Kalman Filtering Based Object Tracking in Surveillance Video System

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Abstract — **In the field of motion estimation for surveillance video, various techniques have been applied. One of the common approaches is Kalman filtering technique and it is interesting to explore the extension of this technique for the prediction and estimation of motion via the image sequences. In this paper, a moving object tracking in surveillance video using Kalman filter is proposed. The typical Kalman filter is good in tracking the position of a moving object. However, when dealing with occlusion, the typical Kalman filter is not able to keep tracking and predicting the position of the occluded moving object. During occlusion, the information of moving object is not available for detection and tracking. The lacking of occlusion scene determination and prediction ability cause the existing Kalman filter fails in tracking occluded object. Besides that, in the case of tracking multiple moving objects, existing Kalman filter will experience difficulties to identify the respective objects. Therefore, in order to encounter these problems, an object tracking method using enhanced Kalman filter will be developed. The ability of tracking occluded moving object will be added to increase the efficiency during tracking. Furthermore, object recognition feature will be added too to increase the accuracy of the object tracking system.**

Keywords - Kalman filter; object tracking; surveillance system

I. INTRODUCTION

The researches for segmenting, estimating, and moving object tracking in video have received great attention for the last few years. The moving object tracking is an important issue in video system, such as surveillance, sports reporting, video annotation, and traffic management system.

Difficulties in tracking objects can arise due to the abrupt object motion, changing appearance patterns of the object and the scene, non-rigid object structures, object-to-object and object-to-scene occlusions. Tracking is usually performed in the context of higher-level applications that require the location or shape of the object in every frame.

The typical Kalman filter has faced the problem in tracking during occlusion. As during occlusion, the information of moving object is not available for detection and tracking. The lacking of occlusion scene determination and prediction ability make the typical Kalman filter fails in tracking the occluded object. Besides that, in the case of tracking multiple moving objects, typical Kalman filter will experience difficulties to identify the respective objects. Therefore, the typical Kalman filter has weakness when dealing with occluded moving object. In order to encounter this problem, an object tracking method using enhanced Kalman filter with the ability of tracking occluded object and object recognition feature will be developed to increase the efficiency and accuracy of the object tracking system.

II. REVIEW OF OBJECT TRACKING METHODS

Object tracking is an important task within the field of computer vision. There are three key steps in video analysis: interesting moving objects detection, tracking of such objects from frame to frame, and analysis of object tracks to recognize their behaviors. Therefore, the use of object tracking may be utilized in the tasks such as motion-based recognition, traffic monitoring, automated surveillance, as well as vehicle navigation.

The complexity of object tracking is due to the noises in images, scene illumination changes, complex object motion, and partial and fully objects occlusion. Most of the tracking algorithms assume that the moving object is moves in smooth and no sudden change.

Templates are simple geometric shapes or silhouettes [1]. For object whose pose does not vary much during tracking are suitable to use templates method. Right features selection plays a critical role in tracking. Feature selection is important in object representation. For example, color is used as a feature for histogram-based appearance representations. The RGB (red, green, blue) color space is usually used to represent color in image processing. The differences of colors in the RGB space do not linearly response to the differences of colors perceived by humans. Therefore, a variety of color spaces have been used in tracking due to this inefficient matter.

Edge detection is used to identify strong changes in image intensities of the object boundaries. An important property of edges is that they are less sensitive to illumination changes compared to color features. Canny Edge detector [2] is the most popular edge detection method.

The interest points in images are found using point detector which have an expressive texture. A commonly used interest point detectors include Moravec's interest operator [3], Harris interest point detector [4], KLT detector [5], and SIFT detector [6].

A background image is modeled and finding the differences with the correspondence in order to find the tracking object. A moving object is categorized with an obvious change in an image region from the background image.

Point tracking methods has two main categories, deterministic methods and statistical methods. The deterministic methods use qualitative motion heuristics [7] to constrain the correspondence problem while the statistical methods explicitly take the object measurement and take uncertainties into account to establish correspondence. The examples of point tracking method include Kalman filter and particle filter.

Kernel is the object shape and appearance. The motion of the moving object from one frame to the next frame is computed in Kernel tracking. The object motion is generally in the form of parametric motion (such as translation, conformal, and affine) or the dense flow field computed in subsequent frames.

III. KALMAN FILTER TECHNIQUE IN OBJECT TRACKING

The differences of the typical Kalman filter and the enhanced Kalman filter are highlighted by the involvement of occlusion scene determination and occlusion rate calculation which making the tracking during occlusion is capable. The occlusion rate feature will be activated once the detection showing that the moving object is fully occluded. Besides that, object recognition capability is also added to the enhanced Kalman filter so that the tracking target can be recognized from others. This feature is running all the time to assure that the targeted object will be recognized all the time.

A. The Typical Kalman Filter

The Kalman filter is a recursive estimator. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. Thus, no history of observations or estimates is required.

The Kalman filter has two distinctive features. One is that its mathematical model is described in terms of state-space concepts. Another is that the solution is computed recursively. Usually, the Kalman filter is described by system state model and measurement model. The state-space model is described as system state model and measurement model as shown in (1) and (2) respectively.

$$s(t) = O(t-1)s(t-1) + w(t) \tag{1}$$

$$z(t) = H(t)s(t) + v(t) \tag{2}$$

Where $O(t-1)$ and $H(t)$ are the state transition matrix and measurement matrix respectively. The $w(t)$ and $v(t)$ are white Gaussian noise with zero mean.

Kalman filter have two phases: prediction step and correction step. The prediction step is responsible for projecting forward the current state, obtaining a prior estimate of the state $s^-(t)$. The task of the correction step is for the feedback. It incorporates an actual measurement into the prior estimate to obtain an improved posterior estimate $s^+(t)$, which is written as shown in (3).

$$s^+(t) = s^-(t) + k(t)[z(t) - H(t)s^-(t)] \tag{3}$$

Where $k(t)$ is the weighting and is described as shown in (4).

$$k(t) = p^-(t)H(t)^T[H(t)p^-(t)H(t)^T + R(t)]^{-1}$$
$$= \frac{p^-(t)H(t)^T}{H(t)p^-(t)H(t)^T + R(t)} \tag{4}$$

In (4), the $p^-(t)$ is the priori estimate error covariance. It is defined as shown in (5).

$$p^-(t) = E[e^-(t)e^-(t)^T] \tag{5}$$

Where $e^-(t) = s(t) - s^-(t)$ is the prior estimate error. In addition, the posteriori estimate error covariance is defined as shown in (6).

$$p^+(t) = E[e^+(t)e^+(t)^T] \tag{6}$$

Where $e^+(t) = s(t) - s^+(t)$ is the posteriori estimate error.

The prediction step and correction step are executed recursively in the definitions as shown in (7), (8), (9), (10) and (11).

Prediction step:

$$s^-(t) = O(t-1)s^+(t-1) \tag{7}$$

$$p^-(t) = O(t-1)p^+(t+1)O(t-1)^T + Q(t-1) \tag{8}$$

Correction step:

$$k(t) = p^-(t)H(t)^T[H(t)p^-(t)H(t)^T + R(t)]^{-1} \tag{9}$$

$$s^+(t) = s^-(t)k(t)[z(t) - H(t)s^-(t)] \tag{10}$$

$$p^+(t) = [1 - k(t)H(t)]p^-(t) \tag{11}$$

The prediction-correction cycle is repeated. Looking at (9), the measurement error $R(t)$ and Kalman gain $k(t)$ are in inverse ratio. The smaller the $R(t)$, the gain $k(t)$ weights more heavily. In this case, the measurement is more trusted, while the predicted result is less trusted. However, as the a priori estimate error $p^-(t)$ approaches zero, the gain $k(t)$

weights the residual less heavily. The actual measurement is trusted less and less, while the predicted result is trusted more and more.

B. The Enhanced Kalman Filter

Basically, the algorithm for the typical Kalman filter and the enhanced Kalman filter would be the same just that an occlusion rate is added into the correction step once the moving object detection in consecutive frame calculated is zero, that is, the moving object is being occluded.

Once the moving object is being occluded, its consecutive predicted position will be relying on the latest last two consecutive frames which are used to calculate the rate of occlusion. After the rate of occlusion is gained, the next position of the occluded moving object will be predicted until the object is moving put from the occluded area. The occlusion rate can be defined as in (12).

$$OcclRate = x(t-1) + \delta(t) \tag{12}$$

Besides that, object recognition feature is also added into the enhanced Kalman filter so that others moving objects will be eliminated from the targeting moving object during tracking. This feature is useful for tracking condition that has multiple moving objects.

The Kalman filter provides an efficient way to estimate the state of a linear process and it minimizes the mean of the squared estimation error. Besides that, the Kalman filter is a recursive estimator. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. No history of observations or estimates is required.

IV. TYPICAL KALMAN FILTER (KF) IN OBJECT TRACKING AND ANALYSIS

In this section, analysis of object flows using typical Kalman filter (KF) will be shown. The typical KF capability will be tested out under some moving object condition such as moving in constant direction and velocity, variable size and shape, and long lasting occlusion. The results of object flow without occlusion will be shown. Some of the results are tested using recorded video and some of them are using animation for the ease of the condition that video recording is difficult to perform.

A. Constant Direction and Velocity

From Fig. 1, the typical KF successfully tracked the moving object in every single frame. The green circle showing that the moving object is tracked and plotted effectively. As a conclusion, the typical KF technique is suitable in tracking moving object in constant direction and velocity.

B. Variable Size and Shape

From Fig. 2, the typical Kalman filter is able to predict and track during the experiment. The first size and shape changing is occurred from frame 4th to frame 6th, however, the typical KF facing no problem in continuing tracking the moving object.

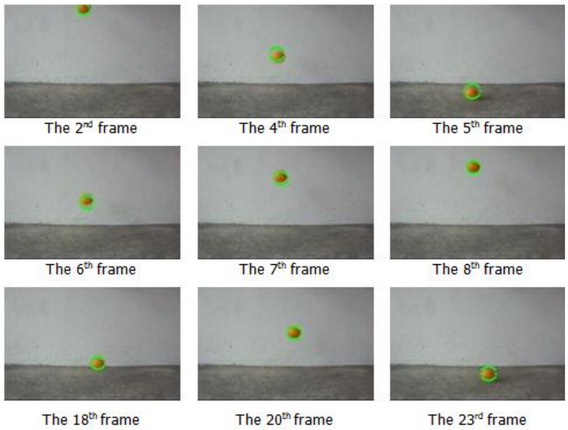

Figure 1. The experimental result of moving object with constant velocity

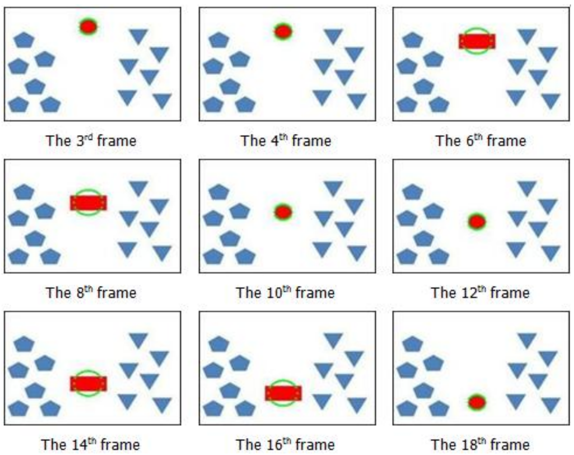

Figure 2. The experimental result of moving object with variable size and shape

C. Sudden Change in Velocity

From Fig. 3, from the beginning until 4th frame, the object was moved in constant velocity and suddenly changed to a fast velocity in 5th frame. At the moment, the typical KF tracked the position that is a bit deviated from the real position, as pointed by the black arrow. However, until the 7th frame, the green circle fast getting back to the real position and keep tracking the moving object until the end. Thus, the typical Kalman filtering method is not so suitable for tracking moving object changing velocity suddenly. However, it will get back to the next true position in a very short time.

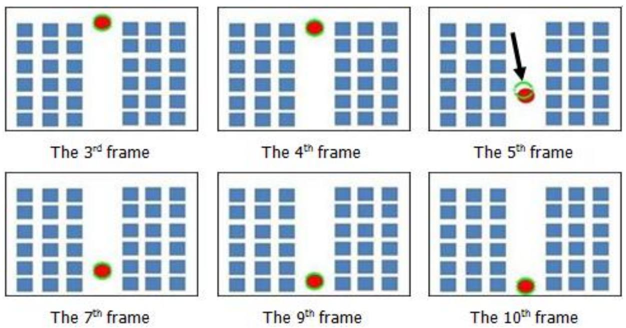

Figure 3. The experimental result of moving object changing direction suddenly

D. Long Lasting Occlusion (KF)

From Fig. 4, there was a table that the moving object will pass through behind it so that a long lasting occlusion scene was created. At frame 13th, the moving object started to pass through from the behind of the table. The moving object was being occluded by the table from frame 17th until frame 29th. During that time, tracking could not be performed and thus no results were shown in the total 13 frames. Finally, at frame 30th, the moving object started to come out from behind of the table, however, the tracking position is far away from the position where it should be, as pointed by the black arrow.

The same phenomenon persisted at frame 31st. Started from frame 32nd until frame 34th, the green circle slowly going back to its right position and continued its tracking mechanism. That is, as a conclusion, the typical KF technique is not suitable in tracking moving object with long lasting occlusion. On the other hand, it is still able to track back the target slowly once the moving object was not been occluded.

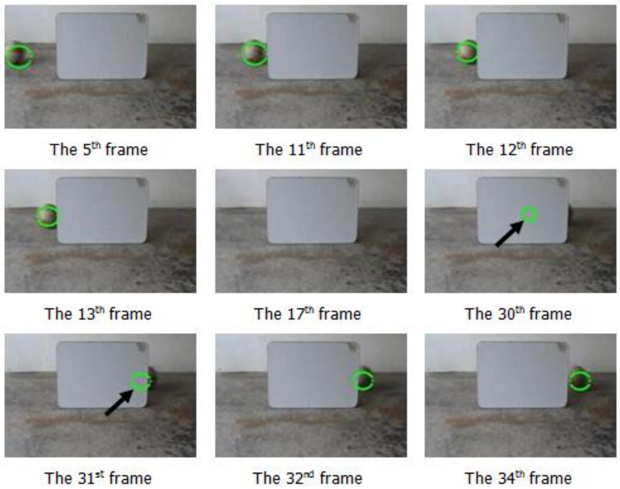

Figure 4. The experimental result of moving object with long lasting occlusion (KF)

E. Occlusion of Two Moving Objects (KF)

From Fig. 5, the targeted moving object is the basketball (brown color moving object) as can be seen at the frame 11th. At first, the typical KF worked well without losing its targeted moving object until frame 21st. However, at frame 2nd, the typical KF tracked the wrong moving object, the football (white color moving object) instead of tracking basketball, as can be seen from the pointed black arrow.

The same mistake repeated in the 23rd frame, 26th frame, 27th frame, and 42nd frame. This is not a good phenomenon as the typical KF always showed a false tracking. Until frame 43rd, the two moving object getting closer and it is the time for the typical KF to filter out the unwanted object. Unfortunately, at frame 58th, the result is not as expected as the green circle tracking the wrong object until the end of the experiment.

As a conclusion, the typical Kalman filter without object recognition capability is not suitable in tracking the occlusion of two moving objects.

Figure 5. The experimental result of occlusion of two moving objects (KF)

F. False Tracking After Occlusion

From Fig. 6, from the beginning until the 6th frame, there was nothing wrong with the tracking of the typical KF. At frame 6th, the yellow moving object started to enter behind of the block. The yellow moving object was being occluded from frame 7th until frame 16th. From the 17th frame until the 20th frame, another red moving object is coming out from the block instead of the initial yellow object.

The typical KF keep tracking the red moving object as this was the only object that can be tracked. At frame 22nd, the initial yellow moving object finally moved out from the block but still the typical KF tracked the wrong object as can be seen from the black pointed arrow. This mistake keep repeated until the end of the experiment. From the results, the typical KF without object recognition ability is not suitable in tracking occluded object where there is other moving object added in to confuse the tracking mechanism.

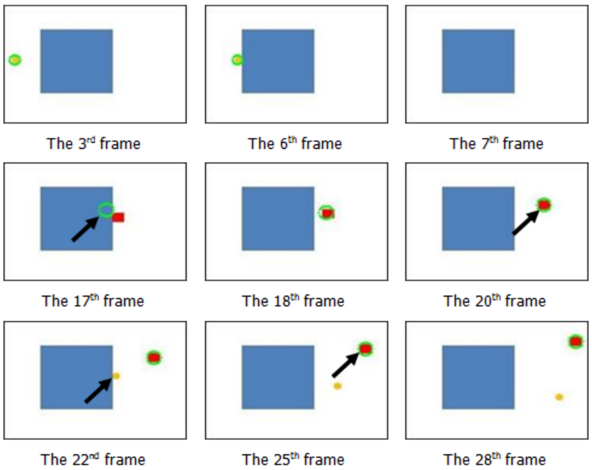

Figure 6. The experimental result of false tracking after occlusion (KF)

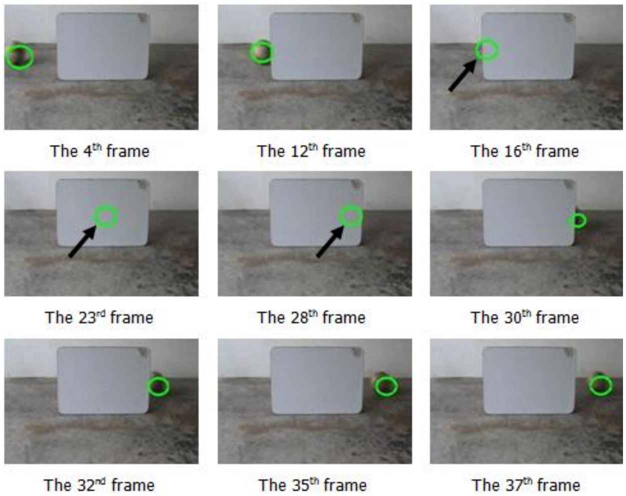

Figure 7. The experimental result of moving object with long lasting occlusion (EKF)

V. ENHANCED KALMAN FILTER (EKF) IN OBJECT TRACKING AND ANALYSIS

In this analysis section, those results which are not giving a well and satisfied results using typical KF will be tested again using the EKF. Most of the results that are not giving a nice tracking performance are related to occlusion condition. Thus, the main focus in this chapter is tried to overcome the occlusion problem that are facing in the previous section.

The occlusion problem that is facing in the previous chapter will be overcome with the occlusion scene calculation feature that is added into the EKF, the moving object position that is being occluded will be predicted and plotted out.

Beside that, some cases that are confuse in recognizing the targeted object will be tested under this section too. The object recognizing feature that is added into the EKF for this paper is object size recognition.

A. Long Lasting Occlusion (EKF)

From Fig. 7, from the beginning of the tracking until the 12th frame, EKF performed well without losing the target. Starting from frame 16th, the moving object (football) entered behind the block and disappeared totally from frame 16th till frame 28th. During this period, the EKF is still able to predict the position of the moving object as indicated by the black arrow. At frame 29th, the moving object started to come out from the occlusion scene, and the EKF tracked the moving object immediately.

Comparing to Fig. 4, the same case but using typical KF, the EKF can capture back its targeted object as soon as it moved out from the occlusion scene. This is much better than the typical KF as the typical KF needs longer time to track back its target. After the occlusion scene, the EKF works well until the end of tracking. Thus, the EKF with occlusion rate feature is able to track the moving object even during occlusion.

B. Occlusion of Two Moving Objects (EKF)

From Fig. 8, the EKF performed well from the beginning until the 43rd frame, which is before the two moving objects occluded. Besides that, at frame 16th, the targeted moving object that the EKF was going to track is the brown moving object (basketball) instead of the white moving object (football). At the 44th frame, indicated by the black arrow, at the moment the two moving objects crossed together, the EKF recognized which moving object was the targeted object from the beginning. The recognizing mechanism was performed throughout the whole tracking system.

Finally, at frame 58th, the EKF successfully recognizing the brown moving object and the tracking mechanism continued till the end. This was a much better result comparing to Figure 5.7, the same case but using typical KF, the EKF did not face the problem of losing its target during occlusion. Furthermore, the case using EKF did not confuse its targeted object throughout the whole tracking system, which the typical KF failed to perform as can be seen from Fig. 5.

As a conclusion, the EKF with object recognizing and occlusion feature would not lose its targeted moving object throughout the whole tracking period even during occlusion.

C. Occlusion with Object Recognition (EKF)

From Fig. 9, the EKF performed well from the beginning until the 6th frame before it entered the blue color block. Started from frame 7th, the moving object moved to behind of the block and this situation persisted until frame 16th. During the occlusion period, the EKF kept predicting the position of every single frame without losing them. For example at frame 11th, the predicting position of the moving object is at around the centre of the block.

Looking at frame 17th, there was another red square object coming out first instead the original yellow object, as indicated by the black arrow. At first, the EKF tracked the red square object as it is the only object moving in the frame. Until frame 22nd, the original yellow moving object coming out and EKF recognized it and tracked it immediately as pointed by the black arrow.

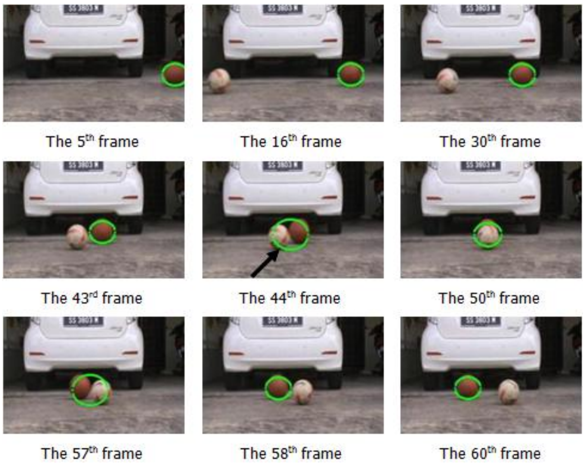

Fig. 8. The experimental result of occlusion of two moving objects (EKF)

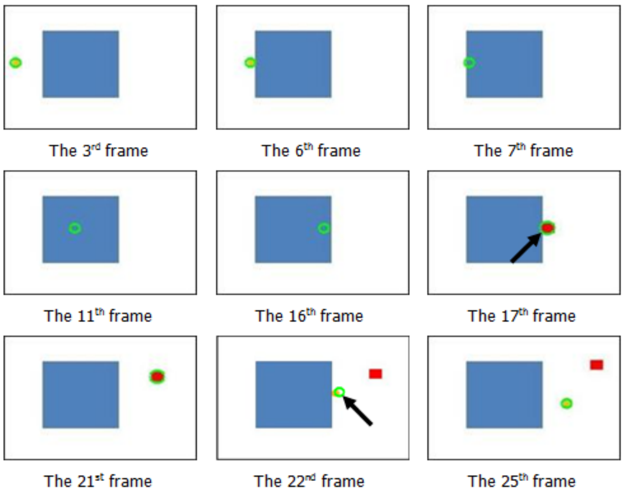

Figure 9. The experimental result of occlusion with object recognition (EKF)

Then, from frame 22nd onwards till the end, the EKF keep tracking the yellow moving object without confusing it with another moving object.

This is a much better result comparing to Fig. 6, the same case but using typical KF, the EKF could recognize its targeted object once another object was trying to confused it. The typical KF failed in recognizing its target.

As a conclusion, the EKF with object recognizing and occlusion feature has the capability to recognize its targeted moving object. The performance is much better than the typical KF.

D. Discussion

From all of the experimental results shown above, the EKF performs well in the condition that has occlusion and requires object recognition feature. The enhanced part in the EKF compares to the typical KF is that the EKF has added occlusion for the condition that the moving object is being occluded. Besides that, object recognition feature added into the EKF will definitely increase the accuracy during tracking.

The tracking speed of the EKF is highlighted. With the ability of tracking occluded object, once the object moving out from the occlusion scene, the EKF can immediately track the object almost with no delay as can be seen from the above result. This is a good improvement compare to the typical KF which needs more frames so that it can capture back its target.

The addition of object recognition feature is also another improvement that helps the EKF to recognize its target without confusing. The previous experimental results showed that the typical KF fails in recognizing targeted object.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

Object tracking using Kalman filter has been proposed in this paper. The typical Kalman filtering method successfully tracks the moving object position in some kind of situation such as the object keep changing shape and size, slightly occlusion, and moves in constant direction and velocity. However, when dealing with the moving objects with occlusion and requires object recognition feature to eliminate the confusion between multiple objects, the typical Kalman filter does not give a satisfied and accurate results.

Difficulties in tracking objects can arise due to abrupt object motion, changing appearance patterns of the object and the scene, non-rigid object structures, object-to-object and object-to-scene occlusions, and camera motion. In this project, the main difficulty that I am facing is that the typical Kalman filter is not suitable to implement in a tracking system where the moving object is being occluded.

Thus, the enhanced Kalman filter is used to overcome the matters faced by the typical Kalman filter. The enhanced Kalman filter has added in occlusion scene handling and occlusion rate calculation as well as object recognition feature to make up the weaknesses of the typical Kalman filter.

In conclusion, the enhanced Kalman filter has make up the weaknesses faced by the typical Kalman filter and the results are encouraging also. Obviously the performance has been improved and the tracking results are more accurate and precise.

B. Future Work

The presented enhanced Kalman filter is not perfect enough as it is not capable to track moving object during occlusion with a pattern of motion such as sinusoidal motion or zigzag motion. The enhanced Kalman filter presented in this paper can only predict the position of the occluded moving object with fixed direction and velocity.

Thus, in future work, perhaps the enhanced Kalman filter technique may incorporate with the equation of the object motion pattern so that it can predict the occluded position by learning the pattern of motion of the moving object. This will definitely increase the efficiency of the enhanced Kalman filter to track and predict the position of the moving object in occlusion, not only in same direction and velocity, but also motion with pattern.

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