A Reliability Point and Kalman Filter-based Vehicle Tracking Technique

Soo Siang Teoh and Thomas Bräunl

***Abstract*—**This paper introduces a technique for tracking the movement of vehicles in consecutive video frames. The technique is based on a Kalman filter and a reliability point system. The Kalman filter predicts the most probable location of a detected vehicle in the subsequent video frame. This information is used by the tracking function to narrow down the search area for re-detecting a vehicle. The Kalman filter also helps to smooth out the irregularities due to the measurement error. The reliability point system provides a simple and fast mechanism to monitor the quality of tracking for the vehicles in the tracking list. Each vehicle is assigned with a reliability point, which can be increased or reduced at every tracking cycle depending on how consistent the vehicle is being re-detected. Experiment on some pre-recorded videos showed that the proposed technique can successfully track the preceding and overtaking vehicles in consecutive video frames.

***Keywords*—**Driver assistance system, intelligent vehicle, image processing, vehicle tracking.

I. Introduction

Vision-based vehicle detection system uses optical sensor such as a normal camera to detect vehicles or other obstacles on the road. The most common approach of vision-based vehicle detection consists of the following two stages: detection and then tracking. The detection stage scans a large area of the captured image to locate all possible vehicles. Different vision-based detection techniques have been proposed in the literature; the most common being the appearance based approach which detects vehicles based on the visual characteristic of a vehicle such as symmetry [1], [2], horizontal and vertical edges [3], color [4], corners [5], shadow underneath the vehicle [6] and texture [7]. Once a vehicle is detected, it is passed to the tracking stage to monitor the movement of the vehicle in the subsequent video frames.

Tracking takes advantage of the temporal coherence of the consecutive video frames to monitor the movement of the detected vehicles. This allows the system to regularly skip the comparatively time consuming detection stage to improve the overall speed of the vehicle detection system.

In this paper, we introduce an efficient technique for tracking the detected vehicles in a forward collision warning application. The technique uses a Kalman filter to estimate the movement of the detected vehicles and a reliability point system to improve the robustness of the tracking.

This paper is organized as follows: In the next section, the application of the Kalman filter for vehicle tracking is explained. Then in section III, the proposed reliability point system is described. This is followed by the experiments and the results of the evaluation. Finally, a conclusion is given in the last section.

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II. Vehicle Tracking With Kalman Filter

A Kalman filter is used in the tracking to predict the locations of vehicles in the future video frames. The advantages of including the Kalman filter in the tracking process are:

1) It provides the best estimated location to search for vehicles in the next video frame and thus improves the re-detection rate;
2) It reduces the search area for re-detecting a vehicle and therefore shortens the processing time;
3) It may reduce the number of false detections since the image area that does not contain vehicle is excluded from the search

In addition, the smoothing effect of the Kalman filter will refine the tracking result from the uncertainty of the measurement noise. It also helps to handle the situations where vehicles are momentarily missed detected.

The following subsections explain the Kalman filtering and its application for tracking vehicles in the image plane.

A. The Discrete Time Kalman Filter

The process and the measurement models of a linear discrete-time system can be defined by the following equations [8], [9]:

$$\mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{w}_{k-1} \tag{1}$$

$$\mathbf{y}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k \tag{2}$$

where $\mathbf{x}_k$ and $\mathbf{y}_k$ are the state and measurement vectors at time step k. $\mathbf{F}_k$ and $\mathbf{H}_k$ are the transition and measurement matrices.
$\mathbf{w}_k$ and $\mathbf{v}_k$ are the process and measurement noise. They are assumed to be independent, zero-means, white Gaussian noise with covariance matrices $\mathbf{Q}_k$ and $\mathbf{R}_k$ respectively:

$$\mathbf{w}_k : (0, \mathbf{Q}_k) \tag{3}$$

$$\mathbf{v}_k : (0, \mathbf{R}_k) \tag{4}$$

The Kalman filter estimates the state of the process by recursively updating the system dynamics. This is done in two phases: the *time update* phase and the *measurement update* phase [10]. It is illustrated in Fig. 1.

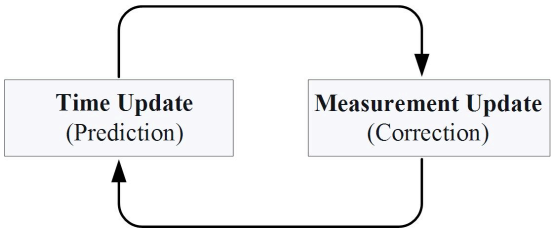

Fig. 1 The cycle of time and measurement update phases of a Kalman filter

The *time update* phase projects forward in time the current state and error covariance to obtain the *a priori* estimates for the next time step. The *measurement update* phase incorporates the latest measurement into the system's model to get the *a posteriori* estimates of the state and error covariance.

The *time update* and the *measurement update* algorithms are summarized in (5) to (9). In the equations, the subscript indicates the time step while the superscripts "-" and "+" indicate the *a priori* and the *a posteriori* estimates respectively. $\hat{\mathbf{x}}$ denotes the estimate for $\mathbf{x}$.

The time update equation for calculating the *a priori* state estimate, $\hat{\mathbf{x}}_k^-$ and the error covariance, $\mathbf{P}_k^-$ are given by (5) and (6) respectively:

$$\hat{\mathbf{x}}_k^- = \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1}^+ \quad (5)$$

$$\mathbf{P}_k^- = \mathbf{F}_{k-1}\mathbf{P}_{k-1}^+\mathbf{F}_{k-1}^T \quad (6)$$

After getting the latest measurement, $\mathbf{y}_k$, the *a posteriori* estimate, $\hat{\mathbf{x}}_k^+$ and the corresponding error covariance, $\mathbf{P}_k^+$ are calculated using the following measurement update equations:

$$\hat{\mathbf{x}}_k^+ = \hat{\mathbf{x}}_k^- + \mathbf{K}_k(\mathbf{y}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^-) \quad (7)$$

$$\mathbf{P}_k^+ = (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_k^- \quad (8)$$

where $\mathbf{K}_k$ is the Kalman filter gain given by:

$$\mathbf{P}_k^+ = \frac{\mathbf{P}_k^-\mathbf{H}_k^T}{\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^T + \mathbf{R}_k} \quad (9)$$

The cycle for the time and measurement updates repeats for every measurement time step. The goal of the Kalman filter is to provide the best estimate for the state of the system based on the current available knowledge in the system's model and the latest measurement data.

B. Applying the Kalman Filter for Vehicle Tracking

The proposed technique uses a Kalman filter to predict the motion and the changes in the image size of a vehicle in the image plane. At video frame rate, the movement of a vehicle's image between two consecutive video frames is small. Therefore, it is sufficient to model such movement as constant velocity [9]. These assumptions allow the system to be modeled using the linear discrete-time Kalman filter described in the previous section. The linear Kalman filter is simpler and not as computationally costly compared to the non-linear models such as the Extended Kalman filter or Particle filter.

The variables that are integrated into the Kalman filter are the center point, *(x,y)* and area, *A* of the detected vehicle in the image plane (see Fig. 2). The determination of these variables is based on symmetry detection and the analysis of the projection maps from the vehicle's horizontal and vertical edges. Details of the algorithms used in the detection can be found in our separate paper [1].

The integration of these variables into the Kalman filter has resulted in the following state and measurement vectors:

$$\mathbf{x}_k = \left[x, y, A, v_x, v_y, v_A\right]^T \quad (10)$$

$$\mathbf{y}_k = \left[x, y, A\right]^T \quad (11)$$

where v_x and v_y are the velocities in the movement of the vehicle's center point in the x and y directions. v_A is the rate of change in the vehicle's image size.

Fig. 2 Figure shows the parameters used in the Kalman filter. They are the coordinates of the vehicle's center point *(x,y)* and the area of the vehicle's image *(A)*.

With these state and measurement matrices, the Kalman transition matrix, $\mathbf{F}_k$ and measurement matrix, $\mathbf{H}_k$ can be constructed as follows:

$$
\mathbf{F}_k = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{12}
$$

$$
\mathbf{H}_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{13}
$$

where Δt is the time difference between the current and the last video frame.

The Kalman filter models the state's probability distribution as Gaussian. This means that each Kalman filter can only track a single vehicle. To overcome this limitation for tracking multiple vehicles, a separate Kalman filter is instantiated for each vehicle in the tracking list.

The *a priori* estimate of the Kalman filter suggests the location and size of the region where a vehicle could possibly appear in the following video frame. This information is utilized by the tracking function to narrow down the search space for re-detecting a vehicle. Once the re-detection is accomplished, the new measurement data will be reconciled into the system's model. The *a posteriori* estimate is then calculated and used as the best estimate for the vehicle's location and size.

III. The Reliability Point System

A reliability point system is used to assess the quality of the tracking. The assessment is based on a simple rule-based technique. When a vehicle is initially detected, it is assigned with some reliability points. The vehicle is then tracked over a sequence of video frames, during which time it may accumulate a number of reliability points. Points are added or deducted depending on how consistent a vehicle can be re-detected.

The following are the rules used by the tracking function to update the reliability point of a vehicle:

1) When a vehicle is first detected, two reliability points are assigned to the vehicle;
2) If the vehicle is not re-detected in the following frame, one point is deducted;
3) If the vehicle is re-detected in the following frame, one to three points may be added. The number of points depends on how consistent the size and aspect ratio between the current and the last detection. However, the maximum of points a vehicle can accumulate is six;
4) If the reliability points of a vehicle are more than two, the vehicle is considered to be valid and will be displayed at the tracking output;
5) If the reliability point of a vehicle falls below zero, the vehicle will be removed from the tracking list.

Based on these rules, a newly detected vehicle has to be tracked for at least one cycle before it is displayed on the output. This is to prevent the display of false detections which usually appear and disappear in short intervals. On the other hand, if a vehicle has attained more than three points, it will keep on being displayed even though it is not being re-detected in the following video frame. This will prevent the "disappearance" of a valid detection from the display due to some momentarily missed-detections. In a situation where a vehicle is not being re-detected, the estimates from the Kalman filter will be used to update the vehicle's status during the tracking cycle.

IV. Experiment and Results

Two experiments were carried out to test the efficiency of the proposed vehicle tracking technique. The first experiment investigated the tracking of a preceding vehicle from a following car. The second experiment tested the tracking of an overtaking vehicle. Both experiments used the pre-recorded video streams taken from a forward looking camera installed behind the windscreen of a test vehicle. The test software was implemented using C/C++ programming language and the OpenCV image processing library [11].

In the test, the coordinate of the vehicle's center point *(x,y)* and the size of the vehicle's image *(A)* were monitored over the consecutive video frames. Both the measured and the Kalman estimated values were recorded and compared. The purpose is to inspect the measurement error and to see how well the Kalman filter can regulate those errors.

A. Tracking of a Preceding Vehicle

In this experiment, a preceding vehicle was tracked over 500 video frames. The test video was taken by a host vehicle that followed closely behind another vehicle along a highway. At around frame 420, the preceding vehicle started to steer to the right lane. The results are plotted in figures 3 to 5.

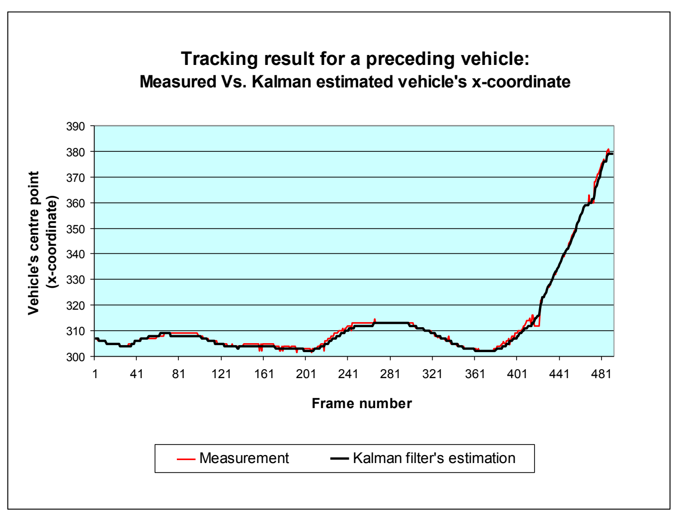

Fig 3 Tracking result for a preceding vehicle: The measured and the Kalman's estimated values for the vehicle's x-coordinate

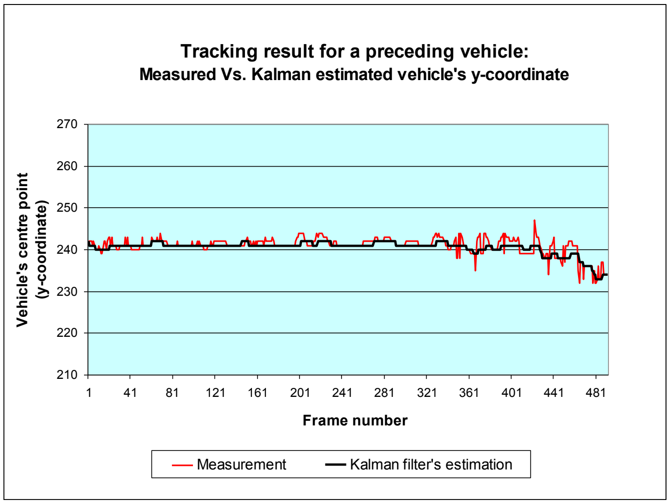

Fig 4 Tracking result for a preceding vehicle: The measured and the Kalman's estimated values for the vehicle's y-coordinate

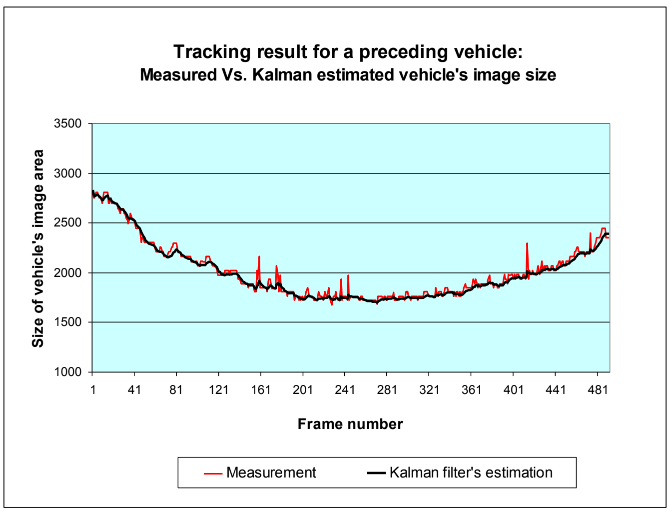

Fig 5 Tracking result for a preceding vehicle: The measured and the Kalman's estimated values for the vehicle's image size

In the figures, the thinner lines represent the measured values while the darker lines are for the values of the Kalman filter's estimates. It can be seen that there are some random fluctuations in the measured values. This is mainly caused by the error in the detection of the vehicle's edges. However, less fluctuation was observed in the Kalman estimated values. This can be seen in the figures where the plots for the Kalman filter's estimates are smoother.

This results show that the Kalman filter can provide a good estimate for the position and size of the vehicle. Using these values to decide on the region for finding a vehicle in the subsequent video frame will improve the re-detection rate.

In Fig. 3, the x-coordinate of the tracked vehicle gradually increased after frame 420. This happened during the preceding vehicle steered to the right lane. Also, the size of the vehicle's image can provide some clues about the vehicle's distance. This can be observed in Fig. 5, where the plot tells that the preceding vehicle was gradually moving away from the test vehicle but became closer again when it was changing lane.

B. Tracking of an Overtaking Vehicle

The test video used in this experiment shows a vehicle overtaking the host vehicle from the left lane. The system tracked the overtaking vehicle in 85 video frames. The results are plotted in figures 6 to 8.

Similar to the first experiment, there were random fluctuations in the measured values. In addition, this test also has recorded two instances of missed detection which happened during frames 8 and 47. These can be seen in the figures where there are two gaps in the measurements plots.

However, despite these gaps, the graphs for the Kalman estimates remained smooth throughout the whole test. The tracking process checks and updates the reliability points of the undetected vehicle and keeps tracking it using the Kalman's estimated values. This result shows that the combination of the Kalman filter and the reliability point system will assure the continuous tracking of a vehicle even though there are some momentarily missed-detections.

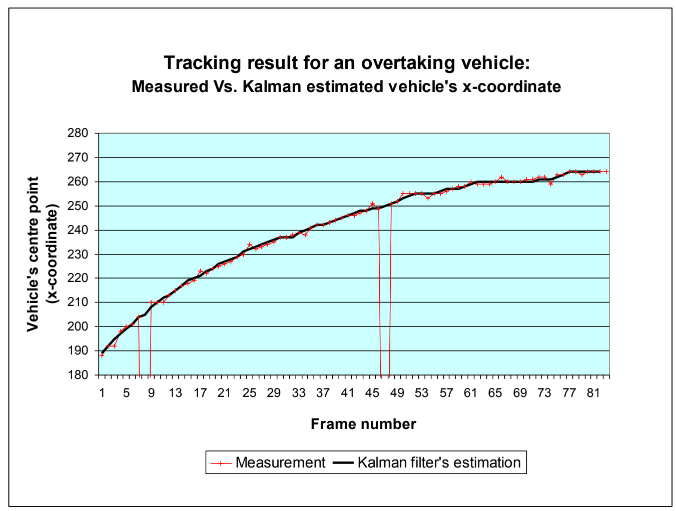

Fig. 6 Tracking result for an overtaking vehicle: The measured and the Kalman's estimated values for the vehicle's x-coordinate

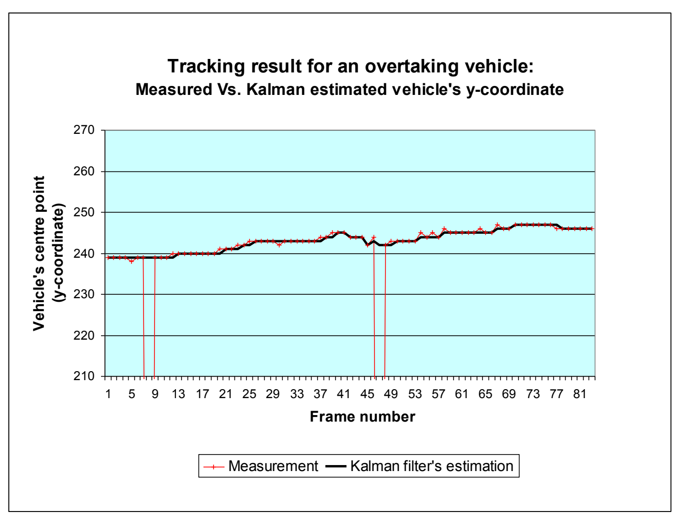

Fig. 7 Tracking result for an overtaking vehicle: The measured and the Kalman's estimated values for the vehicle's y-coordinate

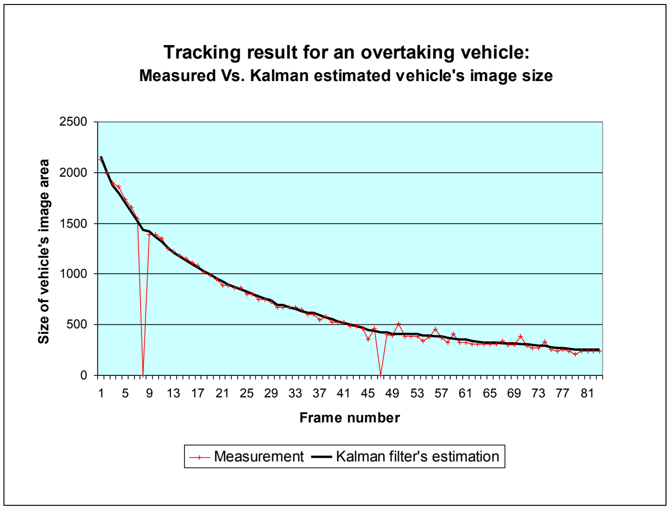

Fig. 8 Tracking result for an overtaking vehicle: The measured and the Kalman's estimated values for the vehicle's image size

V. CONCLUSION

This paper has described a technique for tracking the movement of vehicles in consecutive video frames. The technique incorporates a Kalman filter and a reliability point system in the tracking function. The Kalman filter is used to smooth out the irregularity due to the errors in the detection. It also predicts the most probable location and size of a tracked vehicle in the subsequent video frames. This information is useful for the tracking function to re-detect a vehicle. By narrowing down the search area, the re-detection rate can be improved while the processing time is reduced. The reliability point system provides a simple and fast mechanism to monitor the quality of tracking for the vehicles in the tracking list. A detected vehicle has to acquire a certain reliability point before it is considered a valid detection. Also, a vehicle that has accumulated a high reliability point will not be suddenly removed due to a momentarily missed detection. For these reasons, incorporating the reliability point system into the tracking function has improved the overall robustness of the vehicle tracking system.

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REFERENCES

[1] S. Teoh and T. Bräunl, "Symmetry-based monocular vehicle detection system". *Machine Vision and Applications*, 2011, pp. 1-12, doi:10.1007/s00138-011-0355-7

[2] D. Bin, F. Yajun and W. Tao, "A vehicle detection method via symmetry in multi-scale windows", in *Proc. of the 2nd IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pp. 1827–1831, 2007

[3] V. Leeuwen and F. Groen, "Vehicle detection with a mobile camera: spotting midrange, distant, and passing cars", in *IEEE Robotics & Automation Magazine,* Vol. 12, pp. 37–43, 2005

[4] T. Wei, H. Wei, and F. Chin, "Vehicle Detection Using Normalized Color and Edge Map", *IEEE Tran. on Image Processing*, Vol. 16, pp. 850–864, 2007

[5] M. Bertozzi, S Broggi and A. Castelluccio, "A real-time oriented system for vehicle detection", *Journal of Systems Architecture*, Vol. 43, pp. 317–325, 1997

[6] U. Handmanna. T. Kalinke, C. Tzomakas, M. Werner and W. Seelen, "An image processing system for driver assistance", *Image and Vision Computing*, Vol. 18, pp. 367-376, 2000

[7] P. Lin, J. Xu and J. Bian, "Robust Vehicle Detection in Vision Systems Based on Fast Wavelet Transform and Texture Analysis", *In Proc. of IEEE International Conference on Automation and Logistics*, pp. 2958–2963, 2007

[8] D. Simon, *Optimal State Estimation: Kalman, H Infinity, and Nonlinear Approaches*, Wiley-Interscience, 2006

[9] K. Markus, "Using the Kalman filter to track human interactive motion modeling and initialization of the Kalman filter for translational motion", Tech. rep., University of Dortmund, Germany, 1997

[10] G. Welch, G. Bishop, "An introduction to the Kalman filter", in *Annual Conference on Computer Graphics and Interactive Techniques SIGGRAPH*, Los Angeles, 2001

[11] OpenCV (Open Source Computer Vision) Wiki. URL: http://opencv.willowgarage.com/wiki. Accessed on 1st March 2012