Performance Measures for Assessing Contour Trackers

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Abstract

In this paper we present techniques to compare the quality of tracking performances of B-spline based contour trackers. Three trackers reported to give good tracking performance have been considered for our empirical evaluation. They are the CONT-IMM tracker [21], the CONDESATION tracker [17] and the Baumberg tracker [4]. Four different test conditions were set and for each test, the tracking performance of each tracker was measured against four performance measures. The results presented have revealed some interesting findings about the performance of the trackers under various conditions.

1 Introduction

This paper provides simple empirical evaluation techniques to assess the performance of B-spline based contour trackers (the performance is assessed in terms of the quality of tracked contour). We considered 3 contour trackers (where the contours are represented by B-splines) which have been reported to perform well for the evaluation presented in this paper. They are the Condensation algorithm [17-18], the CONT-IMM tracker [21], and the Baumberg's tracking algorithm [4]. Due to paper space constraints the detail framework of the 3 trackers are not discussed (the interested reader is referred to the appropriate references given for further details).

A literature survey carried out in the area of contour tracking revealed that very little work has been published to compare the performance of trackers (mainly in terms of the quality of tracker output). Most performance comparison methods presented are specific for the tracker considered [4, 5, 6, 9, 10, 11, 13, 14, 17], thus cannot be easily employed to compare the performances of other trackers. Examples of such methods can be found in [1, 15, 16, 19]. Formulating closed form performance measures for tracking is very difficult given the complexity involved, and can give inaccurate results under varied tracking environments. Therefore, in this paper, empirical evaluation methods have been described. The methods cater for a variety of applications and conditions under which the tracker performance can be analyzed. The results presented reveal some interesting facts about the trackers for the test image sequence considered.

We employed a test image sequence of a walking person to carry out various tracking performance tests. The test image sequence considered was relatively free of clutter and occlusion, so that the focus of the experiments designed was to purely assess the quality of

the contour tracked. For the experiments reported in this chapter, the internal parameters of each tracker was tuned to give the best possible result, so that the observations obtained are a fair representation of the performance of the trackers.

The tests that we employ include tracking objects under varied noise conditions (using SNR test measure), tracking objects captured at varied frame rates, tracking using varied number of non-rigid shape parameters to account for contour deformation, and using varied number of control points to represent object shape. The result of each of the trackers was measured against 4 performance measures. Namely: the contour distance error, the contour origin error, the deformable shape parameter error, and the SNR. The description of test methods and performance measures employed are given in sections 4 and 5. This chapter is organized as follows: Section 2 describes the performance comparison methods used to compare the tracker performance. Section 3 gives the results obtained, and Section 4 gives a discussion and interpretation on the results presented. Finally section 5 provides the conclusion.

2 Performance Measures

2.1 Contour Distance Test

A simple distance metric to measure the distance between two sets of landmarks $\mathbf{x} = (x_i, y_i)$ and $\mathbf{x}' = (x'_i, y'_i)$ can be given by,

$$f(\mathbf{x}, \mathbf{x}') = \left| \mathbf{x} - \mathbf{x}' \right| = \left(\sum_{i=0}^{N-1} (x_i - x'_i)^2 + (y_i - y'_i)^2 \right)^{1/2}$$
(1)

Unfortunately for contours represented by B-splines, this measure does not take into account the B-spline metric parameters. For 2 contours represented by B-splines, a better distance metric can be formulated by including the B-spline metric matrix as given in [7, 8].

Given two cubic B-splines P(s) and P'(s) defined by their N control points (x_i, y_i) and (x'_i, y'_i) , a more accurate error metric d, measures the difference between corresponding points on each spline, sampled densely and uniformly over the parametric curves. The distance metric is given by,

$$d(\mathbf{x}, \mathbf{x}') = \left(\int_{0}^{N} |\mathbf{P}(s) - \mathbf{P}'(s)|^{2} ds\right)^{1/2}$$

$$= \left(\int_{0}^{N} \sum_{i=0}^{N-1} ((x_{i} - x'_{i}) B_{i}(s))^{2} ds + \int_{0}^{N} \sum_{i=0}^{N-1} ((y_{i} - y'_{i}) B_{i}(s))^{2} ds\right)^{1/2}$$
(2)

where $B_i(s)$ is the cubic B-spline basis matrix. Equation (2) simplifies to the following form [8]:

$$d(\mathbf{x}, \mathbf{x}') = \left[(\mathbf{x} - \mathbf{x}')^T \mathbf{J} (\mathbf{x} - \mathbf{x}') \right]^{1/2}$$

where \mathbf{J} is the 2Nx2N symmetric metric matrix [10]. There is a unique inner product associated with this metric given by,

$$\langle \mathbf{x}, \mathbf{x}' \rangle = \mathbf{x}^T \mathbf{J} \mathbf{x}'$$

such that

$$d(\mathbf{x}, \mathbf{x}') = \left\langle \mathbf{x} - \mathbf{x}', \mathbf{x} - \mathbf{x}' \right\rangle^{1/2} = \left[(\mathbf{x} - \mathbf{x}')^T \mathbf{J} (\mathbf{x} - \mathbf{x}') \right]^{1/2}$$

We define the distance error as the average of d across the image sequence (F frames), which is given by,

Distance_error =
$$\frac{1}{F} \sum_{k=1}^{F} |d(\mathbf{x}, \mathbf{x}')|_{k}$$
(3)

2.2 Object Origin Test

The object origin is simply the center of gravity of a closed contour, which is calculated for the object of interest (actual and tracked) at each frame (k) of a sequence, then the difference of the origin error (at each frame) is averaged over the number of frames (F). The origin error is defines as,

$$Origin_error = \frac{1}{F} \sum_{k=1}^{F} \left[\left(O_x^{actual} - O_x^{tracked} \right)_k^2 + \left(O_y^{actual} - O_y^{tracked} \right)_k^2 \right]^{1/2}$$
 (4)

with actual object origin

$$O_k^{actual} = (O_x^{actual}, O_y^{actual}) = \left(\frac{1}{N} \sum_{i=1}^N X_i^{actual}, \frac{1}{N} \sum_{i=1}^N Y_i^{actual}\right),$$

and, tracked object origin

$$O_k^{tracked} = (O_x^{tracked}, O_y^{tracked}) = \left(\frac{1}{N} \sum_{i=1}^{N} X_i^{tracked}, \frac{1}{N} \sum_{i=1}^{N} Y_i^{tracked}\right)$$

where $X_i^{tracked}$, X_i^{actual} are the B-spline vectors (with N control points) for the tracked contour and the actual contour respectively. A low value of origin error will reveal the tracked contour-centroid is close to the original contour-centroid in terms of position. The origin error can be used as a secondary measure to the distance error measure.

2.3 Shape Deformation Test

The shape deformation test is a test measure to assess the deviation of non-rigid shape variation from a mean shape. The quantity reveals how much the object shape at k-th frame has deformed from the mean shape. In our analysis we have devised an error measure for the difference in non-rigid shape changes between the tracked shape and the actual shape in terms of the Mahalanobis Distance (MD) measure (All affine changes of shape are disregarded for this test). The non-rigid (deformable) shape parameter error is calculated for the object at every frame (k), then the error between the actual and tracked MD is averaged over the number of frames (F). This is given by,

$$NRSPE = \frac{1}{F} \sum_{k=1}^{F} \left| MD_{actual} - MD_{tracked} \right|_{k}$$
 (5)

Where NRSPE stands for: Non Rigid Shape Parameter Error. The Mahalanobis distance measure for actual and tracked contours are given by [12, 14],

$$MD_{actual} = \left(\sum_{i=1}^{m} \frac{b_i^2}{\lambda_i}\right)^{1/2}$$
, $MD_{tracked} = \left(\sum_{i=1}^{m} \hat{b}_i^2\right)^{1/2}$ respectively.

Where λ_i , b_i , b_i , are the eigenvalue, deformable (non-rigid) shape parameter for the actual contour, and the deformable shape parameter for the estimated (tracked) contour, corresponding to the *i*-th principal vector respectively. m is the number of principal components considered for non-rigid object tracking. It should be noted that to evaluate MD, the object in k-th frame has to be translated, scaled and rotated (if required) to align with the mean shape. This process ensures that only the deformable shape changes of the object are measured (disregarding changes in translation, scaling and rotation).

2.4 Signal to Noise Ratio (SNR) Test

The SNR performance evaluation is a B-spline independent image based method that uses the 'SNR out' measure for tracking performance (similar to that reported in [7]). To evaluate the performance of the trackers under varied noise, a 'SNR in' measure can also be formulated. Both these measures can be determined as explained in the following sections.

2.4.1 Measuring the Accuracy of Tracking

An additional performance measure employed to assess the accuracy of the tracking process (ie. The accuracy of shape, position and orientation of the tracked contour) is an image processing based measure. Thus the error measure is independent of the parameterization of the contour representation. The contour resulting from the tracking process is rendered flat filled in the 'foreground' color (moving object colored with white) into the image I_{track} .

The tracking process is 'local' so that the signal far from the object is never sampled. Hence, in this case, it is more appropriate to measure the signal in terms of the area of 'foreground' pixels in the ground truth image. The signal and noise are calculated using the following quantities.

$$signal = 2 \sum_{images} \sum_{x,y} [I_{ref}(x,y)]^{2}$$

$$noise = \sum_{images} \sum_{x,y} [I_{ref}(x,y) - I_{track}(x,y)]^{2}$$
(6)

where $I_{ref}(x, y)$ is the pixel value at (x, y) for the ground truth image. The pixel value for a 'background' pixel is 0. The scale factor of 2 in the signal value was chosen so that a SNR of 0 (ie. signal = noise) would occur if the tracker silhouette consisted of a shape of the same area as the ground truth shape but inaccurately placed so that there is no overlap between the two. This is the 'worst case' scenario where the tracker has

completely failed to track the object. The output SNR (in dB) denoted as SNR_{out} is calculated by using the following equation.

$$SNR_{out}(dB) = 10\log\left[\frac{signal}{noise}\right]$$
 (7)

An example for finding 'SNR out' is illustrated in Fig. 1 for the 3 trackers considered.

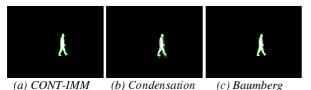


Figure 1: An example of SNR output results. The contour tracked by each tracker superimposed on top of the actual object (the tracked contour is flat filled for SNR calculation).

2.4.2 Adding Noise to Input Test Sequence

Noisy images were generated by adding Gaussian noise to the test image sequence. This type of noise was chosen to test the robustness of the system, for several reasons. Firstly, the noise added (particularly at high levels) can't be thresholded out easily. Secondly, the noise process will result in significant errors in contour measurements over whole sections of the curve. Hence these noisy images are suitable for a rigorous test of the tracking system. Some corrupted images are shown in Fig. (2). It can be seen that the silhouette shape can be disrupted by the noise, and a conventional non-model based approach such as the 'snake' [20] would be unable to recover the object shape correctly.

The signal to noise ratio (SNR_{in}) of the noisy images is calculated over the test image sequence using

$$SNR_{in}(dB) = 10\log\left[\frac{signal}{noise}\right]$$
 (8)

with

$$signal = \sum_{images} \sum_{x,y} [I_{ref}(x,y) - I_0]^2$$

$$noise = \sum_{images} \sum_{x,y} [I_{ref}(x,y) - I'(x,y)]^2$$
(9)

where $I_{ref}(x,y)$ is the pixel value at (x,y) for the ground truth image and I'(x,y) is the corresponding pixel in the corrupted image (the noisy image is binarised for 'SNR in' calculation). The constant I_0 is set to halfway between the 'background' and 'foreground' pixel values, so that a patch of foreground and a patch of background both have the same signal strength, thus ensuring the SNR is independent of the relative image and object size.

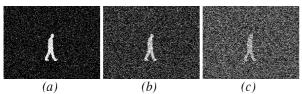


Figure 2: Effects of adding artificial noise (binarised for SNR input calculation). With Gaussian nois variance (a) at 75 (b) at 100, and (c) at 130.

3 Results

3.1 Tracker Implementation Method

The CONT-IMM tracker was implemented as described in [21]. The CONDENSATION algorithm was implemented as described in [17] using 1000 samples per iteration. A second order dynamic motion model was applied to the CONDENSATION translation parameters. The deformable changes were assumed to follow a first order Markov process (for full details of CONDESATION implementation refer to [18]). The Baumberg's tracker was implemented as outlined in [7].

3.2 Frame Rate Test

The frame rate test method was devised to analyze the performance of trackers at varied frame rates. In order to carry out the experiment, test image sequences of a walking man was captured at four different frames rates: 5, 10, 20 and 30 frames/second. Each tracker was allowed to track the man independently at each frame rate. For each test, the B-spline based error measures and the 'SNR out' performance measures were calculated. The results obtained are illustrated in Fig. (3).

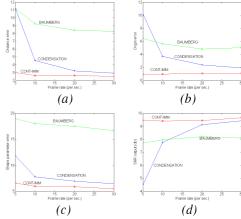
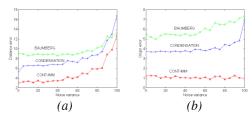


Figure 3: Frame rate test for the 3 trackers. The error quantities are measured in pixels. (a) Perormance using the distance error measure. (b) Using the origin error test. (c) Using the non-rigid shape parameter error test. (d) Performance using the tracked output SNR (db).

3.3 Noise Test

This is a test to evaluate the trackers' capability to track objects under noisy condition. The test sequence captured at 10 frames/sec was corrupted with Gaussian noise at various levels. At each noise level, the trackers were applied to track the walking man. For each test the B-spline based error measures and the 'SNR out' values were calculated. Results obtained are quantitatively illustrated in Fig. (4), and qualitatively displayed in Fig. (5) for a noise free case.



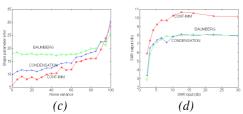


Figure 4: Noise performance test conducted by adding artificial noise (uncorrelated) to the test image sequence. (a) Distance error test result. (b) Origin error test result. (c) Nonrigid shape parameter error test result. (d) SNR input versus SNR out results (see text for details).

3.4 Control Point Test

The object of interest is represented by varying number of control points. We tested and compared the performance of each tracker by employing control points ranging from 12 – 64. Since B-spline error measures are unreliable for comparing performance for this test (see details in section 4) only the 'SNR out' test was carried out, which is shown by Fig. (6) and Fig. (7) respectively.

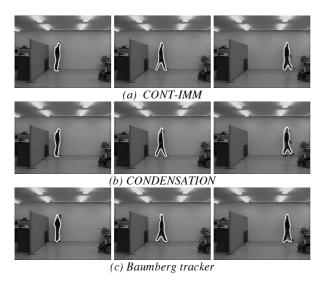


Figure 5: Tracking performance of the 3 trackers (with no added noise). 4 frames of a test sequence are shown with the tracked contour superimposed on top of the object.

3.5 Shape Deformation Test

The non-rigid (deformable) shape parameter test is to assess the error in deformable shape changes of objects (between the actual and the tracked shape). The number of shape parameters (in other words the number of principal components used) employed has a direct impact on the quality of tracked shapes. We carried out experiments by using 1, 2, 3, 4, 5, 10, 15, 20, and 25 non-rigid shape parameters to account for deformable shape variations of the object contour. The results obtained are illustrated quantitatively by Fig. (8) and qualitatively by Fig. (9). It should be noted that for this experiment the deformable shape parameter error quantity (equation (5)) was assessed by averaging the Mahalanobis distance by the number of shape parameters used (for other tests discussed in this chapter, this process is not required).

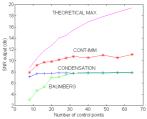


Figure 6: SNR output achieved by the trackers when using varied number of control points to represent the object. The theoretical maximum is the best possible tracking performance achievable (See text for detail). It is shown to indicate how well the trackers perform with varied number of control points.

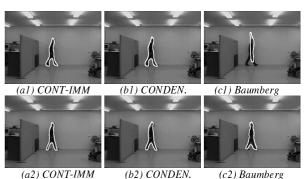


Figure 7: Tracking performance when varying the number of control points (Frame 10 displayed). (a1), (b1), (c1) with 16 control points. (a2), (b2), (c2) with 32 control points.

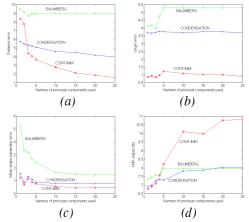


Figure 8: Number of non-rigid shape parameters used (number of principal components) versus error measures. (a) Using the distance error measure. (b) Using the origin error test. (c) Using the non rigid shape parameter error test. (d) Performance using the tracked output SNR (db).

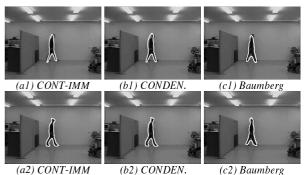


Figure 9: Tracking performance when varying the number of deformable shape parameters (frame 10 is displayed).(a1), (b1), (c1) with 3 parameters, (a2), (b2), (c2) with 25 parameters.

4 Discussion

In this section we discuss the results obtained in section 3. We interpret the results under the four different performance test carried out.

4.1 Tracker Performance Under Varying Frame Rates

All 3 trackers were employed to track an indoor walking person, where the moving person was captured at different frame rates. The purpose of the test was to analyze the robustness of the trackers when the interframe shape differences are varied.

The distance, the origin, and the shape parameter error measures clearly show that the CONT-IMM and the BAUMBERG trackers are less sensitive to frame rate changes (though the CONT-IMM gives much smaller errors, Fig. (3)). The CONDENSATION tracker is observed to be sensitive to changing frame rates. Particularly at lower frame rates, the CONDENSATION gives poor quality results, but at higher rates (at video rates) the performance is remarkable, and does approach the performance of CONT-IMM tracker. The reason for poor quality results for CONDENSATION is that, one of the assumptions for this algorithm is to have small interframe shape changes (particularly for the measurement process to be effective [18]), which is a reasonable assumption at high frame rates (eg: 30 frames/sec.).

Focussing on the SNR test results, the CONT-IMM provides an average 'SNR out' of around 9.5 – 9.75 (db) for the range of frame rates considered (5 – 30 frames/sec), where as the 'SNR out' for the BAUMBERG tracker varied between 7.75 – 8.00 (db). The CONDENSATION SNR output varied from about 4.5 (db) at 5 frames/sec to around 9.5 (db) at rates of 30 frames/sec. The empirical observations suggest that the CONT-IMM method give the best frame rate results followed by CONSENSATION (at high frame rates) and BAUMBERG trackers. It should be noted that the observations obtained from B-spline based error measures are consistent with the SNR output results.

4.2 Tracker Performance Under Varying Noise Condition

This test is a method to evaluate the performance of the trackers under noisy environment. Uncorrelated noise is added (Gaussian distributed) to each frame of a sequence prior to tracking. The performances of the trackers are assessed at varied noise levels using the performance measures described. The results again show that the CONT-IMM tracker gives the best result under noise followed by CONDENSATION and the BAUMBERG trackers. Remarkably all 3 trackers perform well up to a noise variance level of around 50. At very high noise levels, the performance of all 3 trackers starts to deteriorate. This is because each tracker has its own mechanism to eliminate spurious measurements by employing some noise thresholding (filtering) techniques, but such techniques break down at high noise levels as evident from the results. The poor performances at high noise levels are directly attributed to obtaining erronious measurements (for all 3 trackers), which in turn leads to poor quality track results.

An important tracking performance test not covered in this chapter is the ability of the trackers to track objects in cluttered environments. Unfortunately clutter level cannot be measured with reasonable precision, and therefore was not considered in the series of experiments that we carried out. However, as Blake et. al. [8, 17] demonstrated, the CONDENSATION has been shown to track well in cluttered background. This is because CONDENSATION supports multiple hypothesis of pdfs for its observation process [17], and as a result is able to disregard false measurements efficiently. Baumberg tracker was also shown to be agile enough to track under short periods of clutter [4, 7], but was prone to heavy background clutter because of high false contour measurements. CONT-IMM tracker is prone to heavy clutter due to its contour measurement process. Since CONT-IMM uses background subtraction for contour measurements, heavy clutter results in poor quality measurements being obtained, despite having mechanism to reduce noise. Incorrect measurement in turn leads to poor tracking results.

4.3 Tracker Performance by Varying the Number of Object Control Points

For this particular test, the spline based performance measures are not useful, because the tracked contour can only be compared with the actual contour, provided both object contours have the same number of control points. Varying the number of control points on the actual and the tracked contours gives rise to an approximation error (particularly at lower number of control points). Therefore, spline based performance measures do not reveal the true quality of the trackers' output.

In this case, only the SNR output performance was measured, which is an ideal test for this experiment. The number of control points to represent the object is varied from 16 – 64 to test the tracker robustness to control point variation. The tracked 'SNR out' is compared with the theoretical maximum 'SNR out' possible. This value (Max SNR out) is calculated by taking the actual object and approximating the contour by the number of control points considered, and then flat filling the contour with white, while the background remains black. This foreground flat filled area is then used to calculate the maximum SNR output (using Eq. (7)).

As can be seen from Fig. (6) the trackers achieve their best performance level when the number of control points are around 30 (for this object). By extending the control points beyond 30 brings little improvement. Therefore, striking a balance between speed of the tracker and the accuracy of the tracker, it is best to maintain the number of control points to around 30.

Observation of the result shows that the Baumberg tracker is very sensitive to the number of control points used, particularly at lower values. The CONDENSATION tracker is the least sensitive among the trackers, which maintains an 'SNR out' value of around 8 db for the range of control points considered. The CONT-IMM gives the best result reaching an output SNR of around 10.5 db between 28-40 control points

and 11db with 64 control points, but at lower number of control points (< 16) the performance is observed to be rather poor.

The theoretical maximum possible SNR output is a guide to show how well the trackers perform in relation to optimum expectation for the range of control points considered (Fig. 6). It is almost impossible for a tracker to get an SNR output anywhere near the theoretical mark. This is because, a 1 pixel displacement between the tracked object and the actual object can cause about 3-4 % of the flat filled area (object area) to be misaligned. This mismatch alone accounts for about 3.5 - 4 db of 'SNR out' (for the object size we considered). It is also worth noting that the SNR output is dependent on the object size, therefore only the relative SNR output values ought to be taken into account when comparing the results.

4.4 Tracker Performance by Varying the Number of Deformable Shape Parameters

This test is used purely for measuring the deformable shape changes, and therefore, does not take into account any affine contour shape changes (disregarding changes in translation, scaling and rotation).

Varying the number of shape parameters directly corresponds to the number of principal components (PCs) employed in tracking deformable shape changes. The training sequence that we used comprised about 750 different object shapes of moving pedestrians. Our off line analysis showed that about 90% of the shape changes can be accounted for, by using the 10 most significant principal components.

For the experiments reported here, we tested by using 1, 2, 3, 4, 5, 10, 15, 20 and 25 PCs. As can be seen from the results (Fig. 8), increasing the number of shape parameters beyond 10 results in very little improvement. Considering the tracker speed into account, using beyond 10 deformable shape parameters can also be computationally expensive. In terms of quality of results, the CONT-IMM provides better quality results at all levels compared with the other 2 trackers. It should be noted that the shape deformation test is model dependent, and therefore, the number of deformable parameters used for tracking can vary from object to object depending on the object shape size and complexity.

5 Conclusion

In this chapter we have presented empirical techniques for assessing the quality of contour tracker performance. In almost all the tests carried out, the B-spline based error measures were consistent with the SNR output results, which suggests that the performance measures are a credible representation to assess the quality of contours tracked by the three trackers concerned. The experimental methods provided can be utilized for any type of B-spline represented shape comparison test, assuming no re-parameterization of the contour control points are required. The SNR test method is a totally spline independent method, which uses only image processing techniques to evaluate performance, and

therefore, can be used to analyze the output of any contour tracking algorithm with reasonable accuracy.

References

- [1] K. D. Baker and G. D. Sullivan, "Performance assessment of model based tracking", Workshop on Applications of Computer Vision, pp.28-35, 1992
- [2] Y. Bar-Shalom and X. R. Li, *Estimation and Tracking:* principles, techniques, and software. Artech House, Boston, MA, 1993.
- [3] R. Bartels, J. Beatty, and B. Barsky, An Introduction to splines for use in computer graphics and geometric modeling, Morgan Kaufmann.
- [4] A. M. Baumberg and D. Hogg, "An efficient method for contour tracking using active shape models", In *Proc. of the IEEE Workshop on Motion of Non-Rigid and Articulate Objects*, pp.194-199, 1994.
- [5] A. M. Baumberg and D. Hogg, "Learning flexible models from image sequences", ECCV '94, pp.299-308.
- [6] A. M. Baumberg and D. Hogg, "Generating spatiotemporal models from examples", In Proc. *British MachineVision Conference*, 1995, pp.413-422.
- [7] A. M. Baumberg, "Learning deformable models for tracking human motion", PhD thesis, School of Computer Studies, University of Leeds, 1995
- [8] A. Blake and M. Isard, "Active Contours", Springer-Verlag, 1998.
- [9] A. Blake, M. Isard and D. Reynard, "Learning to track the visual motion of contours", *Artificial Intelligence*, 78, pp.101-134, 1995.
- [10] A. Blake, R. Curwen and A. Zisserman, "A framework for spatio-temporal control in the tracking of visual contours", *Int. J. Computer Vision*, 11, 2, 127-145, 1993.
- [11] A. Blake and A. Yuille (editors), Active Vision, MIT press, 1992.
- [12] T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Training models of shape from sets of examples", In *British Machine Vision Conference*, pp.9-18, 1992.
- [13] T. F. Cootes and C. J. Taylor, "Active shape models 'smart snakes' ", In *British Machine Vision Conference*, pp.276-285, 1992.
- [14] T. F. Cootes, C. J. Taylor, A. Lantis, D. H. Cooper, and J. Graham, "Building and using flexible models incorporating grey-level information. In *Proc. ICCV'93*, pp.242-246, 1993.
- [15] J. Denzler and H. Niemann, "Evaluating the performance of active contour models for real-time object tracking", In *Second Asian Conference on Computer Vision*, volume 2, pages II/341-II/345, 1995
- [16] S. Gil, R. Milanese and T. Pun, "Combining multiple motion estimates for vehicle tracking", *ECCV-98*, pp.307-320
- [17] M. Isard and A. Blake, "Condensation: conditional density propagation for visual tracking", *Int. J. Computer Vision*, 28(1), pp.5-28, 1998
- [18] M. A. Isard, "Visual motion analysis by probabilistic propagation of conditional density", *PhD thesis, Dept. of Engineering Science*, Oxford University, UK, 1995
- [19] D. Koller, D. Danilidis, and H.-H. Nagel, "Model-based object tracking in monocular image sequences of road traffic scenes", *Int. Journal of Computer Vision*, Vol.10(3), pp.257-281, 1993
- [20] D. Terzopoulos and R. Szeliski, "Tracking with Kalman snakes", In A. Blake and A. Yuille (editors), Active Vision, pp.3-20, 1992.
- [21] P.Tissainayagam and D. Suter, "Tracking multiple object contour with automatic motion model switching", *International Conference on Pattern Recognition (ICPR)*, 2000, pp.1146-1149