Active Contour Based Visual Tracking Using Levelsets

R.Chitra ramya, V.SrirengaNachiyar, K.Ramasamy

Abstract— In this paper a framework for active contour based visual tracking using level sets. The main component of framework include contour-based tracking initialization, color based contour evolution, dynamic shape based contour evolution for periodic motions, adaptive shape based contour evolution for non periodic motions. For the initialization of contour based tracking, develop an optical flow based algorithm for automatically initializing contours at selected frame. For the color based contour evolution, markov random theory is used to measure correlations between values of neighboring pixels for posterior probability estimation. For dynamic shape based contour evolution, a shape mode transition matrix is used to adding noise in original image, to get more accurate contour tracking. For adaptive shape based contour evolution, two methods are used one is multiphase and singlephase method, used to tracking an accurate object.

Index Terms— Active contour based tracking, Adaptive shape model, Dynamic shape model, Multiphase method, Singlephase method.

1 Introduction

Visual object tracking is an active research topic in computer vision. In contrast to general object tracking which uses predefined coarse shape models, such as rectangles or ellipses, to represent objects, active contour based tracking provides more difficult than general tracking of the same object in the same real-world situation. This is because contour tracking aims to recover finer details of the object, i.e., the boundary of the object [1] and the determination of the boundary of the object is susceptible to influences from the background disturbance. In videos taken by stationary cameras, object motion regions can often be extracted using background subtraction, and object contours can be produced by tracking the edges of the motion regions, making the contour-based tracking more difficult than in videos taken by stationary cameras [2]. Active contour-based object tracking, no matter whether the camera is stationary or moving, has attracted much attention in recent years. 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 [5]. 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 [7]. The edge based methods consider the local information around the contours, such as grey level gradient. In the classical snake models an edge-detector is used, depending on the gradient of the image to stop the evolving curve on the boundary of the desired object. Region-based methods divide an image into object and background regions using statistical quantities, such as mean, variance, or histograms of the pixel values in each region and it is independent for the posterior probability estimation [12]. In approximate an image by a mean image with regions whose boundaries are treated as object edges. In present a statistical and variational framework for image segmentation using a region competition algorithm. In adopt the features of both object and background regions in the level-set evolution model process. Color prior knowledge is usually represented using object appearance models such as color histograms, kernel density estimation, or Gaussian mixture models (GMMs) [14]. Shape prior-based methods are used to recover disturbed, occluded, or blurred contour sections. In construct a pixel-wise shape model in which local shape variability can be accounted and propose an active shape model for the different aspects of rigid objects in a shape prior formulation. In propose a statistical method to learn object shape models which are used to recover occluded sections of a contour [10]. Occlusion is dealt with by incorporating shape information into the weights of the particles. In utilize the symmetry of rigid object shapes to deal with partial occlusions.

2 Proposed Methdology

In this paper, we systematically investigate the aforesaid main limitations in contour tracking, and present a framework for tracking object contours. The framework adopts the region-based evolution of contours which are represented using level sets. At the selected frame, the method is used to compensate for camera motion and then optical flow at each pixel is estimated. Using the estimated optical flows, 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 result of color-based contour evolution, the shape prior is introduced to deal with noise to obtain more accurate contours. We consider shape priors for periodic motions and non-periodic motions, corresponding to dynamic shape models and adaptive shape models respectively. The main components in our framework include contour-based tracking initialization for the first frame, color-based contour evolution, adaptive shape-based

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contour evolution, dynamic shape-based contour evolution.

The main components in our framework have the following contributions:

1) We propose an automatic and fast tracking initialization algorithm based on optical flow detection. In the algorithm, object motion regions are extracted in the selected frame, and closed initial contours near the boundaries of moving regions are constructed.
2) We propose a color based contour evolution algorithm. In this algorithm, correlation between values of neighbouring pixels is constructed using Markov random field (MRF) theory. This ensures that our color-based algorithm is not sensitive to background disturbances and it not sensitive to background disturbances and that it achieves tight and smooth contours.
3) We propose a Markov model-based dynamical hape model. Ading noise is used to obtain the typical shape modes of a periodic motion and to get more accurate contour. The matrix of transitions between these modes is then constructed. In the tracking process, the contour evolved using color information alone and then the contour is further evolved under the constraint of the predicted shape mode.
4) We propose an adaptive shape-based contour evolu tion algorithm. In the algorithm, the results obtained using the color feature alone and the shape priors are effectively combined, adapting to different contour locations, to obtain the final contour. A new incremental PCA technique is applied to update the shape model, making the shape model updating flexible here using two types of method, corresponding to multiphase and singlephase method. In multiphase method track both object and background region. In singlephase method it tracks only the object using the initial contour by using bounding box.

In this paper, analysis the main restrictions in contour tracking, and present a framework for in contour tracking object contours, no matter whether the camera is stationary or moving. The active contour based visual tracking using levelsets are proposed.

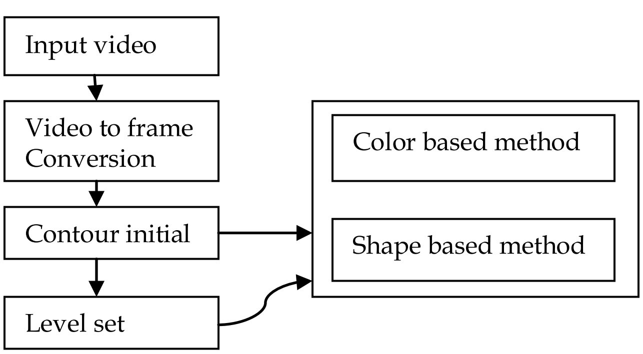


Fig .1Block diagram for level sets

At the first frame, the ego motion compensation is used to compensate for the camera motion and then optical flow at each pixel is estimated .Using the estimated optical flows in which one or more motion regions are detected. The boundaries of these 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. We consider shape priors for non-periodic motions and periodic motions, corresponding to adaptive shape models and dynamic shape models respectively.

2.1 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 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 {Mi}, 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. The size of the shape model is kept fixed and the center of the shape model is moved. Each such region Mi is assigned a weight Φ calculated by:

$$\begin{aligned} \phi(x,y) &= 0 \quad (x,y)\in C \\ \phi(x,y) &= d(x,y,C) \qquad (x,y)\in Rout \\ \phi(x,y) &= -d(x,y,C) \qquad (x,y)\in Rin \end{aligned} \qquad [1]$$

Where Rin and Rout denote the regions inside and outside C and d(x, y, C) is the smallest iteratively in normal direction:

$$\phi_{n+1}(x,y) - \phi_n(x,y) + (F(x,y) + Fcurv)\left|\Delta\phi(x,y)\right| = 0 \qquad [2]$$

2.2 Color Based Contour Evolution

The contour evolution is used to adjust an initial contour awaiting the image is partitioned optimally by the contour into a foreground region and a background region.. 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.

- MRF

$$\xi i = \beta\sqrt{u_2 x + v x_2} - (1-\beta)\Omega \arg(u,v) \qquad [3]$$

Where x is a pixel within the variance of the directions of flow vectors of the pixels.

2.3 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. 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 translating 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.

- Mahalanobis Distance based criterion:

The level set embedding function values of the aligned contour are flattened into a column vector x, forming a k-dimensional vector.

$$a : a = U_{tk}(x-\mu) \qquad [4]$$

According to the definition of α, the following equation is obtained:

$$\gamma_2 \approx (x-\mu)_t U_k (x-\mu) = a_t \sum_{k}^{-2} a \qquad [5]$$

If 'Y2 is larger than a predefined threshold, then the color based evolution result as the final tracking result.

I. Dynamic Shape Based Contour Evolution: Object shape information can be used to improve the results of color-based contour evolution. On the basis of shape registration and construction of a shape subspace, the Mahalanobis distance-based criterion is used to determine whether the shape model is introduced into the contour evolution process. If so, a shape-based evolution which adapts to different contour locations is used to further evolve the contour. Here using the noise that can get more accurate contours. By adding salt and pepper noise in original image and track that image and removing the noise using median filter and to get more accurate contour when compared to color based contour evolution.

- Distance between samples:

$$d(\phi_i,\phi_j) = \left| H_a(\phi_i(x,y)) - H_a(\phi_j(x,y)) \right| \qquad [6]$$

Where Ha is a Heaviside function defined. This distance is symmetrical and it is irrelevant to the contour size due to shape registration.

II. Adaptive Shape Based Contour Evolution: Adaptive shape models are more appropriate than the dynamic shape models to deal with large changes in shapes of non-rigid object contours. In the following, we cluster shape samples of non-rigid object contours to obtain the typical shape modes and the mode transition matrix which is used to predict the shape mode. With the constraint of the predicted shape mode, the contour obtained by the color- based evolution is further evolved to obtain the final contour. The iterations using [14]are repeated for a given number of times or until the mean of differences between φ(x, y) and φs(x, y) at each location (x, y) is less than a predefined threshold.

$$\tau(x,y) = \beta \exp(-(\phi_c(x,y) - \phi_s(x,y))_2) \qquad [7]$$

Where β is a positive constant.Thus, at each pixel location (x, y) where the difference between φc(x, y) and φs(x, y) is large, the evolution of φ(x, y) can still continue when the difference between φ(x, y) and φs(x, y) is getting smaller and smaller.
In adaptive shape based contour evolution, it follows two methods such as multiphase and singlephase methods respectively.

a) **Multiphase Method**: In multiphase method it tracks both object and background region by using optical flow algorithm. By using inner iteration and outer iteration it tracks the object and background region well.
b) **Singlephase Method:** In singlephase method it tracks only the object by using initial contour. Here also use the optical flow it tracks the object accurately when compared to multiphase method.

3 Results and Discussions

3.1 Video to Frame Conversion

The input videos of three seconds time duration are converted into 100 frames here there are six frames of person moving in the track.

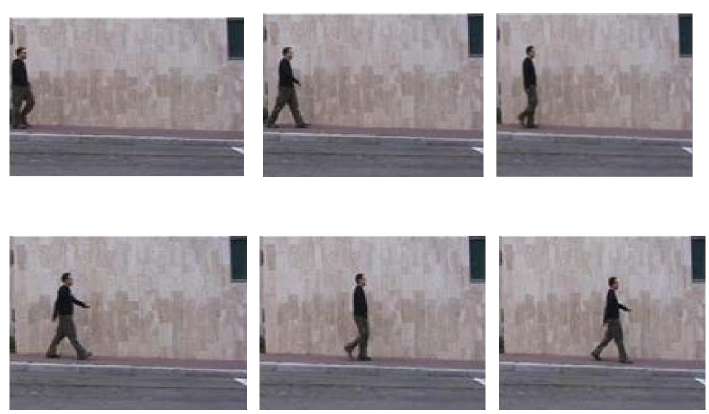
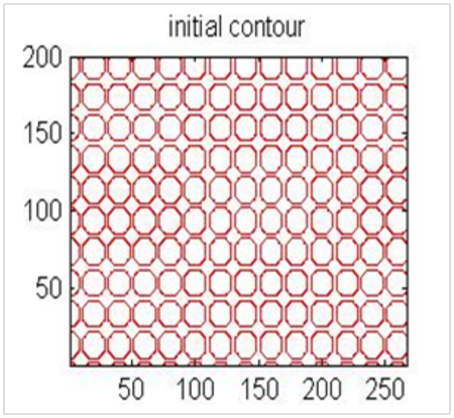


Fig.2 Output of video to frame conversion

3.2 Contour Based Tracking Initialization

Tracking initialization often relies on a manually drawn closed contour around the object. Those methods, in which the boundaries of motion regions detected by background substraction are the initial contour of moving objects. In the initial contour can be placed anywhere in the image, but it may take long time to converge to the correct boundary.



Formation of initial contour

3.3 Color Based Contour Evolution

The contour based tracking is successfully initialized based on the optical flow detection result in the selected frame. Some of the results of the initialization are selected and the automatic initialization of the tracking of a walking person, in which the result of optical flow detection applied to the image. The rectangle shown in the detected motion region with center coordinates. The detected motion region is acceptable and the boundaries of the rectangle are good enough initial contour for color based contour evolution.

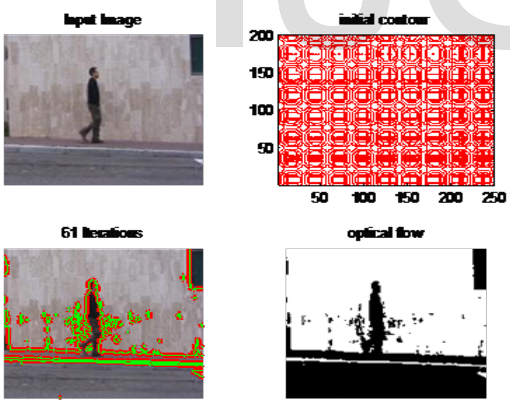


Fig.3 Output of color based contour evolution

3.4 Dynamic Shape Based Contour Evolution

For testing our dynamic shape based contour evolution, contours of walking persons are tracked under various noise. Here adding salt and pepper noise to get more accurate contour initial contour forms only the object side.

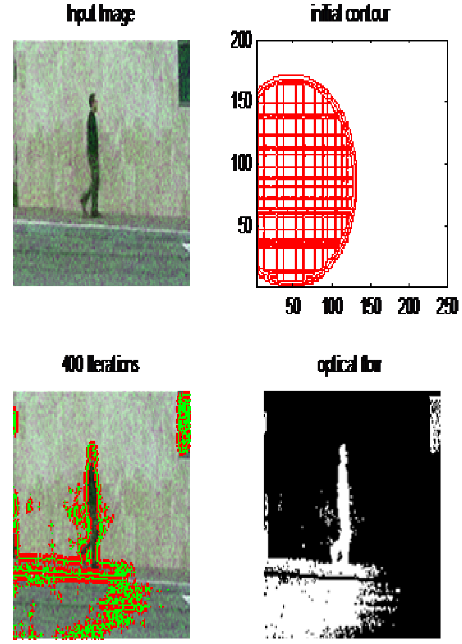


Fig 4.Output of original image with adding two components

After noise is removed by using median filter to get more accurate contours.

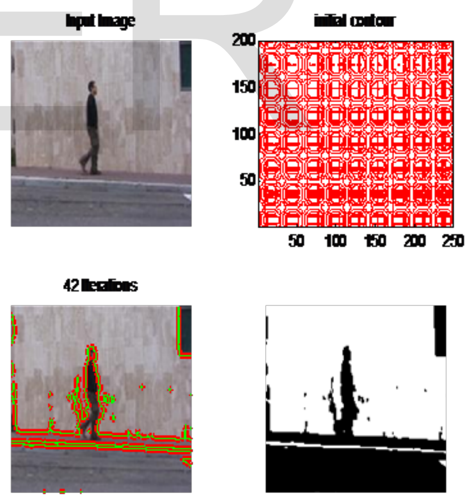


Fig4.1 Removal of noise

3.5 Adaptive Shape Based Contour Evolution

In adaptive consists of two methods which are multiphase and single phase respectively. Both methods using the initial contour in iteration method.

Multiphase Method: In multiphase method it tracks both object and background region by using iteration.

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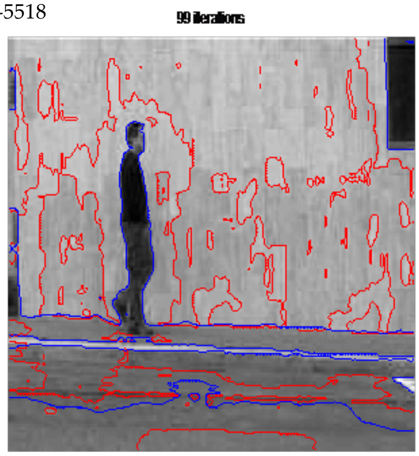

Fig5. Output of multiphase method

Fig5.1 Segmented region

Singlephase Method: In singlephase method it tracks only the object by using bounding box in initial contours.

Fig 5.2 Output of Singlephase method

Fig5.3 Final output of tracking an object using singlephase method

4 Conclusion

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 neighboring 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 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.

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