Sajad ein / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 2, Issue4, July-august 2012, pp.2302-2305

Motion Tracking Using By Pillar K-Mean Segmentation

Sajad einy
mtech spatial information technology JNTU university Hyderabad
Abouzar Shahraki Kia PG Scholar
DEP of Electrical and Electronic Engineering JNTU,Hyderabad,INDIA

Abstract

In this paper , we present pillar k-mean segmentation and regions tracking model, which aims at combining color, texture, pattern, and motion features. in the first the pillar algorithm segmented the objects which are tracking and realized them ;second the global motion of the video sequence is estimated and compensated with presenting algorithms. The spatio-temporal map is updated and compensated using pillar segmentation model to keep consistency in video objects tracking.

Key words: image segmentation, object tracking, region tracking, pillar k-mean clustering

Introduction

Image segmentation and video objects tracking are the subjects of large researches for video coding and security of area. For instance, the new video standard allows chose one possible is to use adapted coding parameters for the video object during several frames. To track objects in a video sequence, they need to be segmented. Spatial-temporal shape characterized by its texture, its color, and its own motion that differs from the global motion of the shot. In the literature, several kinds of methods are described, they use spatial and/or temporal [1] information to segment the objects on temporal information need to know the global motion of the video to perform an effective video objects segmentation. Horn and Schunck [2] proposed to determine the optical flow between two successive frames. Otherwise, the motion parametric model of the successive frames can be estimated [3]. Studies in motion analysis have shown that motion-based segmentation would benefit from including not only motion, but also the intensity cue, in particular to retrieve accurately the regions boundaries. Hence the knowledge of the spatial partition can improve the reliability of the motion-based segmentation with pillar algorithm. As a consequence,we propose a pillar segmentation combining the motion information and the spatial features of the sequence to achieve an accurate segmentation and video objects tracking. This segmentation process includes a new mechanism for clustering the elements of high-resolution images in order to improve precision and reduce computation time. The system applies K-means clustering to the image segmentation after optimized by Pillar Algorithm. The Pillar algorithm considers the pillars' placement which should be located as far as possible from each other to withstand against the pressure distribution of a roof, as identical to the number of centroids amongst the data distribution. This algorithm is able to optimize the K-means clustering for image segmentation in aspects of precision and computation time.

Motion estimation based on tubes

To extract motion information correlated with the motions of real life objects in the video shot, we consider several successive frames and we make the assumption of an uniform motion between them. Taking account of perceptual considerations, and of the frame rate of the next HDTV generation in progressive mode, we use a GOF composed of 9 frames [4,5] The goal is to ensure the coherence of the motion along a perceptually significant duration Figure 1 illustrates how a spatiotemporal tube is estimated considering a block of the frame f_t at the GOF center an uniform motion is assumed and the tube passes through the 9 successive frames such as it minimizes the error between the current block and those aligned [8,7]

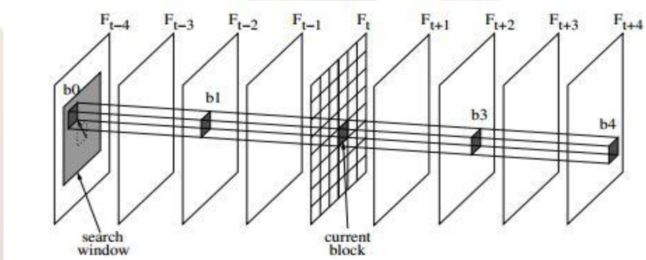


Fig. 1. Spatio-temporal tube used to determine the motion vector of a given block [8]

We get motion vectors field with one vector per tube, and one tube for each block of the image f_t . This motion vectors field is more homogeneous (smoother) and more correlated with the motion of real life objects, this field is the input of the next process: the global motion estimation.

2.2. Robust global motion estimation

The next step is to identify the parameters of the global motion of the GOF from this motion vectors field. We use an affine model with six parameters. First, we compute the derivatives of each motion vector and accumulate them in an histogram (one respective histogram for each global parameter).The localization of the main peak in the histogram produces the value retained for the parameter. Then, once the deformation parameters have been identified, they are used to compensate the original motion vectors field. Thus, the remaining vectors correspond only to the translation motions. These remaining motion vectors are then accumulated in a two dimensions (2D) histogram. The main peak in this 2D histogram represents the values of the translation parameters [4].in the fig2 the amount of motion can estimate.

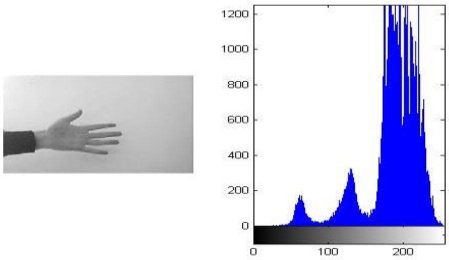


Fig2.histogram of gray level

Motion segmentation using pillar k means clustering

The image segmentation system preprocesses three steps: noise removal, color space transformation and dataset normalization. First, the image is enhanced by applying adaptive noise removal filtering. Then, our system provides a function to convert RGB of an image into HSL and CIELAB color systems. Because of different ranges of data in HSL and CIELAB, we apply the data normalization. Then, the system clusters the image for segmentation by applying K-means clustering after optimized by Pillar algorithm. Fig. 3 shows the computational steps of our approach for image segmentation.The Pillar algorithm is described as follows. Let $X=\{xi \mid i=1,\ldots,n\}$ be data, k be number of clusters,$C=\{ci \mid i=1,\ldots,k\}$ be initial centroids, $SX \subseteq X$ be identification for X which are already selected in the sequence of process, $DM=\{xi \mid i=1,\ldots,n\}$ be accumulated distance metric, $D=\{xi \mid i=1,\ldots,n\}$ be distance metric for each iteration, and m be the grand mean of X. The following execution steps of the proposed algorithm are described as:

1. Set $C=\emptyset$, $SX=\emptyset$, and $DM=[\ ]$
2. Calculate $D \leftarrow \text{dis}(X,m)$
3. Set number of neighbors $nmin = \alpha.\ n / k$
4. Assign $dmax \leftarrow argmax(D)$
5. Set neighborhood boundary $nbdis = \beta\ .\ dmax$
6. Set i=1 as counter to determine the i-th initial centroid
7. $DM = DM + D$
8. Select ж $\leftarrow$ $xargmax(DM)$ as the candidate for i-th initial centroids
9. SX=SX U ж
10. Set D as the distance metric between X to ж.
11. Set $no \leftarrow$ number of data points fulfilling $D \leq nbdis$
12. Assign DM(ж)=0
13. If $no < nmin$, go to step 8
14. Assign $D(SX)$=0
15. $C = C\ U$ ж
16. $i = i + 1$
17. If $i \leq k$, go back to step 7
18. Finish in which C is the solution as optimized initial centroids.

However, the computation time may take long time if we apply the Pillar algorithm directly for all elements of high resolution image data points. In order to solve this problem, we reduce the image size to 5%, and then we apply the Pillar algorithm. After getting the optimized initial centroids as shown in Fig. 3, we apply clustering using the K-means algorithm and then obtain the position of final centroids. We use these final centroids as the initial centroids for the real size of the image as shown in Figure 4, and then apply the image data point clustering using K-means. This mechanism is able to improve segmentation results and make faster computation for the image segmentation[6].

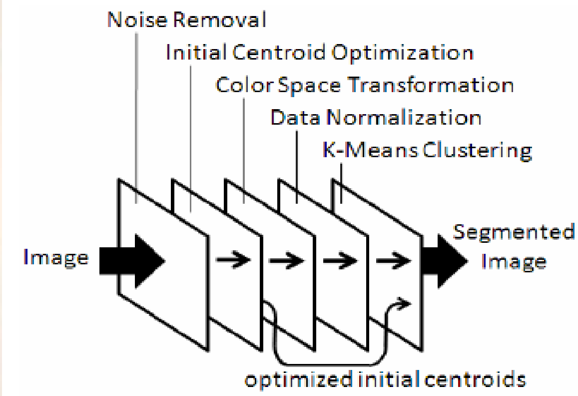
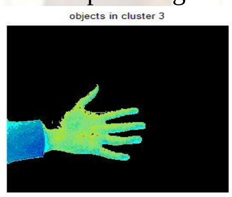
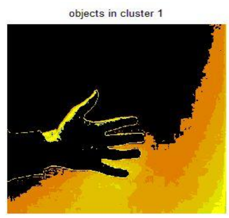
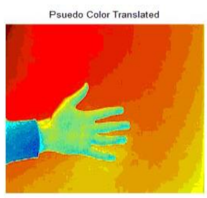


Fig3.main algorithm of pillar segmentation[6]







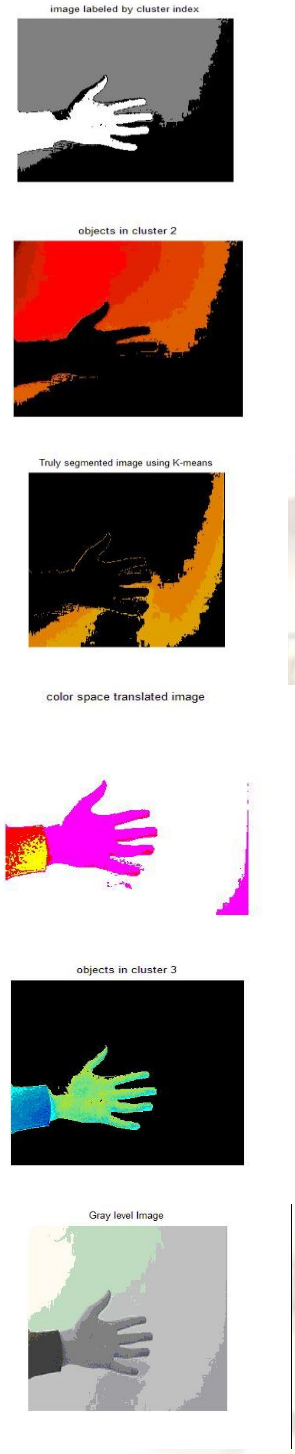


Fig4.image is segmented

Motion features

Inside a GOF, the main criterion for the segmentation is often the motion: for a given region, the motion vectors of its tubes should have close values. Therefore we want to associate energy to assess the difference between the motion of a tube and the motion of a region. So the motion vector associated to a peak is also the estimated motion of the region in the GOF. The distance between the motions of a tube, and a region, according to their norms and their directions, follows[8]:

$$d_m = \frac{\overrightarrow{mv_s}}{\max(\overrightarrow{mv_s},\overrightarrow{mv_{r\varepsilon_s}})} * \frac{\overrightarrow{mv_{r\varepsilon_s}}}{\max(\overrightarrow{mv_s},\overrightarrow{mv_{r\varepsilon_s}})}$$

Where $\overrightarrow{mv_{r\varepsilon_s}}$ and $\overrightarrow{mv_s}$ are respectively the motion vectors of the site s; and of the region $r\varepsilon_s$ formed by the sites labelled ε_s . In order to constrain this distance between 0 and 1, we compute[8,9]

$p_m(\overrightarrow{mv_s},\overrightarrow{mv_{r\varepsilon_s}}) = (d_m + 1)/2$

.1.4. Regions tracking

In order to track the regions between two successive GOF, we compare their segmentation maps. Exactly the segmentation map of the previous GOF, is first compensated using all of the motion information (global motion, motion vectors of its objects). Next we compare the labels of the regions in the previous and in the current GOF. A metric based on the color, the texture, and the recovery between the regions, is used. For the color, and the texture, we adapt the Bhattacharyya . A region of the current GOF takes the label of the closest region of the previous GOF (if their distance is small enough).The compensated map of the previous GOF is used to improve the current map through the potential function:

$$\begin{cases} v_{ct} = \beta_t & if\ e_s(t) \neq e_s(t-1) \\ v_{ct} = -\beta_t & if\ e_s(t) = e_s(t-1) \end{cases}$$

> 0, and where e_s (t), and e_s (t-1) are respectively the labels of the site for the current, and the motion compensated previous GOF. Here C is the set of temporal second order cliques. Each clique corresponds to a pair of adjacent tubes between the previous and the current GOF:

$w_5(e_s(t))=\sum_{c_t} v_c\,(e_s(t), e_s(t-1))$

Where c_t is the set of all the temporal cliques of S. Inside a GOF, when the motions of the potential objects are very similar, the motion-based segmentation failed to detect them. In this case, the initial segmentation map for our pillar segmentation model contains no information, hence, we use the motion compensated map from the previous GOF as initialization for our MRF segmentation model. This process allows to keep consistency for video objects tracking through the sequence GOF[8,9].

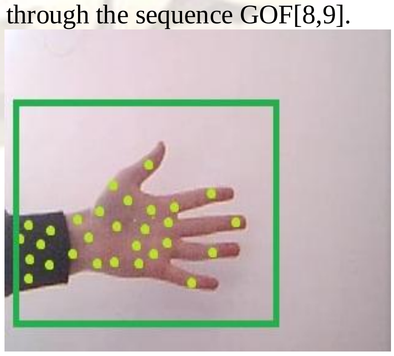


Fig5.tracking object in area

Experimental result:

In order to have better object tracking results we use threshold values. For better results pillar segmentation is implemented along with the Gof algorithm in case tracking and removal of noise particle. The performance analysis of these two parameters is discussed below with various images acquired from the camera shown in Figure 4,5 consecutively. In fact the tracking of an object also depends on the distance and positioning of the camera. In this paper we have tested the tracking on Objects such as hand shaking tracking. For testing purpose we have tested the algorithm with real time with an Image Size of 150x150. Motion tracking purely depends on the size of the object and center of segmentation objects.The performance analysis of these two parameters is discussed below in the out put images with various images acquired from the camera shown in Figure 4,5 consecutively and its statistical data for various HSV - Value and Threshold values are shown in Figure 5, 6 and 7 respectively. All the results have been computed by varying the segmentation value particularly parameters which plays an vital role during tracking any objects. This particular parameter has to be adjusted depending upon the lightening conditions under various environment.

Conclusion:

In this paper we present the pillar k-mean clustering for segmentation the object in the area which should be located as far as possible from each other to withstand against the pressure distribution of a roof, as identical to the number of centroids amongst the data distribution.this is realized for a GOF of nine frames and to keep consistency between the successive GOF segmentation maps in the video image tracking.

References:

[1] R. Megret and D. DeMenthon, “A survey of spatio-temporal grouping techniques,” Tech. Rep., LAMP-TR-094/CS-TR-4403, University of Maryland, 1994.

[2] B.K.P. Horn and B.G. Schunck, “Determining Optical Flow,”Artificial Intelligence, vol. 17, no. 1 – 3, pp. 185 – 203, 1981.

[3] J. M. Odobez and P. Bouthemy, “Robust Multiresolution Esti-mation of Parametric MotionModels,” Journal of Visual Com-munication and Image Representation, vol. 6, December 1995.

[4] O. Brouard, F. Delannay, V. Ricordel, and D. Barba, “Robust Motion Segmentation for High Definition Video Sequences using a Fast Multi-Resolution Motion Estimation Based on Spatio-Temporal Tubes,” Lisbon, Portugal, in Proc. PCS 2007.

[5] O. LeMeur, P. Le Callet, andD. Barba, “ACoherent Computa-tional Approach toModel Bottom-Up Visual Attention,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 28, no. 5, pp. 802 – 817, May 2006.

[6] "A New Approach for Image Segmentation using Pillar-Kmeans Algorithm" Ali Ridho Barakbah and Yasushi Kiyoki in World Academy of Science, Engineering and Technology 59 2009

[7] "Spatio-temporal segmentation based on region merging "Pattern Analysis and Machine Intelligence, IEEE Transactions on: Sep 1998

[8] "Spatio-temporal segmentation and regions tracking of high definition video sequences based on a Markov Random Field model "Pattern Analysis and Machine Intelligence, IEEE Transactions on Sep 1998 [9]"Combining motion segmentation with tracking for activity analysis "Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on 17-19 May 2004