Interacting Multiple Models and Probabilistic Data Association

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1 Introduction

This report discusses and displays the result of different implementations of filtering techniques for target-tracking. Specifically the the extended kalman filter (EKF) in junction with a probabilistic data association filter (PDAF), and an interacting multiple model (IMM) with a PDAF. This report will investigate how the IMM-PDAF performs on simulated- and real-world data, and comparing the IMM-PDAF with the EKF-PDAF on real-world data.

2 Simulated data

Analysing the simulated data leads to a couple of observations. The ground truth track is divided up into easily separable straights and turns. The sensor measurements are generally close to the ground truth. It is also visible that the measurements follow the actual path closely, which means a small gate size and high detection probability should work well. From these observations some initial estimates for both the measurement noise, the gate size, the clutter density, detection probability and the transition matrix are given, respectively.

$$\sigma_z = 3 \;\; g = 5 \;\; \lambda = 10^{-4} \;\; P_D = 0.90$$

$$\pi = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$$

These values gives a starting point for further tuning of the different filter variables. Namely the process noise for acceleration in both the CV and CT model, as well as the turning radius noise for the CT model. After trying a few values, the resulting final values were

$$\sigma_z = 3 \;\; g = 5 \;\; \lambda = 10^{-4} \;\; P_D = 0.95$$

$$\pi = \begin{bmatrix} 0.85 & 0.05 \\ 0.15 & 0.95 \end{bmatrix}$$

$$\sigma_{CV} = 0.05 \quad \sigma_{CT} = 0.05 \quad \sigma_\omega = 0.03$$

The resulting RMSE in position was 17.0,

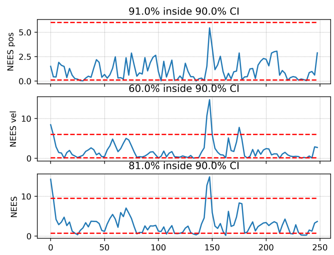

Figure 1: NEES on simulated data

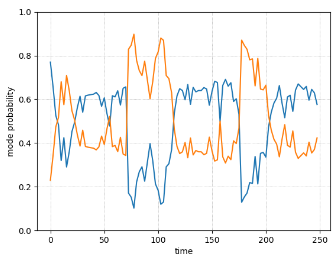

Figure 2: Mode probability on simulated data

RMSE in velocity was 6.80, ANEES in position was 1.10 with CI $[1.68, 2.34]$, ANEES in velocity was 1.85 with CI $[1.68, 2.34]$ and ANEES was 2.99 with CI $[3.55, 4.48]$. The resulting plots are shown in 1, 2 and 3 These results give a satisfactory performance with its fast convergence rate and low amplitude in the estimate errors.

Increasing the gate size made no difference in the performance, but decreasing it below

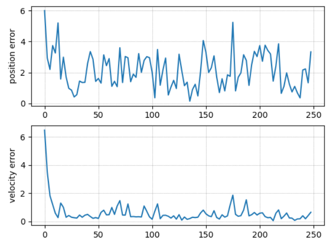

Figure 3: Velocity error and position error on simulated data

2.5 made the filter diverge. From which it can be concluded that the measurements are closer to the ground truth than 5m in general. It is also sensible that a larger search area for measurements does nothing to performance if all the measurements are closer than the larger search radius.

Tuning the measurement and process noise have an inverse effect on the filter. Increasing σ_z reduces the amount of trust put in the measurements, and reducing the process noise has the same effect on the model estimate. A lower process noise than measurement noise, makes the filter trust the process more than the measurements which makes sense given the simple track it is tracking. With a more complicated track, the ratio between the noises should change.

3 Joyride data

The real-world data is more complex and the track is as well. To tune the IMM-PDAF to this data an increase in measurement noise was necessary, but also an increase in process noise and to a higher degree. This means the filter trusts the process more than in the simulated case. Gate size was increased, detection probability decreased and the transition matrix

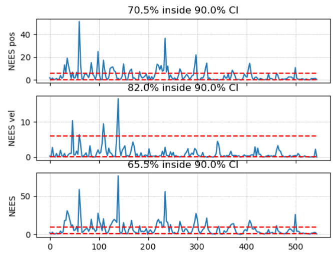

Figure 4: Joyride NEES

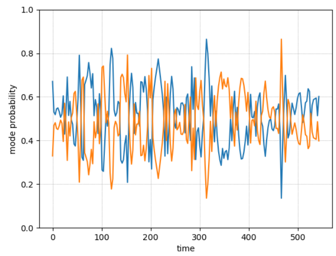

Figure 5: Joyride Mode change

was changed to allow more mode changes. Resulting in the parameters as follows:

$$\sigma_z = 10 \quad g = 40 \quad \lambda = 10^{-5} \quad P_D = 0.9$$

$$\pi = \begin{bmatrix} 0.70 & 0.10 \\ 0.30 & 0.90 \end{bmatrix}$$

$$\sigma_{CV} = 0.8 \quad \sigma_{CT} = 0.4 \quad \sigma_\omega = 0.3$$

The resulting RMSE in position was 282.0, RMSE in velocity was 55.5, ANEES in position was 4.07 with CI $[1.77, 2.24]$, ANEES in velocity was 1.02 with CI $[1.77, 2.24]$ and ANEES was 7.48 with CI $[3.68, 4.33]$. The resulting plots are shown in 9, 10 and 11

On this data set, a single EKF-PDA solution was also tried. The results are shown in 12 and 13 with resulting RMSE in position 435.9, RMSE in velocity 68.7, ANEES in position 22.56 with CI $[1.77, 2.24]$,

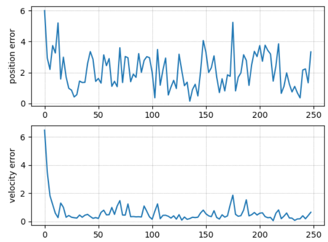

Figure 6: Joyride position- and velocity error

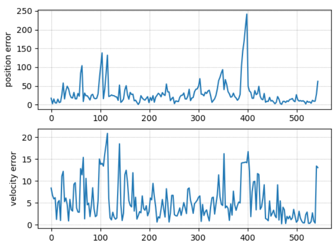

Figure 7: Joyride position- and velocity error using only EKF

ANEES in velocity 1.94 with CI $[1.77, 2.24]$ and ANEES 28.96 with CI $[3.68, 4.33]$

We see a drop in performance from the IMM-PDAF, which comes from the single EKF process model which cannot capture the same amount of detail as the two process models in the IMM can. The EKF only uses a CV model which will struggle in turns. This can be seen in the large spikes in the NEES position and NEES velocity. These are located where the target turns quickly. To compensate for this loss of detail the process noise is increased which gives a less optimal estimate than the IMM.

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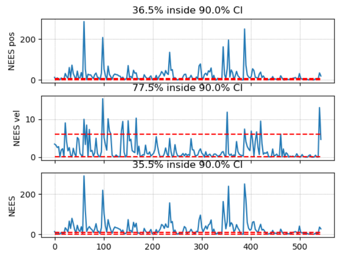
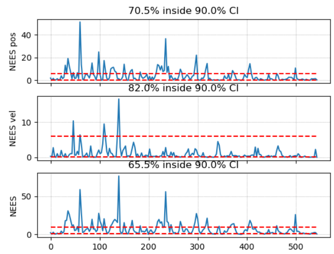


Figure 8: Joyride NEES using only EKF



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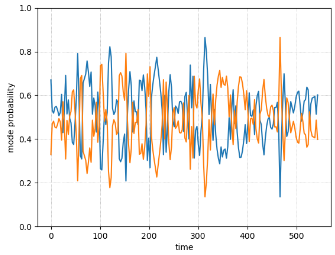


Figure 10: Joyride Mode change

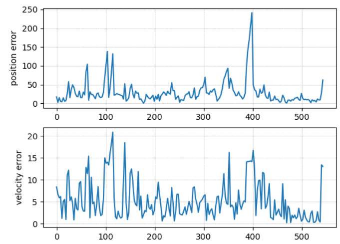


Figure 12: Joyride position- and velocity error using only EKF

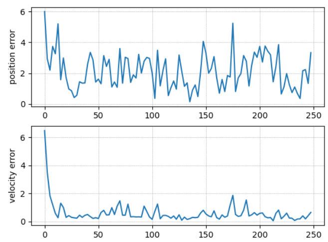
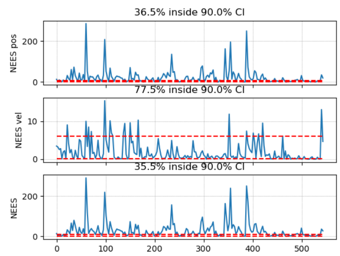


Figure 11: Joyride position- and velocity error



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4 Conclusion

This report shows that when tracking a complex entity through a detection sensor it is beneficial to use an IMM-PDAF over just a single EKF-PDAF. The complex movement possible by the object demands a better process model than that which is possible in a single EKF. Through analysis of the NEES and ANEES of the filters we can easily compare the benefits and disadvantages of each approach and conclude with the fitting method.