PERFORMANCE OF ADAPTIVE TRACKING ALGORITHMS

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Abstract: This paper compares the performance of adaptive trackers based on multiple algorithms. The aim of using multiple algorithms is to increase the robustness of the trackers under varying conditions. We perform two estimation algorithms UKF and IMM to measure the performance of tracking on outdoor scenes with occlusions. The purpose of this paper is to measure and evaluate tracker reliability for be able to determine the position of a target. The performance is evaluated using metrics related to truth track. We give a positional evaluation and statistics values of the performance of visual tracking systems, which adapt to changing environments.

1 INTRODUCTION

Automatic tracking algorithms are employed in many industrial and military applications. In practice, automatic target tracking systems need to operate around the dynamic environments and require high accurate determination of target position, velocity, acceleration and other parameters to increase the detection probability and reduce false alarms and missed targets probabilities.

There are many algorithms for tracking, such as, correlation trackers (Kishore and Rao, 2001; Ronda and Shue, 2000) that perform well with structured targets, even in highly cluttered background conditions. However correlation walk-off and false peak problems are critical in these trackers. The centroid-based tracking algorithms are also used in surveillance systems (Jae-Soo Cho and Park, 2000). These trackers are especially susceptible to changes in object shape and orientation between successive images. Another approach used is edge tracking, which presents drawbacks in low contrast images.

In most cases tracking algorithms fail due to low contrast, noise, scale and illumination changes. Several approaches have been developed to improve the tracking of a moving target based on multiple trackers (Ronda and Shue, 2000; Kishore and Rao, 2001; Tao Yang and Li, 2005). However, these proposals have not solved the occlusion problem that an object presents in its trajectory. For the solution is necessary to estimate the target position, by means of motion models and estimation filters.

The aim of these approaches is to increase the adaptability of the tracking to varying conditions; the adaptability degree of the algorithms can be obtained with the measurement of the uncertainty. Therefore, several techniques have been proposed to measure and compare different tracking algorithms.

Some papers evaluate the performance of full tracking algorithms through occlusions. In (J. Black and P., 2003) a methodology for evaluating the performance of tracking systems is presented. They test the performance of a tracking algorithm that employs a partial-observation tracking model for occlusion reasoning. Needham and Boyle (Needham and Boyle, 2003) compare two tracking systems for different objects by using a set of metrics for positional evaluation. The work in (L. M. Brown and Lu, 2005) presents a comparison of two background subtraction algorithms with indoor/outdoor scenes. The number of false negatives and false positives of each algorithm is obtained for comparison. Lefebvre et. al. (Tine Lefebvre and Shutter, 2004) compares the quality of the estimates of the common Kalman filter variants for nonlinear systems. This quality is expressed in terms of consistency and information content. Hall, et. al. (D. Hall and Crowley, 2005) present and evaluate five adaptive background subtraction techniques with background models of different complexity.

In this paper, we compare three trackers based on

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multiple algorithms in order to maintain the target trajectory. To track objects through occlusions we used UKF and IMM filters. The trackers are evaluated on the same benchmark data set which allows a more objective comparison. The metrics for comparing trackers evaluate the positions estimated and the detection's reliability.

The paper is structured as follows: Section 2 presents a brief review of tracking algorithms. Section 3 describes the motion models and estimation filters used in order to increase the robustness of the algorithms. In section 4 we describe the process used to obtain the truth track and evaluation performance metrics applied. Section 5 describes the data set used and shows the performance results on data set. Finally, we give our conclusion of the comparative analysis in section 6.

2 TRACKING ALGORITHMS

Tracking algorithms are divided mainly in two main categories: region trackers and edge trackers. For a region tracker, a region of the image is selected as search pattern and one similarity measure is used to decide on the best matching region in the next image. These algorithms fails in the case of changes in in object size, illumination changes, and surface reflectance. Their challenges are to make possible a gradual adaptability to different conditions in the images and to avoid to slowly drifting from the tracked region into the background.

On the other hand, edge trackers follow edges produced by changes in the reflected light (variation in colour or illumination). However, an edge detection algorithm requires smoothing and differentiation of the image. Differentiation is an ill-conditioned problem and smoothing results in a loss of information. Therefore, it is difficult to design a general edge detection algorithm which performs well in many contexts.

2.1 Correlation

Correlation is performed by overlapping a correlation window holding a reference image at the location of each pixel in a search region from the current frame. A correlation metric is used to define the best matching of the correlation window in the current image. The portion of image most similar is registered as a new reference image for correlation at the next frame.

The correlation process might give an incorrect registration because low contrast of the reference pattern, sensor noise, occlusion, etc. In applications, where the reference has to be updated in each frame to reduce the effect of magnification, occlusion, etc, a single incorrect registration will lead to false track. For these applications, it is necessary confidence measures in order to validate a correct registration. Ronda et al. in (Ronda and Shue, 2000) define a confidence measure, to prevent false updating of the reference pattern. They present a mean-subtracted fully normalized correlation algorithm (MSFNCA) that is an improvement to simple correlation. The objective of this approach is the robustness to variations in image intensity. The confidence measure is the following:

$$\begin{aligned} MSFNCA(i,j) &= \frac{\sum\sum\left[(R(l,m)-\bar{R})(S_{ij}(l,m)-\bar{S}_{i,j})\right]}{\left[\sum\sum(R(l,m)-\bar{R})^2 \sum\sum(S_{ij}(l,m)-\bar{S}_{ij})^2\right]^{\frac{1}{2}}} \\ &= \frac{\sum\sum\left[R(l,m)S_{ij}(l,m)-M^2\bar{S}_{i,j}\bar{R}\right]}{\left[\sum\sum R^2(l,m)-M^2\bar{R}^2\right]\left[\sum\sum S_{ij}^2(l,m)-M^2\bar{S}_{ij}^2\right]} \end{aligned} \quad (1)$$

where R is the reference image, of size $M \times M$. And the $M \times M$ window of the search image at pixel (i, j) is denoted by S_{ij}.

The target might drift out of the reference image due to the discrete pixel size and the target motion, even using the MSFNCA confidence measure. This drift has to be corrected locally using others detection algorithms.

2.2 Centroid Tracking

Centroid tracker is one of the most common algorithms used (Jae-Soo Cho and Park, 2000), which determines a target aim point by computing the intensity or geometric centroid of the target object based on target segmentation process. The Figure 1 shows the target's centroid. The performance of centroid tracker is largely dependent on the segmentation algorithm which needs to extract the moving target even in complex background conditions. There are many algorithms for image segmentation (Sezgin and Sankur, 2004), such as histogram-based methods, clustering-based methods and local methods that adapt the threshold value to local image characteristics. In this work, we define a threshold for each sequence.

2.3 Edge Tracking

Edge detection concerns the localization of variations of the grey level image and the identification of the physical phenomena that originated them (Djemel Ziou, 1998). To detect the target edges was implemented the SUSAN algorithm, which performs:

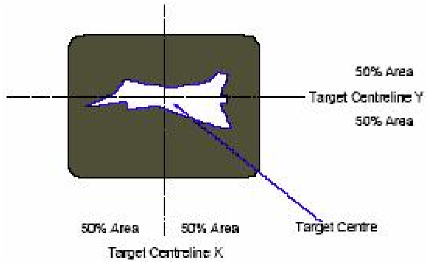

Figure 1: Centroid of a target.

edge and corner detection and structure preserving noise reduction.

This algorithm is a type of neighborhood voting method to enhance the edges and corners of 2D images. The speed and localization are quite good. The SUSAN algorithm is implemented using digital approximation of circular masks (Smith and Brady, 1997). If the brightness of each pixel within a mask is compared with the brightness of that nucleus of the mask, then an area of the mask can be defined which has the same brightness as the nucleus. In this approach no image derivatives are used and no noise reduction is needed. However, the method produces incorrect results with noisy images.

2.4 Adaptive Trackers

In tracking applications where a target changes shape and size frequently, conventional tracking algorithms as correlation are also applied. However, if a false registration occur and is not detected, the system could fail due to the reference pattern is updated in each frame.

False registration problem occurs when the reference pattern drifts away from target area. In order to solve this problem, some works use correlation algorithms as MSFNCA with a confidence measure which ensures a better registration than a simple correlation. This correlation performs well in many situations. However the drift problem and incorrect registration still persist.

In these cases, where the information of one algorithm is not sufficient for maintaining the target trajectory, we can apply multiple tracking algorithms in order to increase the reliability of the system.

Figure 2 shows the three algorithms used in this paper. Tracker 1 (Correlation + Centroid) performs a correlation tracking and if coefficient correlation is greater than a threshold then centroid algorithm is performed. We set the threshold of the confidence measure to 0.3. Tracker 2 (Correlation + Centroid + Edges) uses three trackers to maintain the truth trajectory, this tracker integrates edge detection algorithm to increase the performance. Tracker 3 (Correlation with gradual updating) performs a correlation algorithm where the reference image is updated at the next frame, replacing each pixel (i, j) of the reference image by using equation 2.

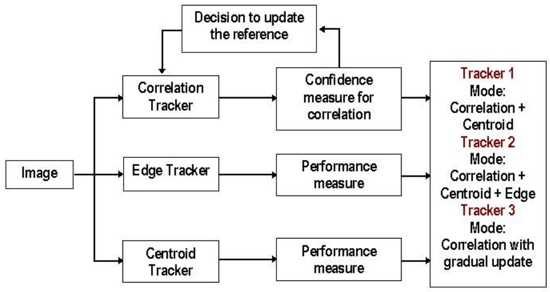

Figure 2: Tracking with multiple algorithms.

$$R_{ij} = (t+1) = R_{ij}(t)\alpha + (1-\alpha)S_{ij}(t) \qquad (2)$$

where α was set to 0.01.

3 ROBUST TRACKING

Occlusion is one of the problems for maintaining the trajectories of the targets. Target features are lost during an occlusion. Therefore, in the absence of information about the target, the state prediction can be useful. In this paper, robust tracking is achieved by an Unscented Kalman filter (UKF) and Interacting Multiple Model filter (IMM).

For predicting object state is necessary a motion model, which represents the kinematic of the object. For this comparative analysis we are using two mathematical models (Li, 2000): acceleration constant model (AC) and velocity constant model (VC). The state space for the models is of four dimensions, defined by $x-$ and $y-$position and $x-$ and $y-$velocity.

3.1 Estimation Filters

The Unscented Kalman filter (UKF) is a minimum mean squared error (MMSE) state estimator for a nonlinear system (Julier and Uhlmann, 1997). To estimate the effect of the nonlinear and non-Gaussian models, this filter uses a deterministic sample based approximation. The basic component of this filter is the unscented transformation which uses a set of appropriately chosen weighted points to parameterize the means and covariances of probability distributions.

Moreover, the IMM approach estimates a target state when the target maneuver is unsure and it is subject to changes (Bar-Shalom and Blair, 2000). The

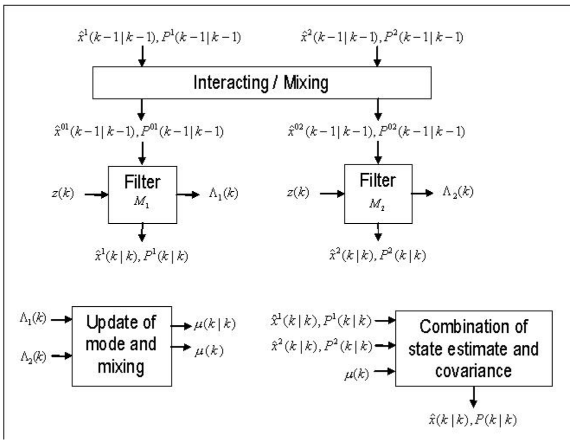

Figure 3: IMM filter.

IMM includes a finite set M of different maneuver models that cover the possible maneuver spectrum. Each model $m \in M$ describes a different dynamical system.

One cycle of IMM estimator includes the following steps (Figure 3): interaction/mixing, filter M_r, update of mode and mixing probabilities, and combination of state estimate and covariance. The IMM mode-set was designed with two linear Kalman filters and two motion models (AC and VC).

4 CONFIDENCE MEASURES

In order to achieve reliable performance, it is necessary to have confidence measures of the results. There are many error metrics for tracking. They can be divided into two categories: (1) statistical methods that compare the measurement data obtained from the tracker with the truth data, and (2) accuracy measures.

This analysis lies in comparing the tracking algorithms, their applicability on different scenes and the error obtained from prediction process. First, we compare the trajectories using positional metrics, and then we assure the performance of the robust trackers with accuracy measures.

4.1 Truth Track

In order to identify trajectories of poor quality for the tracking, the truth tracks are checked for consistency with respect to path coherence (Xu and Ellis, 2002; J. Black and P., 2003). The objective of applying this measure is to consider the complexity of the target motion in the scenes.

The path coherence is given by:

$$\varepsilon_{pc} = \frac{1}{N-2}\sum_{k=2}^{N-1}\left\{\begin{array}{c} w_1\left[1-\frac{\overline{x_{k-1}x_k}\cdot\overline{x_kx_{k+1}}}{\|\overline{x_{k-1}x_k}\|\|\overline{x_kx_{k+1}}\|}\right]+ \\ w_2\left[1-\frac{2\sqrt{\|\overline{x_{k-1}x_k}\|\|\overline{x_kx_{k+1}}\|}}{\|\overline{x_{k-1}x_k}\|+\|\overline{x_kx_{k+1}}\|}\right]\end{array}\right\} \tag{3}$$

where N is the number of frames, $\overline{x_{k-1}x_k}$ is the vector that represent the positional shift of the tracked target between k and $k-1$. w_1 and w_2 are weighting factors that define the contribution of the components (direction and speed) of the measure. These weights were set to 0.5.

4.2 Comparison of Trajectories

For comparing trajectories, we apply some metrics used in (Tine Lefebvre and Shutter, 2004). One of the measures consists to know which is the displacement and distance between the target trajectory from the tracker T_E and the truth trajectory T_T with positions (x_i, y_i) and (p_i, q_i) respectively. The displacement $\mathbf{d}_i$ between trajectories at time i is calculated using equation 4.

$$\mathbf{d}_i = (p_i, q_i) - (x_i, y_i) = (p_i - x_i, q_i - y_i) \tag{4}$$

Therefore, the distance between the positions at time i is given in the equation 5.

$$d_i = |\mathbf{d}_i| = \sqrt{(p_i - x_i)^2 + (q_i - y_i)^2} \tag{5}$$

Another metric is to calculate the optimal spatial translation d (shift) between T_E and T_T . This metric show a closer relationship between two trajectories (Needham and Boyle, 2003). They define this metric by equation 6.

$$\mu\left(D\left(T_E + \hat{d}, T_T\right)\right) \tag{6}$$

where $\hat{d}$ is the average displacement of two trajectories, calculated by equation 7:

$$\hat{d} = \mu(d_i) = \frac{1}{n}\sum_{i=1}^{n} d_i \tag{7}$$

Finally, to describe the data obtained previously and evaluate the tracker we are using statistics applied to displacement, distance and shift between two trajectories. These statistics provide quantitative information about distribution of data, such as, mean, median, standard deviation and, minimum and maximum values.

The mean is calculated as follows:

$$\mu(D(T_T, T_E)) = \frac{1}{n}\sum_{i=1}^{n} d_i \tag{8}$$

where n is the number of frames. Besides, the median is obtained by equation 9 and the standard deviation by equation 10.

$$median(D(T_T, T_E)) = \begin{cases} d_{\frac{n+1}{2}} & if\ n\ odd \\ \frac{\left(d_{\frac{n}{2}} + d_{\frac{n}{2}+1}\right)}{2} & if\ n\ even \end{cases} \tag{9}$$

$$\sigma(D(T_T, T_E)) = \sqrt{\frac{\sum_{i=1}^{n}(d_i - \mu(d_i))^2}{n}} \tag{10}$$

The equations 11 and 12 correspond to the minimum and maximum distance values respectively.

$$min(D(T_T, T_E)) = \ the\,smallest\,d_i \tag{11}$$

$$max(D(T_T, T_E)) = \ the\,largest\,d_i \tag{12}$$

4.3 Surveillance Metrics

We also use the metrics described in (J. Black and P., 2003), to measure the tracking performance. We obtain the tracker detection rate (TRDR) for each image sequence. TRDR is obtained by equation 13.

$$TRDR = \frac{Total\,True\,Positives}{Total\,Number\,of\,Truth\,Points} \tag{13}$$

The false alarm rate (FAR) and the TRDR characterize the tracking performance. FAR is given in the equation 14.

$$TRDR = \frac{Total\,False\,Positives}{Total\,Truth\,Positives + Total\,False\,Positives} \tag{14}$$

The object tracking error (OTE) is another metric that indicates the mean distance between real and estimated trajectories. OTE is obtained by equation 15.

$$OTE = \frac{1}{N_{rg}} \sum_{\exists i\ g(t_i) \wedge r(t_i)} \sqrt{(p_i - x_i)^2 + (q_i - y_i)^2} \tag{15}$$

5 EXPERIMENTS

We compared the performance of three adaptive tracking algorithms. These algorithms are robust to occlusions by using estimation filters. Experiments were performed on six real image sequences and two synthetic sequences. We have considered infrared and visible images for testing. The size of the each frame is $640x480$ for real sequences and $752x512$ for synthetic sequences.

Figure 4(a) corresponds to infrared sequence where a ship is the target (it will be referenced as sequence 1). Target has been tracked on 422 frames and presents 40 occlusions during its trajectory. In the Figure 4(b) (sequence 2) a car is the interest object for tracking under occlusions in infrared sequence, the car is occluded in 75 frames of 575 that composes this sequence. Figure 4(c) (sequence 3) shows a visible frame from a sequence where the interest object is a boat that has an horizontal motion, beginning in the left top corner of the image. This sequence has 474 frames, in this sequence the boat is occluded in 75 frames. Figure 4(d) presents a synthetic sequence, the pattern size is 35 pixels, the sequence includes 500 frames where 45 frames were used to simulate occlusions.

Table 1: Coherence path.

Sequence	Coherence Path
1	0.157287
2	0.11906
3	0.499223
4	0.500005
5	0.332765
6	0.206209
7	0.045832
8	0.03558

5.1 Performance and Results

The coherence path obtained of each sequence is presented in the Table 1. The half of the all sequences has a high value in the coherence path.

The metrics between two trajectories were applied. The Table 2 presents results from sequence 1 with UKF algorithm. Tracker 2 provides the best results in the evaluation of the tracked trajectory. The truth trajectory and tracked trajectory are depicted in the Figure 5. The Figure 6 shows the trajectory of the sequence 1 with the simulated occlusions. The trajectory obtained with the tracker (Correlation + Centroid + Edges) does not maintain a correct tracking of the truth trajectory. However when the estimation filter is used, the problem occlusion is solved.

Table 3 and 4 resumes the results obtained on all sequences using trackers with UKF and IMM filter respectively. In both evaluations, correlation with gradual update has the best performance.

In the same way, we have applied the surveillance metrics for sequences. The results for the first sequence are showed in the Table 5. Trackers with UKF filter have high detection rate in comparison with IMM-based algorithms.

Finally in Table 6, we show the mean of the values obtained from all sequences. We can observe that algorithms with UKF filter presents better values of TRDR even when detect more false alarms.

(a) Infrared image (b) Infrared image (c) Visible image (d) Synthetic visible image

Figure 4: Examples used for tracking.

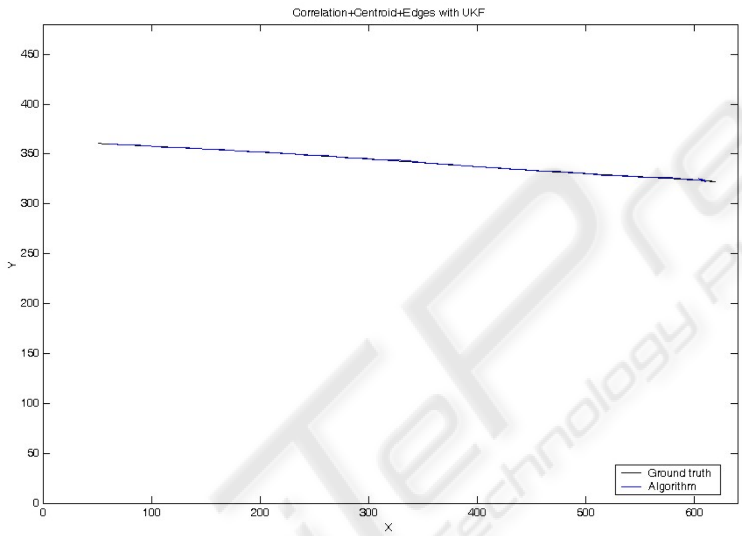

Figure 5: Trajectory of the sequence 1.

Table 2: Results of trajectory evaluation 1 using UKF filter.

Tracker	1		2		3	
Metric	D(TE,TT)	D(TE+d,TT)	D(TE,TT)	D(TE+d,TT)	D(TE,TT)	D(TE+d,TT)
Mean	5.387765	2.128756	3.073779	1.859341	5.336042	2.060513
Median	5.974945	1.178952	3.206711	0.931958	5.974945	1.148738
Std. Dev	2.104545	2.370386	1.744103	1.96903	1.979448	2.103242
Minimum	0.03705	0.022712	0.03705	0.094509	0.03705	0.051058
Maximum	14.296198	18.806309	13.806778	16.029772	13.788579	12.84164

Table 3: Mean of the results of trajectory evaluation using UKF filter.

Tracker	1		2		3	
Metric	D(TE,TT)	D(TE+d,TT)	D(TE,TT)	D(TE+d,TT)	D(TE,TT)	D(TE+d,TT)
Mean	4.9655835	3.8103235	4.7905565	3.8972085	4.4031985	2.99079
Median	3.683516	2.6102135	3.630965	2.588816	3.683516	2.05372
Std. Dev	5.368305	5.4243535	5.2744075	5.5185885	3.1629285	3.07067
Min	0.157494	0.0891545	0.2175505	0.140762	0.157494	0.08424
Max	31.596568	32.6933673	31.0513235	32.2474888	17.2029045	16.5863

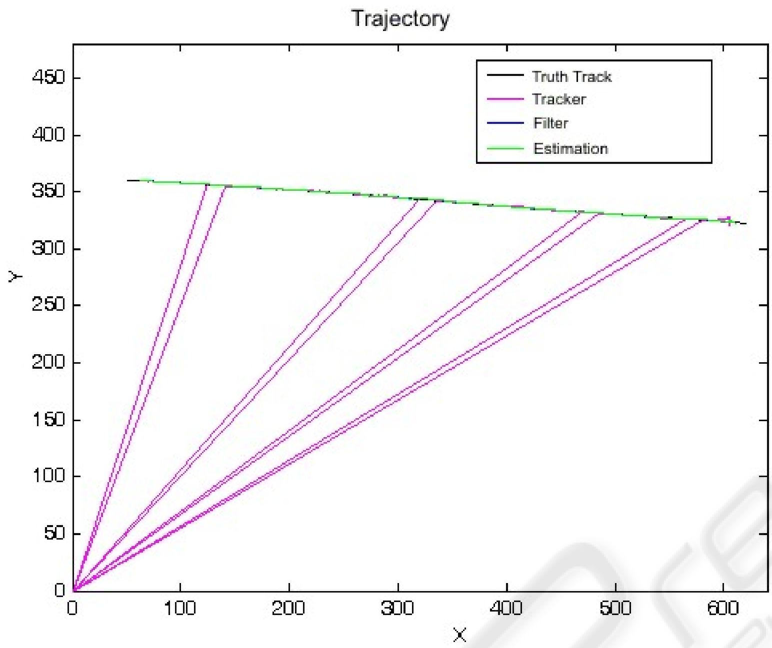

Figure 6: Trajectory of the sequence 1 with occlusions.

Table 4: Mean of the results of trajectory evaluation using IMM filter.

Tracker	1		2		3	
Metrics	D(TE,TT)	D(TE+d,TT)	D(TE,TT)	D(TE+d,TT)	D(TE,TT)	D(TE+d,TT)
Mean	4.71262	3.886235	4.659543	3.985114	4.1161075	3.16768925
Median	3.2919788	2.59886025	3.54485625	2.69846925	3.42166425	2.27020875
Std. Dev	5.661622	5.61342775	5.52120525	5.6409165	3.59892	3.4811025
Minimum	3.092654	0.183317	0.2427665	0.22414025	0.05414675	0.09454175
Maximum	29.32515	30.695778	29.211101	29.919655	16.681788	18.091328

Table 5: Performance results on sequence 1.

Filter	UKF			IMM		
Tracker	1	2	3	1	2	3
TP	416	419	420	414	416	415
FP	7	4	3	9	7	8
TRDR	0.983452	0.990544	0.992908	0.978723	0.983452	0.981087
FAR	0.016548	0.009456	0.007092	0.021277	0.016548	0.018913
OTE	5.745404	3.246693	5.635883	5.658996	3.258433	5.579214

Table 6: Tracking performance.

Filter	UKF			IMM		
Tracker	1	2	3	1	2	3
TP	685.75	684.25	691.75	687.5	687.5	688
FP	60.75	62.25	54.75	59	59	58.5
TRDR	0.92566	0.92119	0.93981	0.92009	0.92009	0.92111
FAR	0.74364	0.07882	0.06019	0.07992	0.07992	0.07881
OTE	5.41712	5.28336	4.73812	5.07317	5.07317	4.51656

6 CONCLUSION

In this paper we present three adaptive tracking algorithms. The trackers are: (1) MSFNCA + Centroid, (2) MSFNCA + Centroid + Edges, and (3) Correlation with gradual update. Trackers adapt to different conditions by means of performance metrics, which indicates the best correlation, reducing the possibility that drift problem occurs.

Moreover, these algorithms have the capability to follow a target trajectory even under occlusions using UKF and IMM filters and using a constant acceleration and constant velocity motion models. We obtain the coherence path for each sequence assessing its complexity before apply the tracking algorithms. The tracking performance was measured on real and synthetic sequences. We used metrics that compare the truth trajectory and the trajectory tracked. Furthermore, we evaluate the algorithms by calculating both false alarms and correct detections. Correlation with gradual update improves the tracking and increase the adaptability to changing environments. The UKF filter had a slightly best behavior than IMM estimator even when an occlusion problem occurs.

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