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An Experimental Study on Vision-based Multiple Target Tracking

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***Abstract* – Multiple target tracking has been an interested topic of research for vision-based traffic monitoring application because of its importance in associating multiple detected vehicles from consecutive frames of video. Before tracking multiple vehicles across frames, target detection algorithm, such as background subtraction is responsible for capturing the position of moving target in every frame. Tracking algorithm uses the measurements from the detection stage to relate the moving targets from previous frame with the current frame. Due to the limitation of performance in the target detection algorithm, it is not reliable to solely depend on the measurements computed from the detection stage. Thus, Kalman filter model has been adopted to compensate the fluctuation and missing measurements whenever the detection stage fails. The missing measurements are predicted based on the center position of vehicle and velocity estimation from the displacement of vehicle. Experimental study has been conducted on the vehicle tracking at road junction. The results showed that Kalman filter model assure the continuous tracking of multiple targets even though there are several lost measurements.**

***Index Terms* – Kalman filter, vehicle tracking.**

I. INTRODUCTION

Traditionally, road-traffic monitoring is analysed based on data collection from electronic sensor (loop detector) and manual observation by human operator. An increasing numbers of vehicles in major highways even aggravate the situation of the traditional system. Since the integration of multiple target tracking algorithms in the vision-based traffic monitoring system, it offers an attractive alternative with additional potential to collect a variety of traffic parameters [1-2]. The parameters are useful for processing semantic results, such as traffic counting, traffic planning, stopped-vehicle detection, speeding, wrong-way vehicle alarms, vehicle gap, vehicle types and driving patterns.

Vehicle tracking is the second processing stage in the existing vision-based traffic monitoring system, as illustrated in Fig. 1. This stage is mainly depends on the output from the first stage, which is vehicle detection. The frames from the video input are recognised as image sequences and fed into the first stage of traffic monitoring system. Moving vehicles that are discovered and segmented from the stationary background are declared as foreground images. Since a moving vehicle is formed by a sequence of images from the consecutive frames, the foreground images are matched and combined into its respective tracked objects.

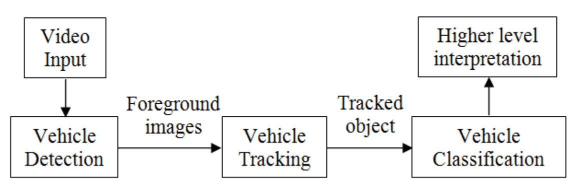

Fig.1. Processing stages for traffic monitoring system.

Background subtraction is the most widely applied algorithm for moving vehicle segmentation. The basic idea of background subtraction algorithm is to subtract (pixel-wise) all consecutive frames from a background frame. As a result, this algorithm can be easily affected

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by sudden changes in background and illumination. Since then, numerous researches on updating the background image have been carried out to create a most adaptive background model, in order to reduce the influence of dynamic scene changes [3-8]. However, the contribution effort is still not able to perform vehicle segmentation perfectly, which indirectly affects the performance of vehicle tracking stage.

Kalman filter started to be introduced in vehicle tracking when Kalman filter has been applied in various engineering field for compensating the measurement errors from the sensors [9-11]. It is due to its ability in predicting the movement of vehicles in the future video frames. The prediction result provides a suitable area for searching vehicles in the next frame. Consequently, it shortens the processing time by excluding the foreground images that is not located in the searching area [12]. Besides, it also assists the tracking process in the situations where vehicles are temporarily missed detected.

In this paper, an experimental study on vision-based multiple target tracking is presented. The study is investigated with the Kalman filter model that is defined in section II. The model is used to predict the missing measurements while tracking multiple vehicles at road junction. The results are reported in section III. Finally, a conclusion is given in the last section.

II. KALMAN FILTER MODEL

In the common road traffic flow, vehicle movements can be sufficiently recorded with an optical sensor (camera) that is at least 25 frames per second. This is because the displacement changes of moving vehicles in x- and y- positions have been monitored to be small and does not show drastic changes, even at the road junction [13]. Thus, a linear estimation model, such as Kalman filter can be adopted for predicting the position of the vehicle, particularly during the lost of detection measurements.

Kalman filter model is a recursive process between prediction and correction phases [12]. The prediction and measurement vectors are defined in (1) and (2). The model incorporates the measurements of center position of a moving vehicle and its velocity. The velocity is calculated in both x and y directions according to (3), where t_s represents the expected sample time of the global discrete estimation process.

$$x_t = \begin{bmatrix} x_c & y_c & v_x & v_y \end{bmatrix}^T \tag{1}$$

$$z_t = \begin{bmatrix} x_c & y_c & v_x & v_y \end{bmatrix}^T \tag{2}$$

$$v_t = \frac{x_t - x_{t-1}}{t_s} \tag{3}$$

The prediction of the next frame is processed with (4) by using the transformation matrix in (5).

$$x_t = F_{t-1} x_{t-1} \tag{4}$$

$$F = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

III. EXPERIMENT AND RESULTS

Two experimental studies were carried out to test the efficiency of Kalman filter model for multiple vehicle tracking. Both experiments used the pre-recorded video streams that are captured from a static camera installed on the pedestrian bridge above the road. The model was implemented with C++ programming language and Open Source Computer Vision (OpenCV) library [14]. The background subtraction method based on adaptive Gaussian mixture model in OpenCV was utilized for the vehicle detection stage [8]. Tracking stage was demonstrated with the Kalman filter algorithm for associating the foreground images with tracked objects from the previous frame.

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The first experiment compared the performance of the Kalman filter model with the measurements from vehicle 23 that is turning at the road junction. The scene of vehicle 23 and tracking results are shown in Fig. 2 and 3.

Fig.2. Vehicle 23 is turning at the road junction.

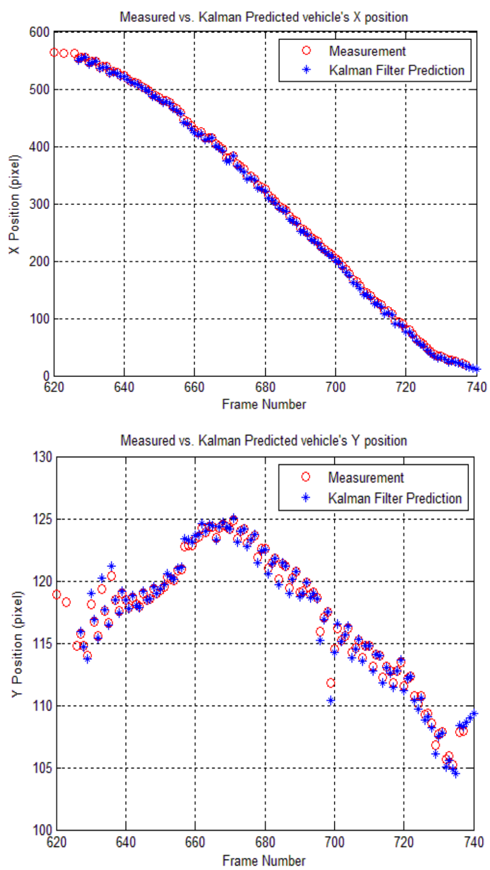

Fig.3. Tracking result for vehicle 23: The measured and Kalman's predicted x- and y- positions.

The tracking results of x- and y- positions for the measurements and prediction are plotted in Fig. 3.

The Kalman predicted positions are closely matched with the measurements obtained from vehicle 23. Variation between measurement and Kalman filter prediction was computed and illustrated in Fig. 4. Among the 110 frames, x- and y-positions experienced the variations that were lower than 6 pixels and 2 pixels respectively. The results verified that the Kalman filter model was able to provide a good prediction in vehicle tracking.

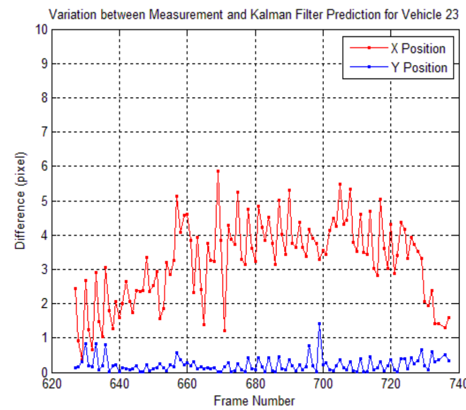

Fig.4. Variation result between measurement and Kalman Filter prediction for vehicle 23.

In the second experiment, one of the output scenes of multiple vehicle tracking is shown in Fig. 5. It has proven the ability of Kalman filter model in tracking multiple vehicles simultaneously. In order to verify the prediction of vehicle's position whenever there are missing measurements, the tracking result of vehicle 8 entering a junction was illustrated in Fig. 6. There were lost detections of the x- and y-positions of vehicle 8 from frame 190 to 197. These can be seen in the figures, where there are gap highlighted in the graph of x- and y-positions. Despite the gap, the Kalman filter prediction was still remained on the tracking path with vehicle 8. Fig. 7 demonstrated the merging process of Kalman predictions with measurements. Although vehicle 8 was not moving in a straight line, the tracking process was able to updates the prediction according to the computed velocity from the model. This result shows that Kalman filter model assure the

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continuous tracking of multiple targets even though there are several lost measurements.

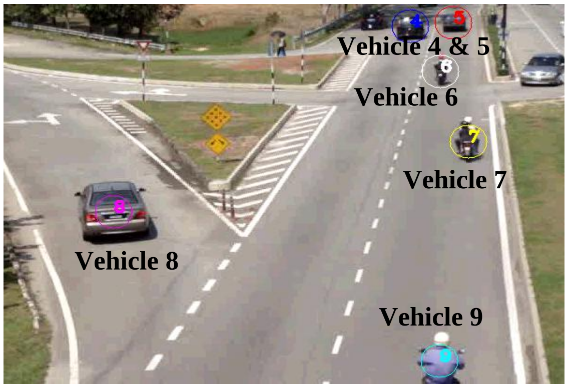

Fig.5. Multiple vehicle tracking at the road junction.

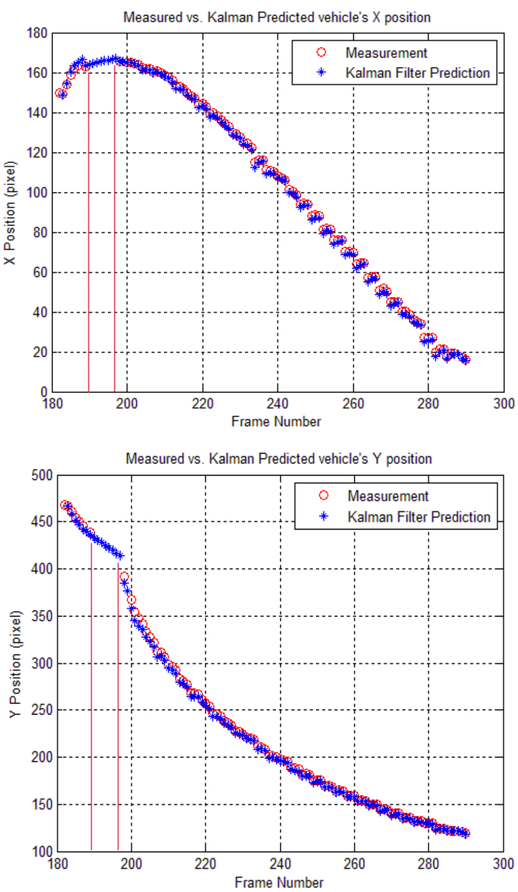

Fig.6. Tracking result for vehicle 8: The measured and Kalman's predicted x- and y- positions.

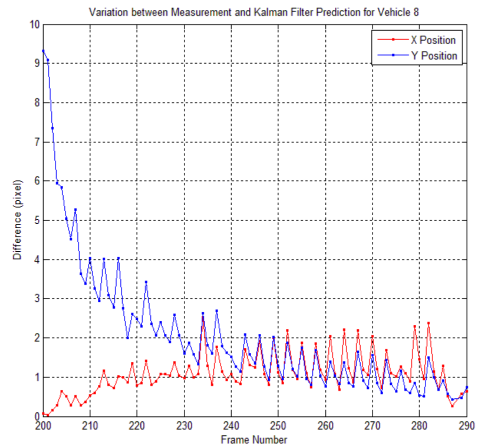

Fig.7. Variation result between measurement and Kalman Filter prediction for vehicle 8.

IV. CONCLUSION

This paper has demonstrated the experimental study of Kalman filter model for multiple vehicle tracking. The model has incorporates the measurements of center position of a moving vehicle and the computed velocity from the displacement changes in the prediction phase. The tracking results have proven that Kalman filter model is suitable for tracking multiple targets even though measurements are lost in a short period of time. Thus, the overall performance of future vision-based multiple target tracking system can be improved by incorporating the model of Kalman filter.

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