Journal of Engineering and Applied Sciences 13 (4): 820-826, 2018
ISSN: 1816-949X

Experimental Analysis of Object Tracking During Occlusion

[1]Lee-Yeng Ong, [1]Siong Hoe Lau, [2]Voon Chet Koo and [2]Xin Ping Khoo
[1]Faculty of Information Science and Technology,
[2]Faculty of Engineering and Technology, Multimedia University, Melaka, Malaysia

Abstract: Object tracking is an essential process for automating various video surveillance applications. In order to obtain the trajectories of every moving objects in a scene, the tracking algorithm has to equip with the ability in handling occlusion. Among the existing tracking algorithms, most of the researches used prediction model to estimate the object's trajectory of the consecutive frames. The estimated position serves as a reference tool to detect and resolve occlusion. This study aims to analyze the performance of Kalman filter prediction model during occlusion incident. Although, Kalman filter is widely applied for object tracking, less effort is done on evaluating the parameter setting and its effect in long-term full occlusion. Experiments are conducted with tracking datasets of varying velocity and acceleration. The experimental result is compared with a conventional predicted motion model to verify the performance of Kalman filter during occlusion.

Key words: Object tracking, occlusion, Kalman filter, video surveillance, conventional predicted motion, verify the performance

INTRODUCTION

Due to the recent advancement of technology in CCTV and IP camera, object tracking has been a popular topic of research in video surveillance. Multiple algorithms have been published for automating the video surveillance applications such as road traffic monitoring, intelligent transportation system, human motion analysis and vehicle controlling system (Sharifzadeh *et al*., 2007; Lee *et al*., 2014; Baldwin *et al*., 2004; Jun *et al*., 2008). Object tracking algorithm plays an important role to retrieve the trajectories of every moving objects in a dynamic scene. According to the general framework of object tracking, distinct features of each object are extracted for identifying the similar object in the future frames. The features matching is carried out in a constrained search space that is nearby the future location of an active object rather than using brute-force matching. Thus, prediction model is employed to estimate the trajectory of each active object prior to the matching task. One of the authentic way to compute prediction model is by learning through the motion pattern of an object from a sequence of past frames.

By computing the object's position of every past frame, the model is able to conclude the velocity and acceleration of a moving object. The pattern of movement from the history is then used to estimate the location of the constrained search space.

The performance of the tracking algorithms, however are normally prone to occlusion incident. Since, decades ago till now, many researches have been published to resolve different severity of occlusion incidents, ranging from partial, full and long-term full occlusion (Lee *et al*., 2014). Whenever the features of an object are hidden from the camera view, the tracking algorithm uses the prediction model to justify the level of occlusion and select a suitable occlusion handling method to resolve it. During partial occlusion, methods such as template matching or features matching were still able to track the unoccluded parts of object (Ong *et al*., 2014a). However, it is impossible to rely on the image appearance or features when a tracked object is fully invisible from the camera view. Hence, most of the literatures proposed to use prediction model to estimate the tracking trajectory while Kalman filter has been well-known and widely applied in object tracking with and without full occlusions. It is because of the less consumption on memory that added the value for real-time applications. Welch and Bishop (1995) have provided an introduction on the simulation of discrete Kalman filter in the physical system of voltage measurements. They also pointed out the importance of parameters tuning for error compensation in the physical system.

MATERIALS AND METHODS

Prediction model: As mentioned earlier in section 1, object tracking algorithm needs to estimate the location of tracked object in the future frames. Besides, reducing the computational load for matching task, prediction model is

Corresponding Author: Lee-Yeng Ong, Faculty of Information Science and Technology, Multimedia University, Melaka, Malaysia

extremely helpful for resolving full occlusion incident. In order to increase the reliability of the prediction result, predictor needs to investigate the history of an object's motion pattern. Predictor can perform better if more and accurate observations are provided. When only a few observations are available before full occlusion, predictor is fully depending on parameters initialization and tuning. Kalman filter model and a simple type of predictor, namely predicted motion model are elaborated in the next section.

Predicted motion model: According to the study of human visual system, the observer imagines the next position of the observed object corresponds to the observer's assumption on how the object evolve over time. Simple linear dynamics such as velocity, acceleration and direction are normally included in the observer's assumption. Using the fundamental concept of motion model of physics, the velocity of the current time step, v(t) can be computed based on the positions of the previous time steps. The motion model of the velocity, v(t) is expressed in Eq. 1:

$$v(t) = \frac{p(t)-p(t-1)}{\delta t} \quad (1)$$

The series of motion patterns of an object can be eventually summarized from the observations of the previous time steps in a decreasing weightage. The more recent observations are generally reflecting the current motion pattern of an object. Therefore, the expected position of the next time step, p(t+1) is specified in Eq. 2:

$$p(t+1) = p(t)+\delta(v(t)) \quad (2)$$

Where:

$$\delta(v(t)) = \frac{2}{t(t+1)}\sum_{n=1}^{t} n\times v(n)$$

Kalman filter model: Kalman Filter (KF) is built with state-space technique to improve the estimated state with the corresponding measurements in a recursive manner. KF algorithm consists of prediction and measurement process equations. Prediction process equations compute the expected position and process noise covariance. Measurement from the observation is used to improve the expected position and calculate the measurement noise covariance. Thus, the history record can be omitted except the predicted state from the previous time step and the measurement of the current time step.

KF Model is able to perform as a good predictor only if the parameters tuning is well optimized. As mentioned by Welch and Bishop (1995) the covariance matrices are usually measured before implementation in a physical system. Since, measurement noise covariance, R represents error occurred from the measurement observations, the variance can be computed from the sample of offline measurements. In the physical, system that measures the voltage of a device, R is estimated from the error of the measurement equipment or obtained directly from the manual report. The determination of process noise covariance, Q on the other hand is more difficult to be decided in the physical system. It is impossible to observe the estimation process prior to the implementation in the physical system. However, it is a totally different situation for deciding Q and R in the video surveillance applications. Kohler (1997) elaborated the way to initialize both parameters in tracking human motion. R can be estimated indirectly from the false-detection of the segmentation algorithms and Q is measured from the ratio of motion in the real scene (vehicle and human) with the time interval of processing one frame completely. KF model that was demonstrated by Ong *et al.* (2014b) is used in the latter experiments analysis. The model is defined in Eq. 3 which incorporates an object's centroid $(\hat{s}_{t,x}, \hat{s}_{t,y})$ and velocity $(\hat{v}_{t,x}, \hat{v}_{t,y})$:

$$\begin{bmatrix} \hat{s}_{t+1,x} \\ \hat{s}_{t+1,y} \\ \hat{v}_{t+1,x} \\ \hat{v}_{t+1,y} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \delta t & 0 \\ 0 & 1 & 0 & \delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{s}_{t,x} \\ \hat{s}_{t,y} \\ \hat{v}_{t,x} \\ \hat{v}_{t,y} \end{bmatrix} \quad (3)$$

RESULTS AND DISCUSSION

Experimental results: From the existing video surveillance applications, the moving objects are typically consisting of vehicle and human. The mapping of vehicle and human tracking trajectory can be integrated from several combinations of velocity, acceleration and direction. Figure 1 shows three types of possible mapping of an object's motion for y-position in 100 frames which includes constant velocity with no acceleration, inconsistent velocity in the same and varying directions. These sets were used in the rest of the experimental studies for evaluating both prediction models. The variance between the Ground Truth (GT) and expected values from the predictor is recorded to analyze the performance of tracking algorithm. A robust and reliable predictor should yield the lowest Root-Mean-Square Error (RMSE).

Parameters tuning: As mentioned before both parameters (Q, R) are decided before tracking implementation. Three experiments were carried out to analyze the effects of parameter tuning in Kalman filter

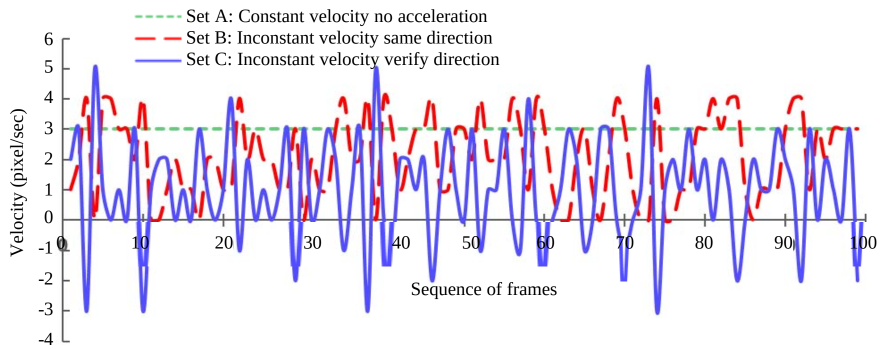

Fig. 1: Different combinations of motion including velocity, acceleration and direction

model. The variation between the ground truth values of an object's y-position and the expected values from KF predictor are show in Fig. 2. Referring to Fig. 2a that demonstrated on the dataset of constant velocity with no acceleration, it is clearly shown that KF predictor is in the midst of adapting to the measurements (GT) in the first eight frames. The similar parameters tuning are applied to the datasets with inconsistent velocity are depicted in Fig. 2b and c. Parameter (Q = 0.1, R = 0.005) indicates that process noise covariance is higher than measurement noise covariance. This implies that the measurements of KF Model is more reliable as compared to estimation. Therefore, the KF Model with parameter (Q = 0.1, R = 0.005) produces the lowest variation while the highest variation occurs in parameter (Q = 0.005, R = 0.1). Although, parameter (Q = 0.1, R = 0.005) performs the fastest adaptation in set A with constant velocity but not in set B and C. The RMSE values for each parameters tuning are summarized in Table 1. Table 1 implied that the parameters tuning of KF Model is closely related to the characteristics of the tracking trajectory. An arbitrary selection of parameters will reduce the performance of KF Model.

Similar experiments are conducted for predicted motion model and represented graphically in Fig. 3. Indeed, the variation computed from the predicted motion model in set A and B are less than Kalman filter model while variation from set C is still less than the RMSE of parameter (Q = 0.1, R = 0.005). In other words both prediction models may be adequate for object tracking only if video surveillance applications are free from occlusion incident.

Full occlusion: Video capturing is the process of projecting the 3D world into 2D image which indirectly lost some of the depth information. Some objects are most likely to be hidden from the camera view if they have the identical x-and y-positions but different in z-position or vice versa. Since, surveillance camera is normally installed at a static location, occlusion is definitely an unavoidable incident in the real-world video surveillance application. Therefore, it is necessary for an object tracking algorithm to equip with the ability in handling occlusion. Four experiments regarding occlusion have been tested to analyze the performance of both prediction models in different characteristics of tracking trajectory. These experiments intend to simulate different periodical of full occlusion in the inconsistent velocity: set B and C. For example, full occlusion may happen from frame 3 until frame 10 which means the object suffers a continuous occlusion in a period of 7 frames. Hence, the predictors have to begin the estimation process by only using the first two measurements of tracking trajectory for the 7 missing frames. Figure 4-7 display the graphical variation between the ground truth values and expected values of both predictors with full occlusion up to a maximum of 50 frames. Each graph line summarized the RMSE of the predictor where occlusion started from the indicated frame (represented in graph Legend) and sustained in a period of frames (represented at y-axis).

Table 1: RMSE for Kalman filter prediction with different parameters tuning

Set	Q = 0.005, R = 0.1	Q = 0.1, R = 0.1	Q = 0.1, R = 0.005
A	1.5652	1.1510	1.0368
B	1.8276	1.6118	1.6372
C	1.8166	2.1378	2.4310

The RMSE of predicted motion model begins with 1.879 at zero missing frame. Subsequently, Fig. 4 shows that the RMSE values are growing exponentially when occlusion happened in more than 10 consecutive frames and fluctuating unexpectedly from 23-50 continuous missing frames. Several RMSE values even struck to more than 6000 which are fatal for prediction motion model. Regardless of the poor performance, the result of prediction motion model during occlusion in 4 consecutive frames are still acceptable (RMSE is <5).

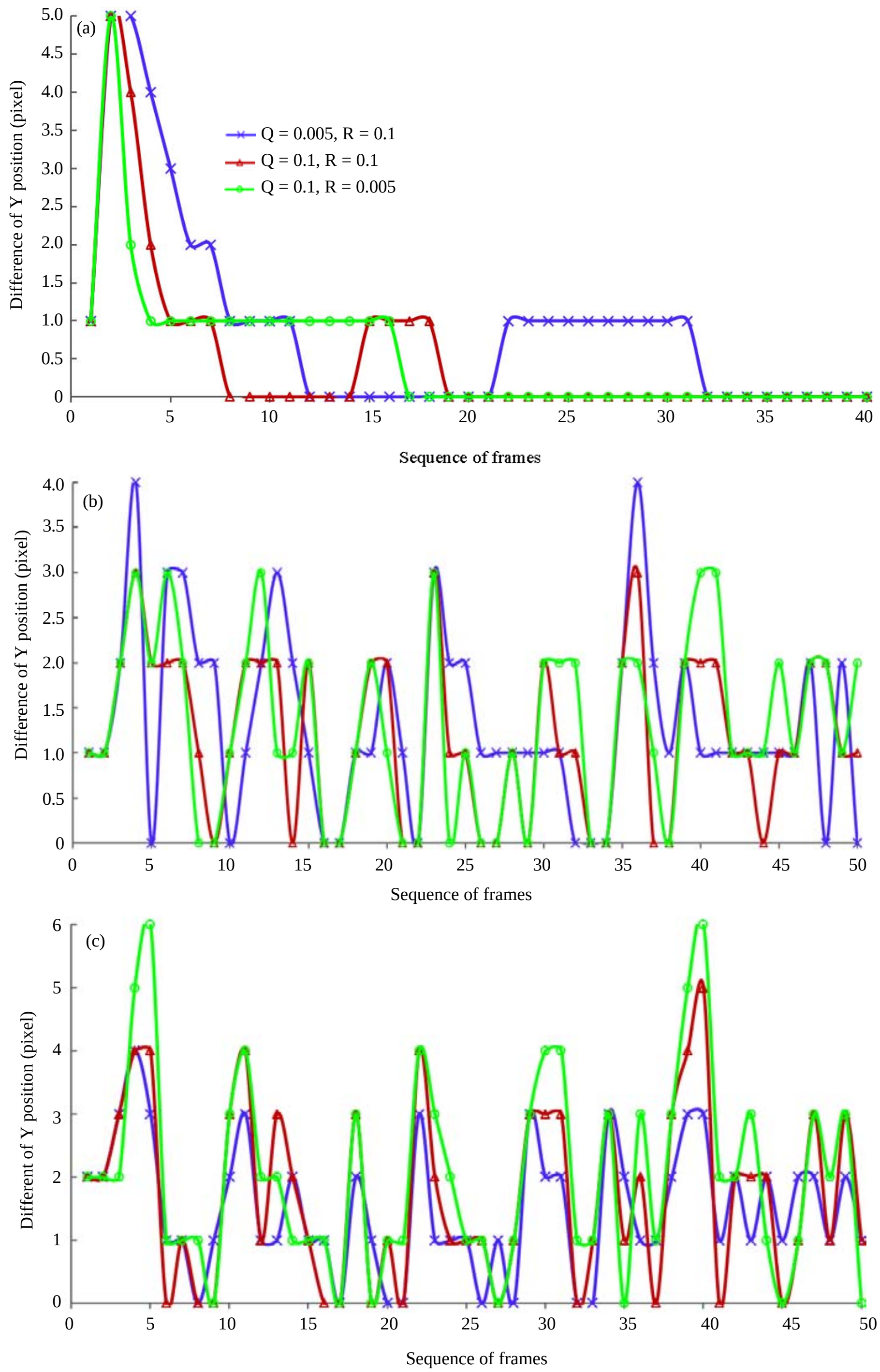

Fig. 2: Effects of parameters tuning in different characteristics of tracking trajectory for: a-c) variation between GT and KF prediction (set A-C)

Unlike prediction motion model, the overall performance of Kalman filter model with three sets of parameter is much better than the prediction motion model. Figure 5-7 show that the difference between all of the RMSE values in 0-6 continuous missing frames are <1. In addition, all of the RMSE values are always within 5 in the 10 continuous missing frames which is obviously better than the prediction motion model. At the same time, the range of RMSE can be used as a reference to limit the radius of the constrained search space. By

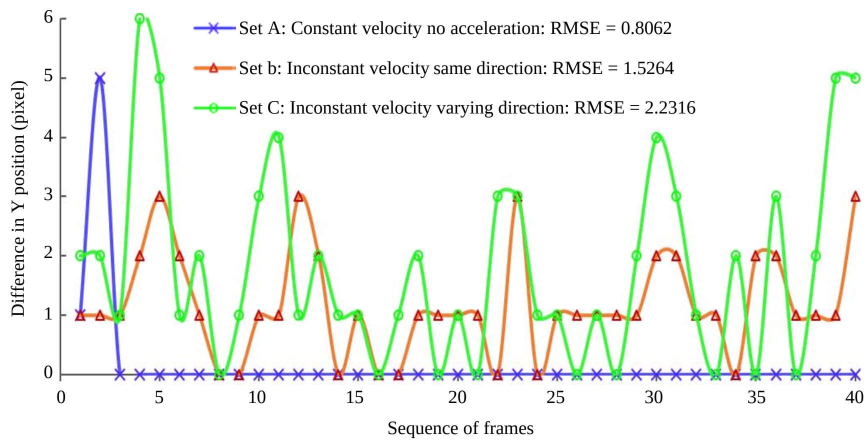

Fig. 3: Performance of predicted motion model in different characteristics of tracking trajectory

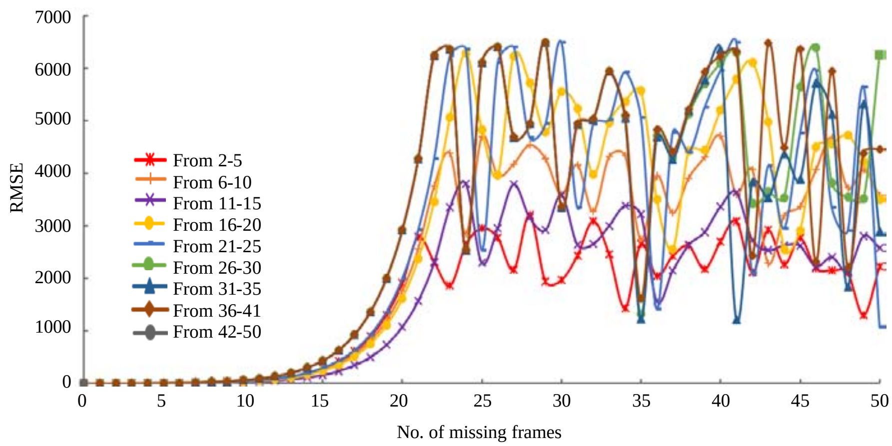

Fig. 4: Using predicted motion model to show the error accumulation during occlusion

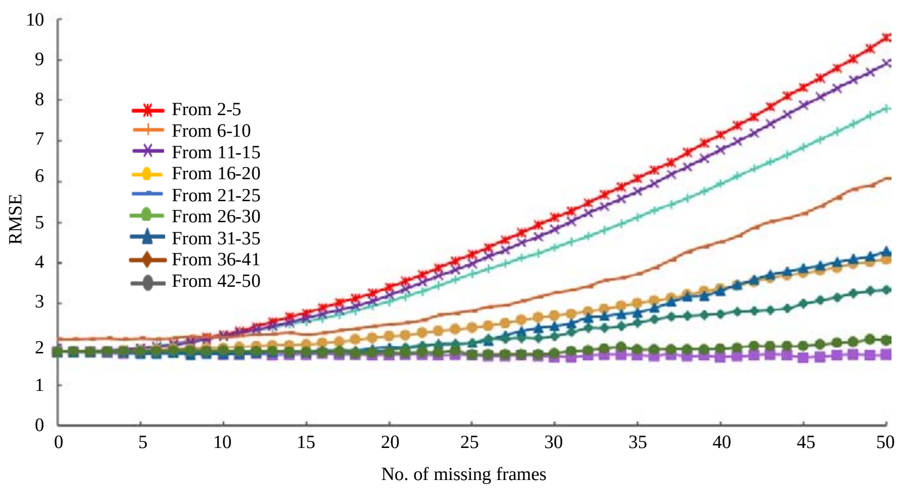

Fig. 5: Using Kalman filter model with parameters (Q = 0.005, R = 0.1) to show the error accumulation during occlusion

using 5 pixels as the reference value, the area of search space is bound to 79 pixel^2. Therefore, the matching task can narrow down the searching area around the predicted position instead of using brute-force matching.

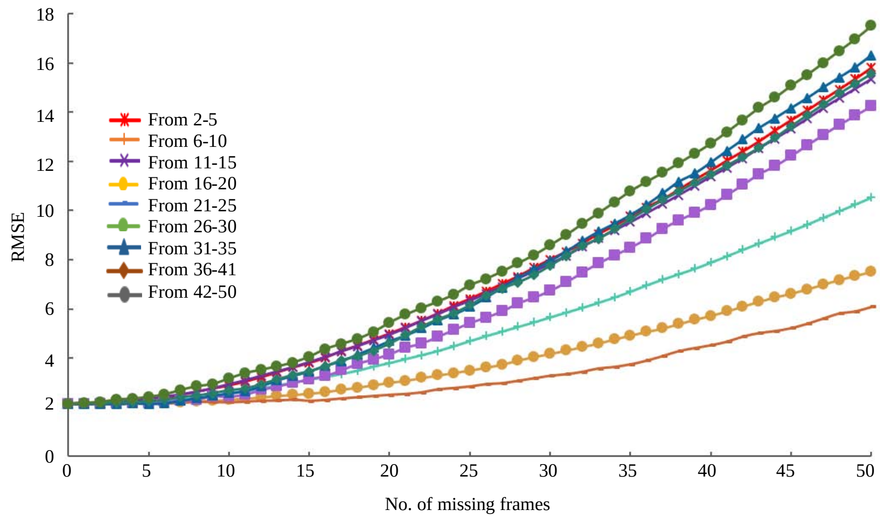

Fig. 6: Using Kalman filter model with parameters (Q = 0.1, R = 0.1) to show the error accumulation during occlusion

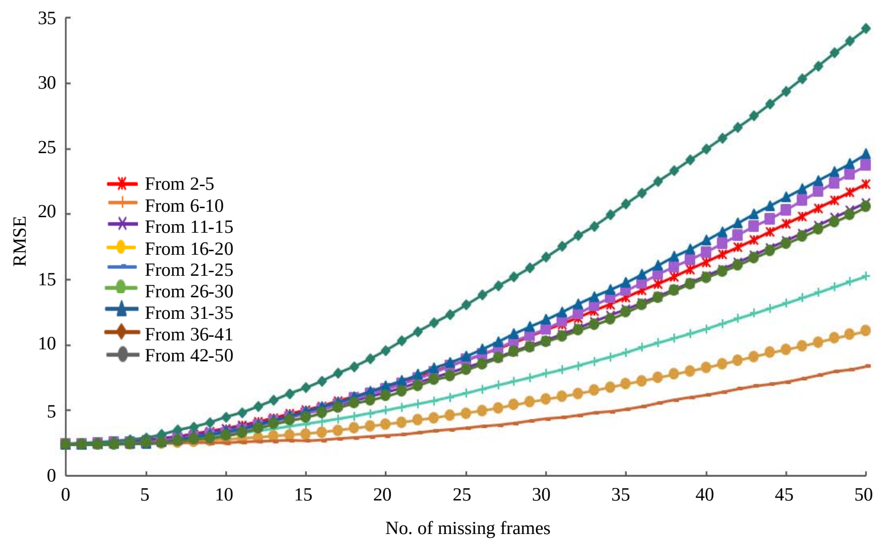

Fig. 7: Using Kalman filter model with parameters (Q = 0.1, R = 0.005) to show the error accumulation during occlusion

In the comparison performance using three sets of parameter, parameter (Q = 0.005, R = 0.1) achieved the lowest RMSE and parameter (Q = 0.1, R = 0.005) gained the highest RMSE in the 50 continuous missing frames. This is because the process noise covariance, Q is higher than measurement noise covariance, R. The higher value of Q indicates that the model has less confidence on the prediction values. Consequently, the model accumulated more prediction error during long-term occlusion.

CONCLUSION

This study has implemented the experimental analysis specifically on Kalman filter model in object tracking algorithm. Two parts of the experimental result have discovered the effects of parameters tuning in the situation with and without occlusion. Kalman filter model shown an out-performed result for long-term full occlusion as compared to the conventional prediction motion model.

RECOMMENDATIONS

There are some recommendations can be drawn from the experimental analysis:

- Parameters tuning of Kalman filter model is closely related to the characteristics of the tracking trajectory
- Kalman filter model can be used for tracking objects with inconsistent velocity and acceleration during full occlusion that suffered up to 10 consecutive frames

- The range of RMSE can be used as a reference to limit the radius of the constrained search space for tracking occlusion in the 10 consecutive frames

The experimental results also revealed the limitation of Kalman filter model. This model is yet to optimise to the fullest if the parameters tuning is not done well. In the future research, perhaps a learning method for parameter tuning can be applied before implementation to figure out the characteristic of the tracking trajectory.

ACKNOWLEDGEMENT

This research was supported by Fundamental Research Grant Scheme from Ministry of Education Malaysia.

REFERENCES

Baldwin, K.C., D.D. Duncan and S.K. West, 2004. The driver monitor system: A means of assessing driver performance. Johns Hopkins APL. Techn. Digest, 25: 269-277.

Jun, G., J.K. Aggarwal and M. Gokmen, 2008. Tracking and segmentation of highway vehicles in cluttered and crowded scenes. Proceedings of the IEEE Workshop on Applications of Computer Vision WACV 2008, January 7-9, 2008, IEEE, Copper Mountain, Colorado, ISBN:978-1-4244-1913-5, pp: 1-6.

Kohler. M., 1997. Using the Kalman Filter to Track Human Interactive Motion: Modelling and Initialization of the the Kalman Filter for Translational Motion. Dekanat Informatik, Vienna, Austria,.

Lee, B.Y., L.H. Liew, W.S. Cheah and Y.C. Wang, 2014. Occlusion handling in videos object tracking: A survey. Proceedings of the IOP Conference Series: Earth and Environmental Science Vol. 18, February 25, 2014, IOP Publishing, Bristol, UK., pp: 1-6.

Ong, L.Y., S.H. Lau, V.C. Koo and C.H. Lim, 2014a. An experimental study on vision-based multiple target tracking. Intl. J. Microwave Opt. Technol., 9: 134-138.

Ong, L.Y., S.H. Lau and V.C. Koo, 2014b. A new approach of local feature descriptors using moment invariants. J. Comput. Sci., 10: 2538-2547.

Sharifzadeh, S., G. Ardeshir and H.M. Naimi, 2007. Statistical background modeling based on velocity and orientation of moving objects. Intl. J. Eng. Trans. B. Appl., 21: 39-54.

Welch, G. and G. Bishop, 1995. An Introduction to the Kalman Filter. University of North Carolina at Chapel Hill, Chapel Hill, North Carolina,.