Target Motion Analysis with Passive Data Fusion

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Abstract - We consider in this paper the passive multisensor Target Motion Analysis (TMA) problem. The ownship, typically a submarine, is equipped with a Cylindrical Antenna (CA) and a Towed Antenna (TA), whose outputs are made of bearing tracks for the first one and bearing or bearing/frequency tracks for the second. The aim is to take advantage of the multisensor data fusion to improve the TMA process that can be obtained with one of the two sensors on a possibly manoeuvring target. We first describe our algorithms and then show some results on simulated data.

1 Introduction

In the following, we make the assumption that the sonars provide tracks but that the plot, or measurement, that has been used in the sonar tracking process is also available. This sometimes refers to tracklets and this assumption will enable a plot fusion filtering process which is known to be better than a track fusion scheme if we want to obtain the best state vector in a MMSE sense. In a real situation, some targets are detected by the CA, some by the TA and a certain number by both antennas. Furthermore, the TA may not give frequencies measurement. Of course the best results will be obtained in a situation where both antennas detect the target and where the TA is able to detect a frequency line. To see the improvement in these different cases on a test scenario, we consider four situations:

- bearing only tracking (BO),
- bearing and frequency tracking (BF),
- two bearing tracking (2B) and
- two bearing and frequency tracking (2BF)

keeping in mind that the reality will be a mix of this different situations.

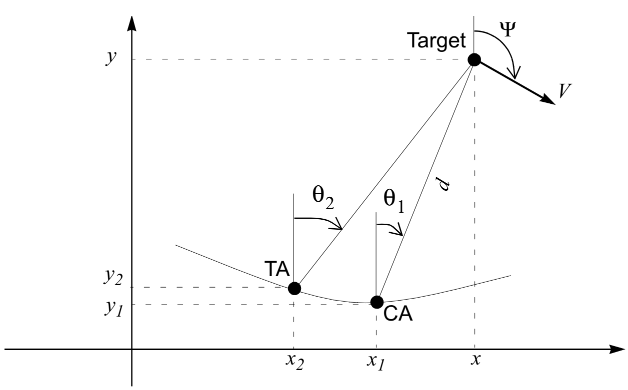

Fig.1 Notations and geometry

2 Algorithm description

The algorithm we use to perform the TMA is based upon the Unscented Kalman Filter (UKF). The reason is that this algorithm is more robust than the widely used Extended Kalman Filter, requires no data storage and is compliant with a real time application where there are numerous target in the environment. Another advantage is that this filter can easily handle manoeuvring targets. Though we use the recursive approach, the multisensor TMA process can also be resolved with the least squares algorithm, such as in [5].

2.1 Filter description

We consider the Cartesian representation, $\mathbf{x} = (x, v_x, y, v_x)$ or, if a frequency measurement is available, $\mathbf{x} = (x, v_x, y, v_x, f_0)$ with f_0 the unknown assumed constant emitted frequency. This representation is widely used and is very easy to implement compared to polar coordinates or even more complex modified polar coordinates ([4]) if we want to describe correctly the motion of the target. Here, the non linearity is reported in the measurement equation and we use the classical CV model, possibly augmented if a frequency measurement is available. The measurement, depending of the context, is made of θ_1, (θ_2, f), (θ_1, θ_2) or (θ_1, θ_2, f) for our four considered cases with

$$\theta_i = \operatorname{atan}\left(\frac{x - x_i}{y - y_i}\right)_{i = 1, 2}$$

$$f = f_0\left(1 - \frac{v_r}{c}\right) \quad \text{with} \quad v_r = (v_x - v_{x2})\sin(\theta_2) + (v_y - v_{y2})\cos(\theta_2)$$

for a bearing measurement coming from sensor 1 (CA) or 2 (TA) and a frequency measurement coming from sensor 2. The position and velocity of the two sensors are assumed to be known. The equations of the UKF corresponding to this model are not recalled and can be found in [1].

2.2 Adaptive process noise

To take into account possible manoeuvres of the target, we use the simplest choice: a two level process noise logic. More complex schemes can be used, in particular with multiple models as in [3]. Here, the NIS of the filter is smoothed with a fading memory filter and compared to a threshold. For more details, see [2].

3 Simulation results

The following pictures show some results obtained on a scenario where we compare the result obtained by the UKF in the four cases. The ownship starts on $(0, 0)$ with a 8 knots course and 90^{o} heading. At $t = 20'$, the ownship performs a 180^{o} turn with turn rate $\omega = 0, 15$ °/s, and a second one at $t = 90'$. The target starts at $(-8000, 8000)$ with a 4 knots course and 270^{o} heading and turns at $t = 70'$. The sensor features used are $\sigma = 1^{o}$ for θ_1 and θ_2 and $\sigma = 0.15\ \mathrm{Hz}$ for f, f_0 being set to $300\ \mathrm{Hz}$. The sampling period for both sensor is set to $T = 4\mathrm{s}$. The distance between the two antennas is set to $800\mathrm{m}$. The filter is initialized in every case with the first bearing measurement (and first frequency for the BF and 2BF cases) and a default distance of $15\ \mathrm{km}$, the velocity components are set to zero.Fig.2 below, left hand side, shows the estimated trajectory (x, y) when only bearing measurements are processed, with the 2.58 σ ellipse in the (x, y) plane corresponding to the 99% confidence interval for the last estimation. As expected, no convergence occurs before the ownship ends the first manoeuvre. The adaptive BO UKF is not able to track properly during the target's manoeuvre because the detection is very slow due to bearing only measurements processing.

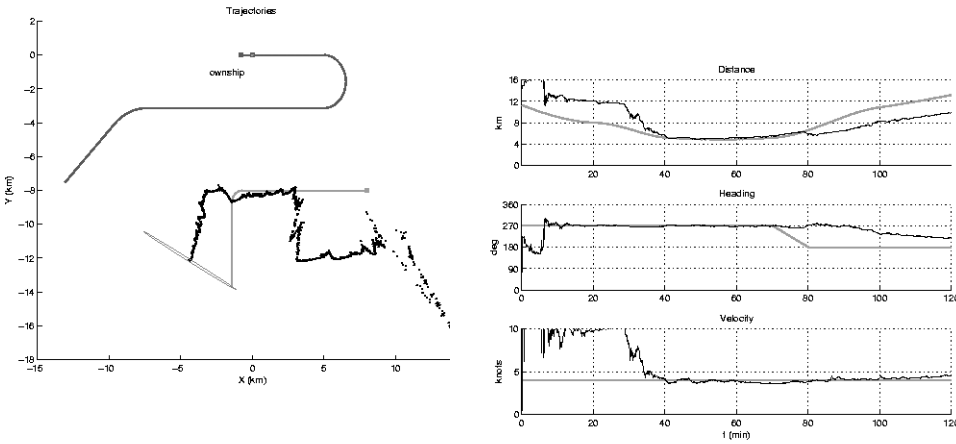

Fig.2 BO estimated trajectory

Fig.2, right hand side, plots the target kinematics features of interest: the distance from the ownship to the target, the heading angle and the velocity (d, ψ, V), as shown on Fig.1. The heading angle plot confirms that the filter reacts very slowly.

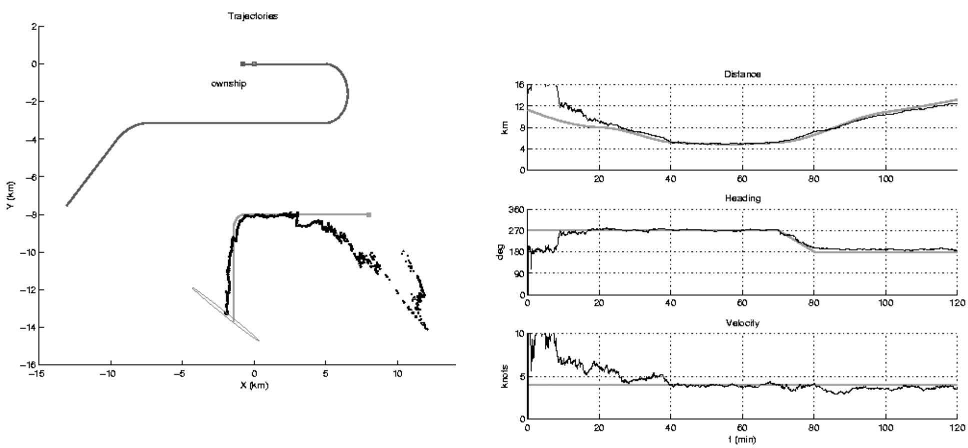

Fig.3 BF estimated trajectory

Fig.3 shows the case where angle and frequency measurements coming from sensor 2 (TA) are used. The effect of a frequency measurement is obviously beneficial though we have another component in the state vector. The convergence of the algorithm is faster than in the case of BO because the problem is observable. The second benefit is the estimation during the target manoeuvre phase where we can see that the estimated trajectory is close to the true one and that the heading angle is well estimated. A frequency is related to the speed and is very relevant during the target manoeuvre phase. We can notice that the ellipse, based upon the covariance matrix for the position components, is only a little smaller than in the BO case. Fig.4 shows the 2B case where, as in the BF case, the problem is observable and hence the filter converges at the beginning of the scenario, more quickly than the BF case on this scenario (it depends on the geometry).

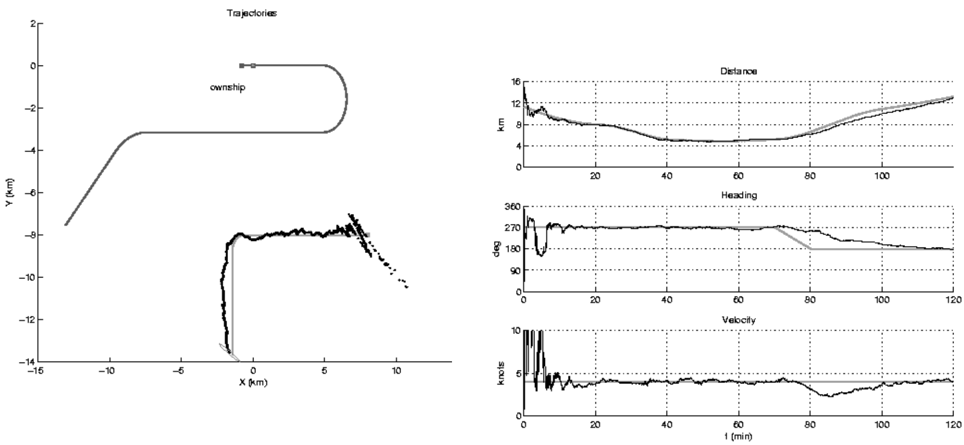

Fig.4 2B estimated trajectory

During the target manoeuvre phase, though a favorable geometry, the second angle measurement seems less pertinent than a frequency measurement as it can be seen on the heading curve and on the second rectilinear phase of the target trajectory. On the other hand the (x, y) ellipse is much smaller, indicating a strong reduction in the position uncertainty which seems in accordance with the fact that a second angle measurement allows for a cross bearing position.

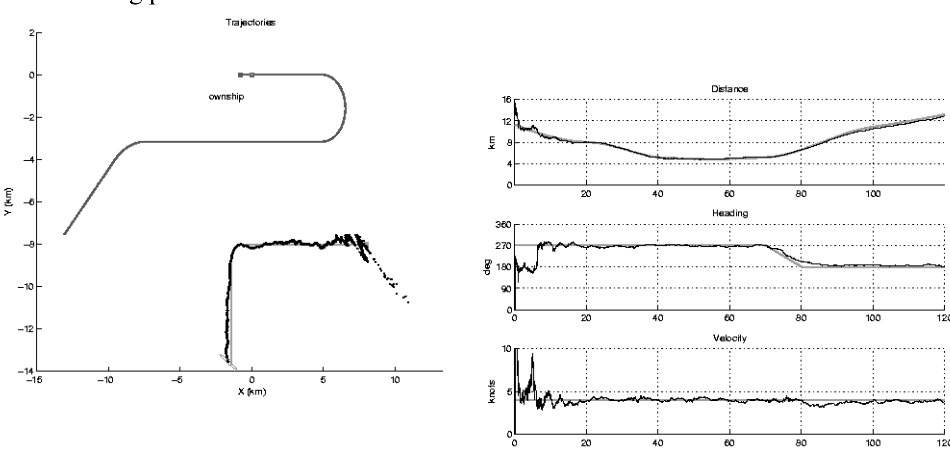

Fig.5 2BF estimated trajectory

Fig.5 definitely shows the benefit of the two bearing and frequency data fusion. Compare to the previous case, the frequency processing improves the estimation during the manoeuvre phase as it was the case for the BF case, and compare to the BF case, the second angle improves the initial convergence and reduces the position uncertainty.
Finally, we show on Fig.6 the results obtained on a more realistic simulated scenario with no detection from the TA antenna when the ownship manoeuvres and possibly no detection from the CA antenna due to propagation phenomena so that there is a mix of three amongst the four previously discussed situations, BO, BF and 2BF. The context is a submarine against submarine chase and the turn rates during the manoeuvres are much more important as it can be seen on the heading plot.

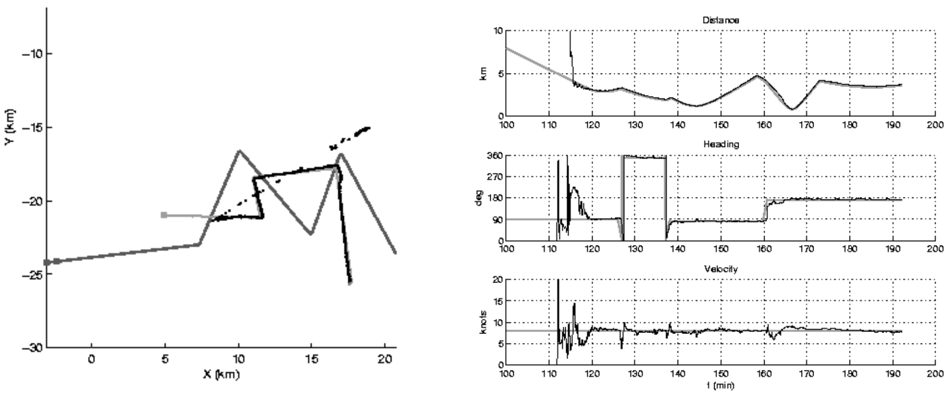

Fig.6 Mix of BO, BF and 2BF TMA

4 Conclusion

The results we have shown highlight the advantage of a multi sensor fusion architecture that takes advantage of each measurement to achieve the best precision in a multi sensor TMA process. It could be interesting to compare this approach (plot fusion because we have the plot information attached to the track) to track fusion where we the sonars would only give the bearing or bearing/frequency tracks and also to a non-recursive TMA filter such as the least squares scheme used in [5] to see the pros and cons of both approaches.

References

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