



Integrating Colors, Shapes and Motions Using Active Contour Based Visual Tracking

P. Kiruthika¹, J.Sathya priya², S.P. Prakash³

PG Scholar, Dept of ECE, Bannari Amman Institute of Technology, Sathy, India^{1,2}

Assistant Professor (sr.gr), Dept Of ECE, Bannari Amman Institute of Technology, Sathy, India³

ABSTRACT: The visual tracking is the major process in finding the spot of moving object over time using a camera. Object tracking is challenging task when the object moves fast relative to the frame rate. The active contour algorithm is used for tracking the object in a given frame of an image sequence. In videos particular object motion can be tracked by using stationary cameras but in moving camera the particular object cannot be extracted from background subtraction. Active contour based visual tracking using level sets is proposed which does not consider the camera is stationary (or) moving. The optical flow based algorithm is used for initializing contours at first frame. The correlations between the values of neighboring pixels for posterior probability estimation is done by Markov random field theory in the color based contour evolution. The Independent Component Analysis (ICA) is used to deal with noise (or) partial occlusion to obtain the more accurate contours in the shape based contour. To handle the abrupt motions the particle swarm optimization is used to track the object from first frame to last frame and it is applied to current frame to produce an initial contour in next frame. This visual tracking can be used in real time applications like vehicle guidance and control, surveillance and identification, user interface, video processing and medical applications.

KEYWORDS— Abrupt motion, active contour-based tracking, adaptive shape model

I. INTRODUCTION

Visual object tracking is the active research topic in computer vision. The rectangles or ellipses are used to represent the object in general object tracking[1], where active contour based tracking afford more details about the object shape information[2], but in general it is more difficult than general tracking of object in the real world situation. This is because the contour tracking aims to recuperate finer details of the object and extract the object from background disturbances. A number of different approaches to region tracking have been developed to date, starting from the early tracking algorithms which concentrated on tracking feature points and edge segments. The region tracking algorithm is used to track the whole regions and not only attribute points in the region, depend on the shape of the region and motion of the points, in order to allow the region to be recovered from its feature points. In videos the object motion region can be extracted in stationary cameras, but in moving camera the object cannot be extracted from the background disturbance. Active contour-based object tracking does not consider whether the camera is stationary or moving, To describe object contours two general ways are explicit representations which are characterized by parameterized curves such as snakes and implicit representations, such as level sets which represent a contour using a signed distance map. The level set representation is more popular than the explicit representation because it has a stable numerical solution and it is capable of handling topological changes. Active contour evolution methods are classified into three categories: edge-based, region-based, and shape prior-based. The edge based methods consider the local information around the contours, such as grey level gradient, the snake model[3], geodesic model[4] are used in edge based method. It is sensitive to image noise. Region-based methods divide an image into object and background regions using statistical quantities, such as mean[5], variance,

or histograms of the pixel values in each region and it is independent for the posterior probability estimation. Shape prior-based methods are used to recover disturbed, occluded, or blurred contour sections.

II. PROPOSED WORK

In this paper, analysis the main restrictions in contour tracking, and present a framework for tracking object contours, no matter whether the camera is stationary or moving. The active contour based visual tracking using level sets are proposed. At the first frame, the ego motion compensation is used to compensate the camera motion and then the optical flow at each pixel is estimated in which one or more motion regions are detected. The boundaries of these motion regions are used as the initial contours. These initial contours are then evolved using color information. Based on the color-based contour evolution result, the shape prior based ICA technique is used to deal with noise or partial occlusion etc to obtain more accurate contours. Abrupt motion is checked with first frame, when there is no abrupt motion, the progress result in the current frame is used as the initial contour of the object in the next frame. If there is abrupt motion, the affine motion parameters are estimated using a stochastic algorithm, and applied to the contour in the current frame to obtain the initial contour for the next frame. The region based level sets include contour-based tracking initialization. For the first frame, color-based contour evolution, shape-based contour evolution, and abrupt motion handling

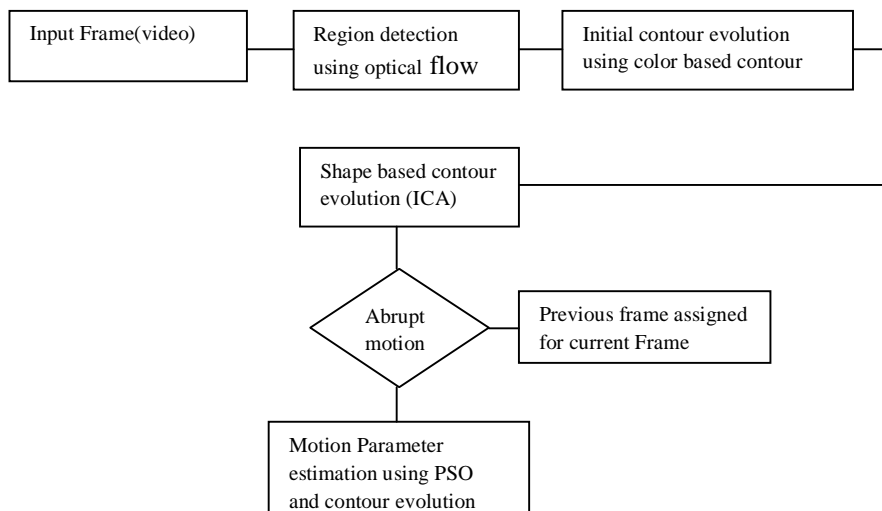


Fig 1 Flow Chart for Level Sets

A. Tracking Initialization

Tracking initialization which consists of the contour initialization in the first frame and modeling the object and background regions. The automatic and fast tracking initialization algorithm based on the optical flow detection is used. In the first frame, the optical flow magnitude and direction[6] is used to detect motion regions whose boundaries are used as the initial contours. The ego-motion compensation is used to compensate camera motion. Each pixel in optical flow is represented by (u, v) , where u and v are the optical flow velocity vector's components in the x and y directions respectively. For a pixel the magnitude is less than a predefined threshold, its optical flow is set to $(0, 0)$, it is assigned to the background. The detection algorithm includes the size of the shape model is fixed and the centre of the object is moved



then the series of regions $\{M_i\}$, of various sets of pixels is produced. The object and background regions are both modelled in the active contour based object tracking algorithm to compete for pixels in the image. To model the object and background regions the hierarchical method[7] is used, which fuses color and texture features using a Gaussian mixture model (GMM).

B. Color Based Contour Evolution.

The contour evolution is used to adjust an initial contour awaiting the image is partitioned optimally by the contour[8],[9] into a foreground region and a background region. According to bayes rule the pixel values in the object region or a background region are independent for posterior probability and likelihood estimation. The independence of pixel values for posterior probability and likelihood estimation is too strong, especially when there are local associations between pixels, such as for textured regions or regions with repeated patterns. As a result it is easy to misidentify pixels around object boundary sections where the contrast between the object and the background is low. To overcome a problem the correlations between values of neighbouring pixels are constructed using Markov Random Field theory and it is incorporated into estimation of the posterior probability of segmentation. It is not sensitive to background disturbances and that it achieves tight and smooth contours

C. Shape based contour evolution

To obtain a contour closer to the true contour, the global shape information and the local color information are combined in hierarchical shape-based contour evolution algorithm .the shape based contour evolution includes shape registration and construction of subsequence, and the mahalanobis distance based criterion. A novel incremental ICA[10] is applied to update the shape model in a more flexible way than in the previous shape model updating algorithm. The Paragios' variational method is used to implement the shape registration. Each contour shape is represented using its corresponding level-sets signed distance map ϕ . Shape registration from shape A to shape B involves scaling, rotating, and trans- lating shape A to obtain a new shape which best matches shape B. The contour shape subspace is constructed from a training sequence, it obtain a series of training shape samples of the object which is to be tracked in the test sequence. The shape registration aligned each sample in the signed distance maps. The level set embedding function values in each distance map are flattened into a coned each column vector. The Mahalanobis distance-based criterion is used to determine whether the shape model is introduced into the contour evolution process. If it occurred the shape-based evolution which adapts to different contour locations is used to further evolve the contour.

C.1.Independent Component Analysis

Incremental updating of shape model using the contours obtained from the recent frames is necessary for shape based contour tracking, as the recent years provide more accurate information about the current shape of the object. In signal processing, independent component analysis (ICA) is a computational method for separating a multivariate signal into additive subcomponents and pretentious the subcomponents are non-Gaussian signals and that they are all statistically independent from each other. ICA is a unique case of blind source separation. When the statistical independence statement is correct, blind ICA separation of a mixed signal gives very good results. It is also used for signals that are not supposed to be generated by a mixing for analysis purposes. The two broadest definitions of independence for ICA are Minimization of mutual information, Maximization of non-Gaussianity. Typical algorithms for ICA use centering, whitening and dimensionality reduction as pre-processing steps in order to simplify and reduce the complexity of the problem for the actual iterative algorithm. Whitening and dimension reduction can be achieved with principal component or decomposition. The updating of shape model is done by independent component analysis. When the shape change is large the shape model update frequently as one frame, it is more flexible and rapid shape updating.



D. Abrupt motion

When the shape contour evolution is completed it checks for abrupt motion [11] in previous frame and current frame. If the abrupt motion is occurred the particle swarm optimization is used to estimate the motion parameters and it is applied to contour in previous frame to obtain initial contour in current frame. After that the initial contour is evolved to endow with segmentation of the object.

D.1. PSO Algorithm

Traditional contour tracking methods cannot handle abrupt motion or low frame rate video. This is because the basis of the traditional tracking lies in the hypothesis that the motion is smooth between consecutive frames, but the abrupt motion destroy the hypothesis of that motion. As a two-layer hierarchical level set-based tracking framework in which Particle Swarm Optimization (PSO)[12] and level set evolution are fused seamlessly. In the first layer, the PSO is adopted to capture the global motion of the object. The coarse contour is obtained by applying the global motion to the contour in the previous frame. For the second layer, the level set evolution based on the coarse contour is carried out to track the local deforming, which results in the actual contour. Particle Swarm Optimization (PSO) into level set evolution which can successfully handle the contour tracking in abrupt motion and low frame rate (LFR). The proposed algorithm possesses the following features which distinguish it from the conventional level set based contour tracking approaches: first, the parametric optimization (PSO) and non-parametric optimization (level set) are combined under a unified framework to the solve the difficulty induced by the abrupt motion. Second, the training process to learn the motion model is not need due to evolution strategy. The approach does not require prior knowledge of motion which is not always available. Third, prior appearance model for the level set evolution fuses color and texture seamlessly to make our approach more tolerant to noisy environments. Finally, it shows theoretically that our approach is essentially a combination of the deterministic and heuristic stochastic search to cope with the abrupt motion.

III. EXPERIMENTAL RESULTS

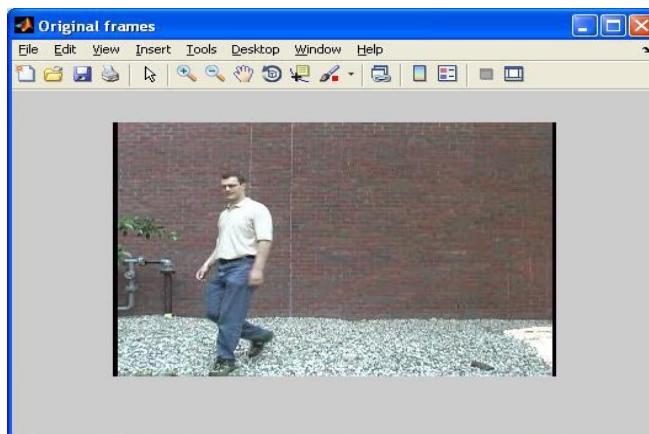


Fig 2 Original Video

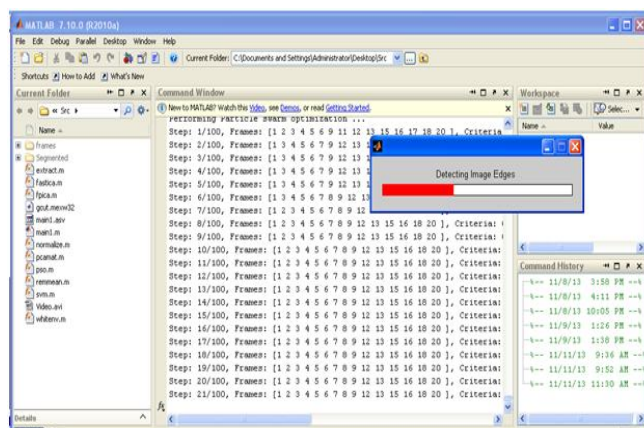


Fig 3 Detecting Image Edges

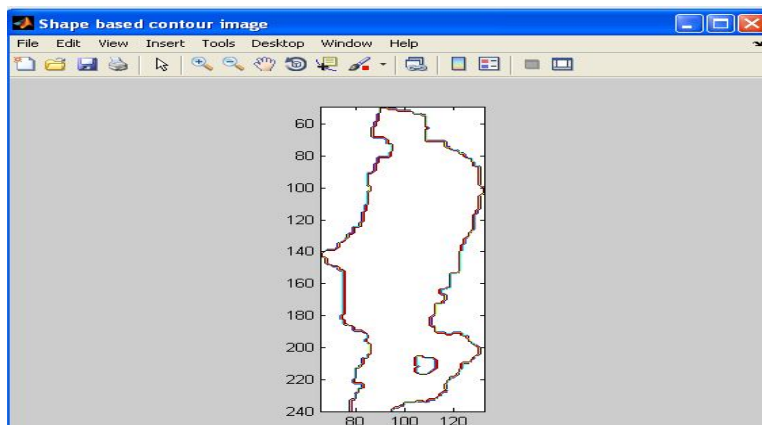


Fig 4 Shape Based Contour Image

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department of CSE, JayShriram Group of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

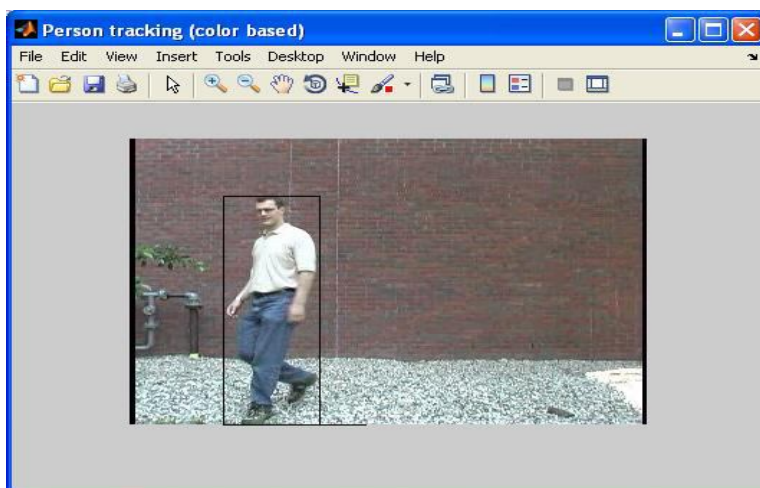


Fig 5 Color Based Contour Evolution

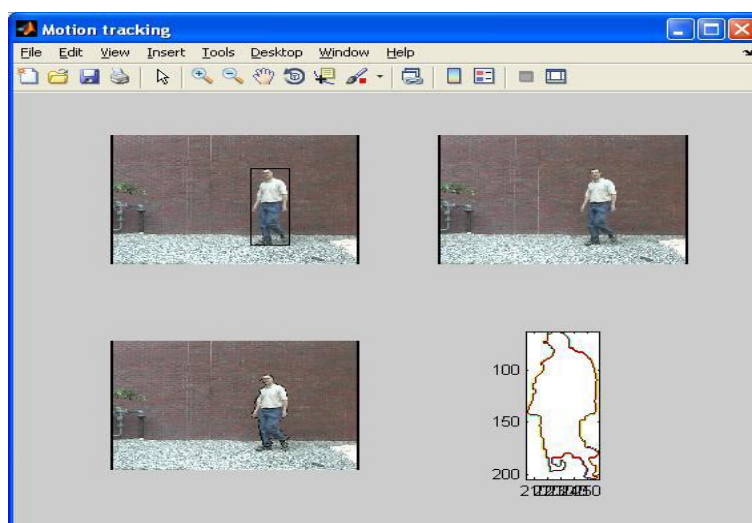


Fig 6 Initialization of Tracking Walking Person

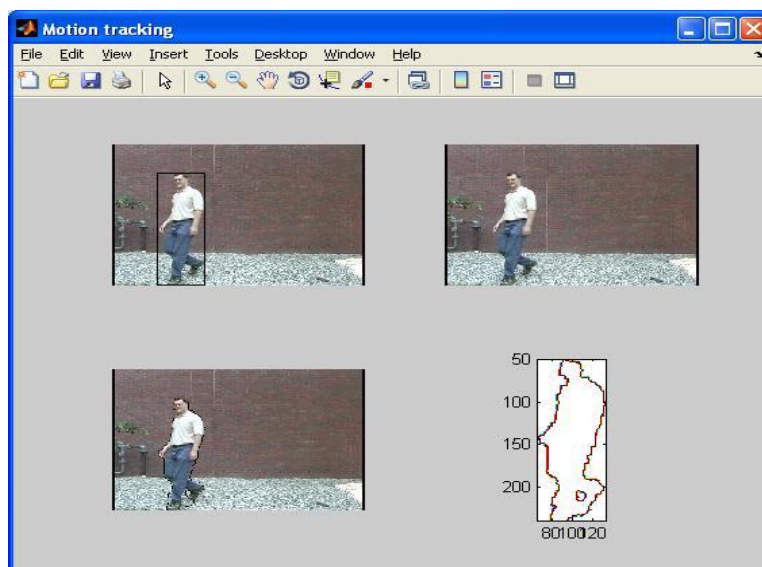


Fig 7 PSO based algorithm for low frame rate

IV. CONCLUSION AND FUTURE WORK

The color-based contour evolution algorithm which applies the MRF theory to representation the correlations between pixel values for posterior probability estimation is more to background disturbance than the region-based method which does not consider correlations between the values of neighbouring pixels for posterior probability estimation. The adaptive shape-based contour evolution algorithm, which efficiently fuses the global shape information and the local color information and uses a flexible shape model updating algorithm, is robust to partial occlusions, weak contrast at the boundaries, and motion blurring, etc. The PSO based algorithm can effectively deal with contour tracking for videos with abrupt motions, and it outperforms the particle filter-based algorithm. The future work is done for the tracking of multiple moving objects by graphical based method. In this shape, color along with this structure of the object is also considered.

REFERENCES

- [1] X. Zhou, W. Hu, Y. Chen, and W. Hu, "Markov random field modeled level sets method for object tracking with moving cameras," in Proc. Asian Conf. Comput. Vis., 2007, pp. 832–842.
- [2] D. Cremers, M. Rousson, and R. Deriche, "A review of statistical approaches to level set segmentation: Integrating color, texture, motion and shape," Int. J. Comput. Vis., vol. 72, no. 2, pp. 195–215, Apr. 2007.
- [3] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," Int. J. Comput. Vis., vol. 1, no. 4, pp. 321–331, 1988.
- [4] V. Caselles, R. Kimmel, and G. Sapiro, "Geodesic active contours," Int. J. Comput. Vis., vol. 22, no. 1, pp. 61–79, Feb. 1997.
- [5] T. F. Chan and L. A. Vese, "Active contours without edges," IEEE Trans. Image Process., vol. 10, no. 2, pp. 266–277, Feb. 2001.
- [6] B. Horn and B. Schunck, "Determining optical flow," Artif. Intell., vol. 17, pp. 185–203, Aug. 1981.



ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department of CSE, JayShriram Group of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

[7] C. Stauffer and W. E. L. Grimson "Adaptive background mixture models for real-time tracking," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., vol. 2. Jun. 1999, pp. 246–252.

[8] S. C. Zhu and A. Yuille, "Region competition: Unifying snakes, region growing and bayes/MDL for multiband image segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 18, no. 9, pp. 884–900, Sep. 1996.

[9] Yilmaz, X. Li, and M. Shah, "Object contour tracking using level sets," in Proc. Asian Conf. Comput. Vis., 2004, pp. 1–7.

[10] M. Fussenegger, P. M. Roth, H. Bischof, and A. Pinz, "Online, incremental learning of a robust active shape model," in Proc. DAGM-Symp. Pattern Recognit., 2006, pp. 122–131.

[11] J. Sullivan and J. Rittscher, "Guiding random particles by deterministic search," in Proc. IEEE Int. Conf. Comput. Vis., vol. 1. Jul. 2001, pp. 323–330.

[12] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in Proc. IEEE Int. Conf. Neural Netw., Nov.–Dec. 1995, pp. 1942–1948.