Kalman Filters in Constrained Model Based Tracking

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Abstract

Model-based vision allows the recovery and tracking of the 3D position and orientation of a known object from a sequence of images. A Kalman filter can be used to improve the tracking stability with three main benefits. Firstly it is an optimal filter in the least squares sense, with the added advantage that the physical dynamics and constraints of the tracking problem can easily be built into the system model. Secondly the measurement model allows for uncertainty in the measurement of the recovered model position. Thirdly, data on the empirical error are generated which can, for example, be used to control the model matching process used in the tracking.

1 Introduction

Within the Esprit P2152 VIEWS project we have recently adapted our previously reported model based methods for detecting known objects in single images to classify and track moving objects (vehicles) in a complex and cluttered scene (Figure 1). The models consist of 3-D geometrical representations of known objects together with carefully constructed camera and scene models. Using these models it is possible to maximise an "iconic match" to recover the 3-D position and orientation of each object in a given image. By applying these techniques to successive image frames of data, using each previously recovered position as a seed to initiate the maximisation algorithm, it is possible to track an object though time (see [1] for details and examples of the tracking problem).

The parameters recovered are noisy, as illustrated in Figure 2, where a typical track has been projected onto the ground plane map of the scene (a roundabout) and Figure 3 where the recovered speed and orientation have been plotted. It can be seen that the tracked vehicle undergoes quite unrealistic motion (its path was in fact "smooth"), and without filtering it would be difficult to recover with any accuracy its position and velocity at any given time or to make any short term forward predictions. Furthermore, the recovered parameters are fed back into the tracking algorithm (by seeding the next frame), so these inaccuracies seriously

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affect the robustness of the tracking. The need for some kind of filter is therefore apparent. Model based vision allows us to work in the scene coordinate reference frame, so that the filtering can be applied directly to the physically meaningful parameters of object position and its time derivatives in the real world.

2 Model implementation

The Kalman filter is a linear recursive algorithm in which both the dynamic and statistical properties of a random process are used to derive a description of its state which minimizes the mean-square estimation error (see [2] and [4]). These properties are embodied in two mathematical models, the system model which describes the physical dynamics of the process and its development with time, and the measurement model which states which measurements are being made on the system and how much uncertainty is associated with them.

2.1 Dynamics model

In tracking vehicles we use a world coordinate frame. Vehicles on a ground plane are subject to three physical constraints, leaving only three degrees of freedom: movement on the X-Y ground plane and rotation about the vertical Z axis. However, to track a road vehicle the number of degrees of freedom may be further reduced to two: given an initial position, the track of a vehicle is normally determined solely by its speed (V) and orientation (α), these being related to the two degrees of freedom in driving - the positions of accelerator/brake and steering wheel. In the system model we use very simple Newtonian mechanics to model the dynamics, only the speed and orientation and their first derivatives are subjected to Kalman filtering.

We denote the state variable representation as

$$\mathbf{x} = \begin{bmatrix} v & \alpha & \dot{v} & \dot{\alpha} \end{bmatrix}^T, \qquad \text{and use} \qquad \Phi = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

for the transition matrix which describes their development through time.

2.2 Measurement model

The measurement matrix takes the form:

$$\mathrm{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \tag{2}$$

ie. the only two measurements made are of speed and orientation. The orientation was simply that of the instantiated model on completion of the model fitting, and the speed measurement was derived from the model's position relative to its previously recovered position resolved in the direction of its orientation (thus ignoring sideways motion likely to be due to errors in 3D model fitting). The noise associated with these measurements has mean **0** and covariance

$$R_k = \begin{bmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{bmatrix}_k . \tag{3}$$

The cross terms R_{12} and R_{21} were set at 0, the main diagonal terms were set heuristically.

3 Results and conclusion

Figure 4 illustrates the effects of using the Kalman filter in the tracking algorithm and the much smoother track which results. Figure 5 shows the improvement in the parameters recovered from the model fitting process. Figure 6 shows the filter output (note that the speed axis has been greatly expanded; 500mm/frame = 45 Km.p.h).

The seed position for the hill climbing algorithm was obtained by extrapolation from the previous position using the filtered speed and orientation values derived from the Kalman filter. The resulting pose was then used to obtain a new estimate of the current state. This was repeated for all frames for a single vehicle. Additionally the error analysis output from the Kalman filter was used to control the range over which searching took place in the hill-climb algorithm (the variance in speed gave a measure of the uncertainty of the seed position). An important assumption made was that the model matching process results in an error which may be regarded as Gaussian with zero bias. This appeared to hold true except for the first frames where a bias developed due to mismatching of the geometric model with "spurious" structure in the image (the car was in the far background at this point, where a single pixel subtends approximately 250 mm., and was not very clearly visible). This accounts for the dip in the speed at the beginning of Figure 6 as the model at first began to lag behind the image and then caught up.

Many physical models are possible. That demonstrated here, is one based on a "natural" physical description of a moving road vehicle in which physical constraints have been incorporated to leave only two semantically significant parameters to be tracked.

References

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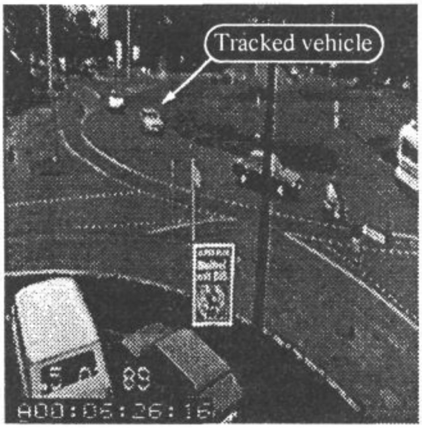

Figure 1 Frame 200 of image data

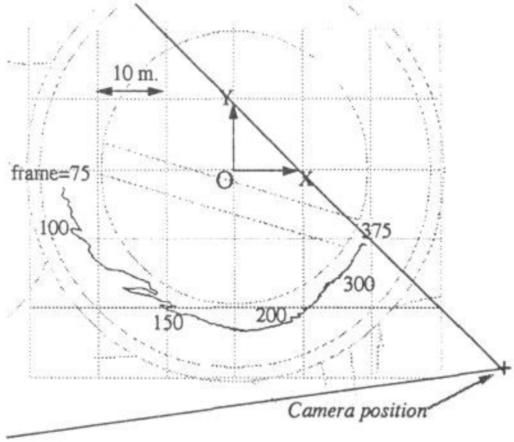

Figure 2 Track of object 5, frames 75-375

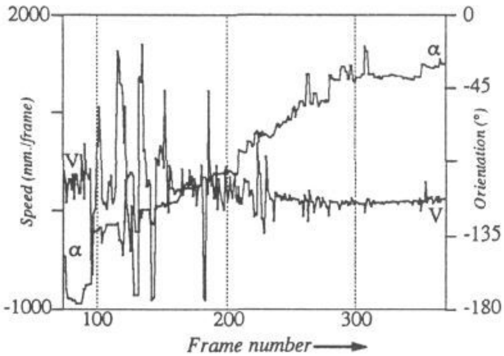

Figure 3 Speed (V) and orientation (α).

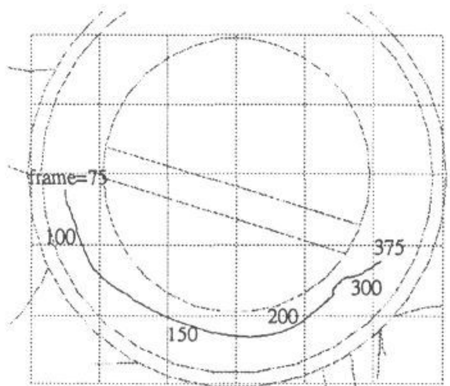

Figure 4 Track resulting from filtering

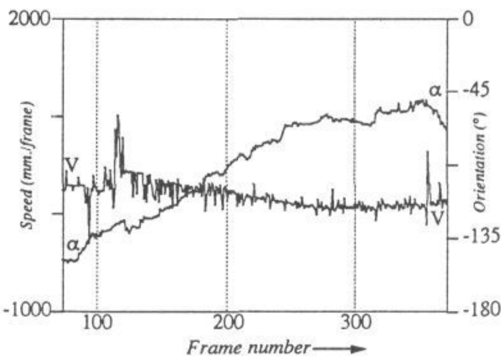

Figure 5 Speed & orientation for filtered track

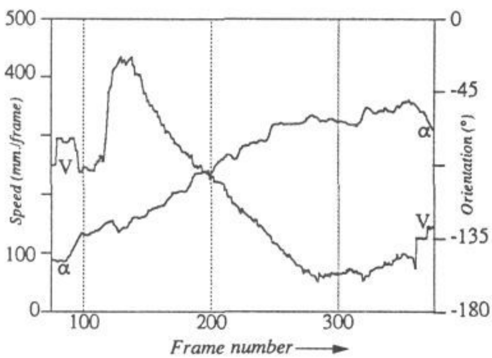

Figure 6 Kalman filter output