Department of Engineering Cybernetics

Sensor fusion

Graded assignment 1

Group:
Sensor fusion Group 65

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1 Problem 1 - Make sure the PDA class is general

Implemented in Python and delivered on Blackboard.

2 Problem 2 - Tune the IMM to given data

2.1 Considerations about the dataset and initial tuning

Because the data is fairly accurate with low measurement it allowed for a fairly accurate tracking. The values for the dynamics of the target is assumed to be quite similar to the CT model considered on page 81, table 5.1 in the book and then adjusted slightly. $\sigma_{a,CT}$ is given double the value of $\sigma_{a,CV}$ in order to separate the models sufficiently to allow for switching in mode probabilities.

Using low measurement noise, along with low noise in the CV and CT model allowed for good tracking. Because of the structure of data being separated into larger turning movement and fairly long straight paths a transition probability matrix, π of

$$\pi = \begin{bmatrix} 0.90 & 0.10 \\ 0.10 & 0.90 \end{bmatrix} \tag{1}$$

resulted in good tracking attributes. Figure 1a illustrates how the mode probabilities switches between constant velocity and constant turn, which is to be expected given the data.

(a) Ground truth and predicted track with mode probabilities

(b) NEES

Figure 1: Figures for simulated data with initial values

The tuning of this is suboptimal, since NEES only has 85% of its values within the 90% confidence interval, with a low NEES dominating. The model is thus slightly conservative.

2.2 Reflection on the parameters and further tuning

The probability in this dataset of remaining in the same state (CV or CT) is high, represented by the π matrix in Eq (1). The noise is quite low, and ended up somewhat lower than initially to get the trend of NEES to increase, as the filter was a bit conservative. For the process noise, the values ended up with the values in Table 1, producing a NEES of 88% within the 90% interval, with NEES velocity and NEES position at 88% and 89% respectively. RMSE ended up at $2.797m$ for position and $0.782m/s$ for velocity. Although RMSE is somewhat better with the initial parameters, the final filter is better fitted and thus a better approximation. A low NEES is usually associated with a quite good RMSE as it corrects in terms of measurements in a more strict manner (conservative) providing a lower upper bound for the RMSE.

—	CV-CT
$\sigma_{a,CV}$	0.14 m/s
$\sigma_{a,CT}$	0.06 m/s
$\sigma_{a,\omega}$	0.02 rad/s
σ_z	1.9 m
λ	10^{-4}
P_D	0.90
g^2	3^2
Average NEES (ANEES)	3.66
Confidence interval (Conf)	[3.55, 4.48]

Table 1: Values for the final PDA-IMM (CV/CT) filter

3 Problem 3 - IMM-PDAF on the real radar data set "joyride"

3.1 Considerations about the dataset and initial tuning assumptions

The filter is implemented to run on "Joyride" data. This data describes a boat maneuvering quite violently, and is a hard object to track. Yet, by using an IMM-PDA with CT,CV and CV-High EKF filters as modes, a reasonable tracking was obtained. Compared to the previous set from problem 2, this target is maneuvering harder. Thus, higher σ_a are required. In the textbook, frequent misdetections are signalized, signalizing a quite low P_D. As an initial estimate, 0.90 will be used although it is assumed to be lower than in the previous problem. By the looks of it, there are quite a few measurements that stand out from the surrounding measurements indicating either high clutter or measurement noise. This seems to be related to turns, as it intensifies with turning. Zooming in on the measurements and the ground truth reveals that the spread varies between 5 and 30 metres quite frequently. Thus, a quite high measurement noise can be assumed.

As apposed to the simulated data in Section 2, the joyride data is more complex with increased measurement noise and, generally, a more complicated track. When only using CV and CT models, the transition matrix following transition matrix was used:

$$\pi = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix} \tag{2}$$

This matrix produces higher probabilities of remaining in the same mode (CV or CT) which we found to increase the distinction of mode switching.

Judging from figure 2 velocity looks to be fluctuating between a relative stable speed and spikes where the velocity is greatly increased. This motivates for a relatively high probability of transition between CV High and the other modes. The physical interpretation of this yielded the matrix:

$$\pi = \begin{bmatrix} 0.900 & 0.050 & 0.050 \\ 0.025 & 0.950 & 0.025 \\ 0.100 & 0.050 & 0.850 \end{bmatrix} \tag{3}$$

3.2 Tuning σ_a

σ_a were perhaps the most difficult parameters to tune. Given the physical interpretation, a low σ_ω yielded a good result. σ_ω too large resulted in the model diverging from the ground truth, which is to be expected given the slow turn rate observed in the data. When it comes to σ_a for the modes, CV, CT and CV High, order of magnitude, alongside the relationship between the three values was important. Any on of these values too large compared to the remaining two would result in fairly constant mode probabilities, making the track diverge from the ground truth. This is to be expected as the model emphasises one mode significantly more. With that being said, due to the spread in measurements, i.e. more noise, it is reasonable to use σ_a for CV High larger than for CV and CT. For the remaining two modes, CV and CT, it is reasonable to assume that CV is higher than CT. Physically, the boat will most likely travel with a forward motion. CV can be visualized as a covariance ellipse along the direction of the velocity, while CT can be visualized as a covariance ellipse orthogonal to the velocity. Furthermore, with lower speed, waves do not have the same impact in terms of variations in speed. As a general rule of thumb, $CV = 2 \cdot CT$ has been used.

3.3 Bias in Joyride measurements

By looking at Figure 2a, clearly measurements tend to be biased in favour of measuring the boat slightly off compared to the ground truth. This could be due to bias in the GPS in one of the two boats, bias in the RADAR or both. Thus, one may expect a little higher indicated RMSE than the true RMSE. The measurement errors are assumed to be acceptable as zero mean, and this will thus have an impact on the metrics.

3.4 Tuning for RMSE vs Distinct switches between modes

IMM is used for mixing probabilities and assigning a different mode to different part of the trajectory of the boat. Hence for turns we it is desired to have a high probability for CT. In order to achieve this it is necessary to have high probability on the diagonal of the transition matrix, π. Through trial and error, tuning for RMSE, we have discovered that a "flatter" transition matrix works well, i.e. lower probability on the diagonal. This results in less distinct switches between the different modes. Hence, tuning with respect to the joyride data depends on how we wish the model to behaviour. This addresses a trade-off between the IMM-PDAF model and other models and the possible shortcomings when using the IMM-PDAF.

3.5 Clutter, Probability of detection and Gate

Choosing the parameters for clutter intensity (λ), probability of detection (P_D) and gate size is important for fitting the model to the ground truth. For clutter, analyzing the joyride data, we observe varying clutter through the trajectory. However, there is generally low clutter throughout compared to the simulated data in section 2. Hence, setting clutter to $1 \cdot 10^{-5}$ turns out to reasonable. For the gate, a small gate size will result in us potentially missing out on valuable data. On the other hand, if the gate is too large, the gate is pointless, as it lets through measurements that are potentially wrong. However, a gate size of 3 turns out to be good. These are loose assumptions, and highly related to σ_z. If the measurement is gated in one of the filters, then the measurement will be accounted for and update the filter with a Kalman step. P_D is considered to be lower than in the dataset in section 2. By studying 2 a), it is clear that measurements are missed. This is indicated by the gaps in the measurements.

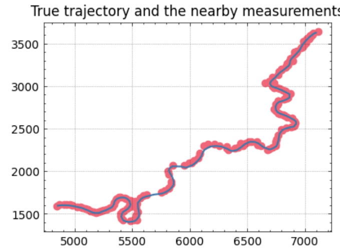
3.6 Results of CV-CT and CV-CT-CV High

When the tuning was as satisfactory as it could be, keeping in mind that this is a challenging dataset, the following values were used:

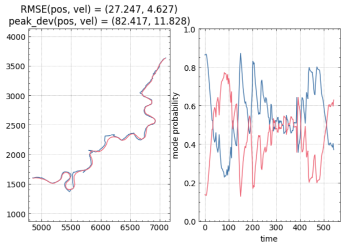
—	CV-CT	CV-CT-CT High
$\sigma_{a,CV}$	2 m/s	1 m/s
$\sigma_{a,CT}$	1 m/s	0.6 m/s
$\sigma_{a,CVhigh}$	—	7 m/s
$\sigma_{a,\omega}$	0.01 rad/s	0.02 rad/s
σ_z	20 m	20 m
λ	10^{-5}	10^{-5}
P_D	0.90	0.90
g^2	5^2	3^2
ANEES	3.66	2.62
Conf	[3.55, 4.48]	[3.68, 4.33]

Table 2: Joyride IMM-PDAF values for CV-CT and CV-CT-CVhigh

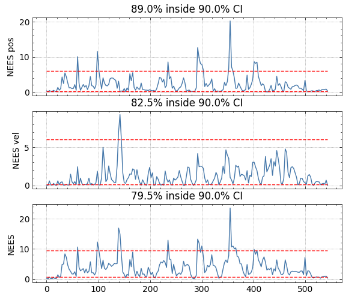
Generally, one could argue that the CV-CT-CT High model performed best with a higher proportion of NEES within the confidence interval and lower RMSE. This is illustrated in Figure 2 and 3. The model is somewhat conservative as the NEES tends to below the lower limit of the boundary. This is, however, better than an overconfident model. The CV-CT-CT High model is indeed more flexible, allowing for another mode where the boat accelerates and thus the result is not surprising. As a final note, notice that both NEES-plots, figure 3c and 2c spike above the confidence interval in turns, suggesting that the model becomes overconfindent in these areas. The measurement is not correcting enough, resulting in the visible short-term divergence in plot . However, this is to be expected with the quite steep turns.



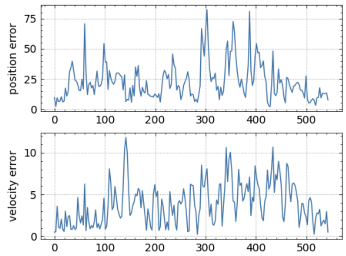
(a) Ground truth and measurements



(b) Ground truth and track with mode probabilities



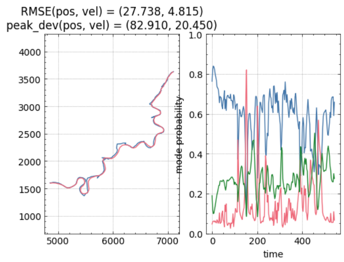
(c) NEES



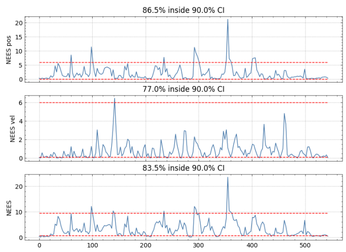
(d) Error in position and velocity

Figure 2: Plots from IMM-PDAF tracking using CV and CT models

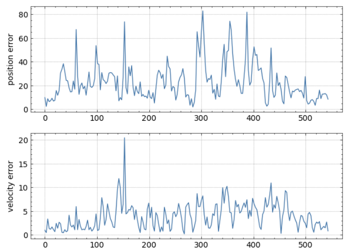
(a) Ground truth and measurements



(b) Ground truth and track with mode probabilities



(c) NEES



(d) Error in position and velocity

Figure 3: Plots from IMM-PDAF tracking using CV, CT and CV high models

3.7 CV-EKF and CT-EKF

Running the joyride data using the EKF yields some predictable results. Running through an EKF emphasises measurements rather than the dynamic model. This results in a relatively high NEES, generally above the confidence interval. This confirms that the confidence in the model is relatively low, while following the measurements. For the CV, the model is assumed to continue straight forward, correcting whenever a turn puts the measurements too far from the trajectory. The plots of these will not be included in this report, but it is noted that the performance of both of these filters are not as good as the IMM-PDA implementations described above.