El-Feghali, and A.-R.Mansouri, "Motion tracking as Spatio-temporal motion boundary detection," Robot. Autonom. Syst., vol. 43, no. 1, pp. 39–50, 2003.

[7] A.Strehl and J. Ghosh, "Cluster ensembles-A knowledge reuse framework for combining multiple partitions," J. Mach. Learn. Res, vol. 3, pp. 583–617, 2003.

[8] Andrea Fusiello. Three-Dimensional Vision For Structure and Motion Estimation. Ph.D thesis, University of Udine, Italy, November 1998.

[9] L. Hubert Segmentation Using a Joint Similarity Measure. IEEE Trans. on Circuits and Systems for Video Technology vol.7 No.2 April 1997, pp.279-286.

[10] Aae Gark Choi, Si-Woong Lee and Seong-Dae Kim. Spatio-Temporal Video and Pattern Recognition and Image Analysis. Pretice Hall PTR Upper Saddle River, NJ, 1996.

[11] E.H.Adelson J.R.Bergen,P.J.Burt and J.M.Ogden.Pyramid methods in image processing.RCA Engineer,29(6)33-41,1996.

[12] O.M.Aodha,G.Brostow,and M.Pollefys."segmenting video into classes of algorithm-suitablity in CVPR 1995.

[13] A.Bab-Hadiasharand D.suter."Robust optical flow calculation"IJCV 29(1), 1995.

[14] C.Zintick,N.Joic and S.Kang"Consistent optical flow estimation"in ICCV Pages,1993