IMPROVING THE MARITIME TRAFFIC SITUATION ASSESSMENT FOR A SINGLE TARGET IN A MULTISENSOR ENVIRONMENT

Gregor Siegert, Paweł Banyś and Frank Heymann

Department of Nautical Systems
German Aerospace Center (DLR)
Neustrelitz, Germany
Email: gregor.siegert@dlr.de

ABSTRACT

Exploiting the diversity of multiple on-board sensors is a promising approach to generate a reliable picture of the traffic situation in the vicinity of a particular vessel. This work focuses on multi-sensor fusion for single target tracking in a loosely-coupled architecture. An Interacting Multiple Model Multi-Sensor Probabilistic Data Association filter is designed to capture rapidly changing vessel dynamics in the presence of possible clutter measurements. The actual target tracking is made up of two Unscented Kalman filters each being conditioned on radar and AIS measurement updates. The benefits of the proposed method will be demonstrated on behalf of real-world measurements obtained from the Baltic Sea.

Index Terms— AIS, IMM-MSPDA filter, UKF, radar image processing, sensor fusion, single target tracking

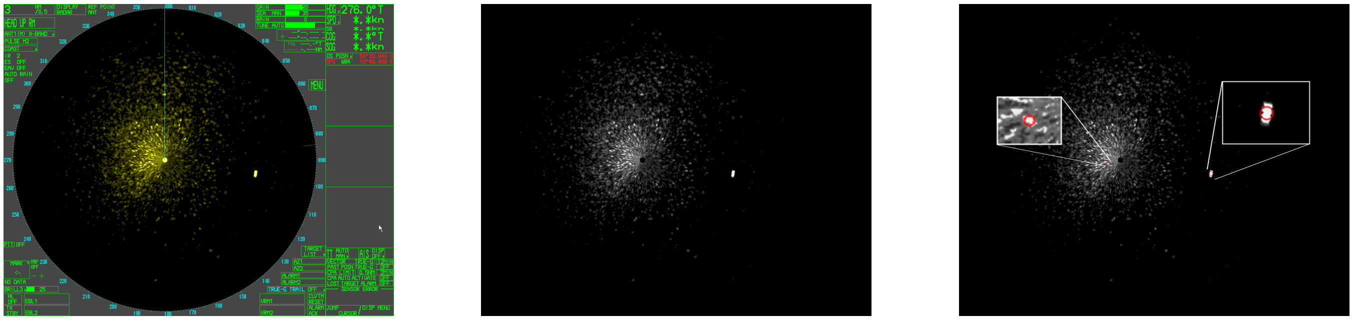
1. INTRODUCTION

The increasing challenges of the maritime traffic domain call for advanced solutions to guarantee safety at sea. Nearly 80 % of the global trade traverses the seas and harbors worldwide (see [1]) stressing the vital economic interests in secure and efficient shipping. Key aspect to all mariners, traffic management and security authorities is a reliable and timely picture of the traffic situation not only in their close vicinity but also with respect to vessels in greater distance. For better identification and localization of maritime traffic participants the Automatic Identification System (AIS) was introduced by the International Maritime Organization (IMO) as an ITU-R recommendation [2] in 2004, yielding a mandatory standard for vessels greater than 300 GRT. AIS can be understood as additional sensor that supports the use of classical surveillance techniques for collision avoidance, e.g., radar, that are used aboard or in shore-based Vessel Traffic Service (VTS) monitoring stations. However, none of the available sensors, neither AIS or radar, can constantly provide sufficient data on their own to establish a reliable and accurate traffic picture at all times. While radar may detect vessels invisible in AIS, it is in general less accurate and will always be subject to external weather phenomena that may result in false echos or clutter measurements. On the contrary, AIS yields great precision of vessel positions, but entirely relies on the cooperative nature of the system. With its open standard AIS is vulnerable to a series of threats, such as availability disruption, ship spoofing or AIS hijacking, as discussed in [3]. Apart from that, unintentional misuse or imperfect equipment may introduce additional error sources compromising the reliability of the system, as was also shown in a comprehensive AIS plausibility analysis in [4]. To encounter these shortcomings, we propose to fuse both, radar and AIS, to establish a more accurate and reliable traffic picture by exploiting the complementary nature of the two sensors. In the literature various approaches have been published to augment maritime surveillance or collision avoidance systems, mostly based on radar target fusion with additional sensors like laser in [5] or multiple radar systems for exploiting aspect diversity as in [6]. The matter of AIS and radar fusion was mainly addressed for anomaly detection, e.g., based on multi hypothesis tests in [7] or by exploiting historical traffic route knowledge for SAR/AIS fusion in [8]. In [9] an overview was given for different AIS/radar fusion techniques incorporating online covariance estimation.

The remainder of this article is structured as follows. In section 2 the general methodology for single target tracking in a radar/AIS environment will be outlined. Section 3 demonstrates the working principle of the proposed scheme w.r.t. measurement data. A conclusion is given in section 4.

2. METHODOLOGY

In this section the proposed methodology for fusing radar and AIS data for single target tracking will be presented in more detail. By designing an Interacting Multiple Model (IMM) Multi-Sensor Probabilistic Data Association (MSPDA) filter that is conditioned on asynchronous radar and AIS measurements a loosely-coupled architecture was chosen.



(a) Original radar image.

(b) Image after background subtraction and gray-scale conversion.

(c) Extracted target candidates (red circles) at time k after blob detection.

Fig. 1: Processing chain for one radar image at time k to extract the target candidates.

2.1. Radar image based target extraction

In order to fuse radar with AIS position data, the target candidates need to be detected and extracted from radar first, to feed them to the filter as measurement updates. The utilized approach to extract radar target information is based on image processing instead of directly working on the radar signal level. This may introduce additional error sources originating from mapping the radar signal to image domain, but also yields the advantage of applying the proposed technique to most commercial radar systems by simply interfacing to the video output. To extract target candidates from the current radar image at time k, the following procedure is applied:

1. Masking the image eliminating static but undesired features, e.g., colored heading lines, blob in center, radar information tables.
2. Conversion of image from RGB to gray-scale (weighted average from color channels).
3. Blob detection with fixed range settings for convexity, circularity, inertia, size and intensity of expected targets.
4. Each detected target candidate per frame is expressed in range and bearing, relative to the radar's, i.e., ship's, position.

The key aspect in this processing chain is certainly the scale-invariant blob detection to eventually detect target candidates. This algorithm is well described in literature and finds many applications in image based target detection and tracking such as described in [10]. For this work the implementation provided by the OpenCV framework was used[1]. Figures 1a to 1c show the different radar processing stages.

2.2. AIS dynamic target data

The typical AIS data set contains numerous static and dynamic parameters, that are distributed over different AIS message types and specified in the ITU-R recommendation [2]. The set of dynamic parameters always comprises the vessel position in longitude and latitude, course over ground (COG) and speed over ground (SOG), but may also contain true heading and rate of turn (ROT) information. The specified time intervals between successive messages range from 2 s to 180 s, depending on the dynamic state of the vessel. As was shown in [4] these reporting rates are violated in a considerable amount of cases, leading to outdated or simply missing AIS messages.

2.3. IMM-MSPDA framework for single target tracking

In this work, an IMM-MSPDA filter was designed for single target tracking in an AIS/radar environment. The IMM, being first proposed in [11], is generally applied to best capture rapidly changing motion dynamics by running a bank of interacting Kalman filters in parallel, with each filter being conditioned on a different process model. The final IMM state estimate as well as the re-initialization of the Kalman filters after each iteration is based on a weighted combination of the individual state estimates, whereas the transition between the models (or modes) is governed by an underlying Markov process. The combination with a Probabilistic Data Association (PDA) filter yields a powerful scheme for associating clutter measurements to the expected target state in a dynamically challenging scenario. The basic steps of the PDA filter are comprehensively described in [12]. Essentially, each sensor measurement gets validated based on a validation region centered around the expected state of the target. The final state update is then based on the weighted sum of the residuals between validated and expected measurements, with the weights being computed from the likelihood of the measurement to origin from the target. In contrast to the standard PDA approach in [12] we apply Unscented Kalman Filtering (UKF) (see [15]) to compensate especially for nonlinearities in the radar measurement domain.

An algorithm combining both approaches to form an IMM-PDA filter in a multi-sensor environment was originally

[1]OpenCV 3.1.0: `https://github.com/Itseez/opencv.git`

proposed in [13], outlining a scheme to combine synchronous measurement updates from 2 to 3 sensors sequentially. An extension to incorporate multiple sensors providing asynchronous or delayed measurements was published in [14]. In our work, the latter is adopted to the particular scenario of observing high rate radar measurements and low rate AIS updates, both running asynchronously. In contrast to the original algorithm, in our implementation the standard IMM cycle is continued on arrival of any sensor measurement. Otherwise, if low rate AIS messages would solely trigger the update of the IMM model probabilities, the IMM could not adopt to changing motion dynamics as quickly as if radar measurements were also used for initiating the model probability update of the IMM cycle.

2.4. UKF filter design

For the actual target tracking an Unscented Kalman filter (UKF) was designed incorporating state augmentation by the process noise during state prediction and additive correction steps for each of the sensors. Details on the basic idea of the unscented transform as well as the implementation based on state augmentation can be found in [15]. In our particular application the UKF was found to outperform the Extended Kalman filter (KF) (EKF) in the presence of highly nonlinear radar measurement updates, as was already discussed in [6] and [16]. In the context of vessel dynamics two dominant motion scenarios were identified, that are *nearly straight-path* and *turn-maneuver* based motion. For that reason, two process models were defined, namely the Constant Velocity (CV) and the Constant Turn Rate Velocity (CTRV), assuming the former to provide best fit to straight-path and the latter to turn-maneuver motion respectively. Further details on the definition of CV and CTRV process models can be found in [17].

Within each filter hat implements one of the modes from above, the predicted state $\mathbf{x}_{k|k-1}$ and its associated covariance will be corrected based on measurements of sensor $s \in \{radar, ais\}$. The corresponding measurement models are expressed as functions $h^s(\mathbf{x}_{k|k-1}, \boldsymbol{\epsilon}_k^s)$, with

$$h^s(\mathbf{x}_{k|k-1}, \boldsymbol{\epsilon}_k^s) = \left[x_{k|k-1}, y_{k|k-1}\right]^T + \boldsymbol{\epsilon}_k^s \tag{1}$$

for $s = ais$ and

$$h^s(\mathbf{x}_{k|k-1}, \boldsymbol{\epsilon}_k^s) = \begin{bmatrix} \sqrt{(x_{k|k-1} - x^s)^2 + (y_{k|k-1} - y^s)^2} \\ \arctan\left(\frac{y_{k|k-1} - y^s}{x_{k|k-1} - x^s}\right) \end{bmatrix} + \boldsymbol{\epsilon}_k^s \tag{2}$$

for $s = radar$, mapping the target position from state to radar measurement domain. In that context, (x^s, y^s) denotes the radar reference position and $\left(x_{k|k-1}, y_{k|k-1}\right)$ the predicted position in the target's local ENU frame respectively. The vector $\boldsymbol{\epsilon}_k^s \sim N(\mathbf{0}, \mathbf{R}^s)$ captures the additive sensor measurement noise.

Careful attention has to be paid to the interaction of models with state spaces of different dimensions within the IMM cycle. In this work the strategy from [18] is followed, which is based on state augmentation. In this context, the extra element from the CTRV state space is essentially replicated to obtain a combined IMM state estimate.

3. RESULTS

In this section the proposed algorithm for fusing AIS with radar in an IMM-MSPDA filter shall be evaluated based on a dynamically challenging measurement scenario.

3.1. Baltic Sea experiments

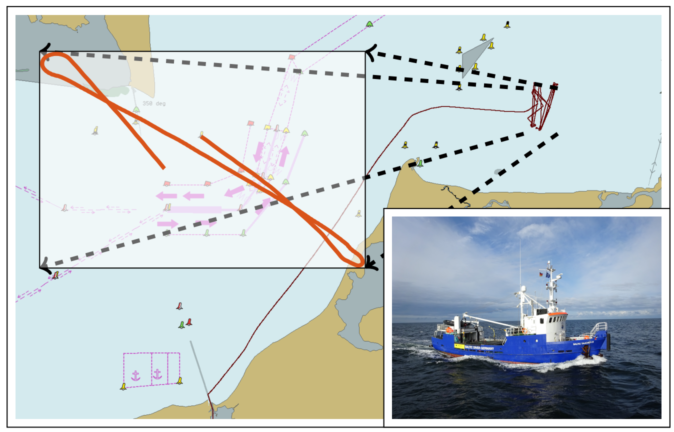
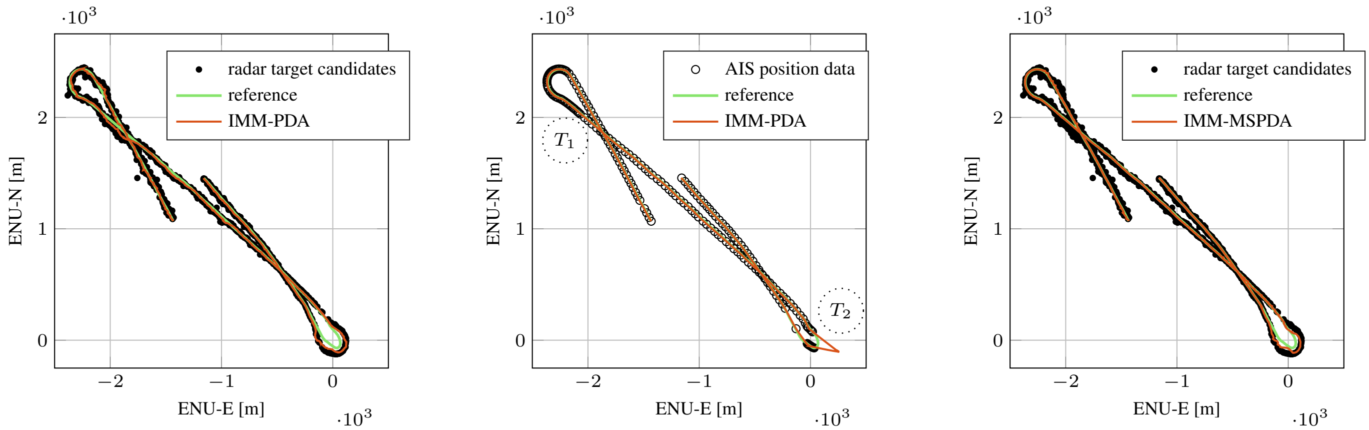


Fig. 3: Nautical chart depicting the area of the measurement campaign at the Baltic Sea, zooming into the selected test trajectory. The bottom right picture shows the vessel to be tracked.

For validating the proposed method a dedicated measurement campaign with two chartered vessels was conducted in October 2015. The offshore supply ship BALTIC TAUCHER II was conducting sea trial maneuvers for two successive days in the Baltic Sea (see Fig. 3). Its transmitted AIS messages were recorded at a shore-based AIS station at the Darßer Ort Lighthouse, Germany[2]. Additionally, this ship was equipped with a multi-frequency GNSS receiver, that allowed for computation of a PPP reference trajectory in post-processing. A second ship, the tug vessel AARON remained anchored in the center of the sea trial area, monitoring the scenery by radar at an interval of 1 Hz. With this scenario the feasibility of the proposed method for maritime situation awareness w.r.t. to a single target shall be demonstrated. For the validation of the

[2]Courtesy of German Federal Waterways and Shipping Administration (WSV)



(a) Trajectory of tracked vessel based on **radar data only**, running an IMM-PDA only.

(b) Trajectory of tracked vessel based on **AIS data only**, running an IMM-PDA filter.

(c) Trajectory of tracked vessel, **fusing radar and AIS data**, running an IMM-MSPDA filter.

Fig. 2: Comparison of filtered vessel trajectories from two IMM-PDA filters conditioned on either radar or AIS alone and an IMM-MSPDA filter fusing both sources.

proposed filter, the subset highlighted in Fig. 3 was selected due to its two distinct turn maneuvers, covering 1708 s or 201 valid AIS messages respectively.

3.2. Evaluation

For evaluation and to demonstrate the potential benefits of the proposed scheme, three different filters were tested. At first, an IMM-PDA filter was conditioned on plain radar target candidate data. Secondly, the AIS messages from the same track were used as sole input to this filter. Figures 2a and 2b show the filtered trajectory in comparison to the reference and original measurement updates. Thirdly, the proposed IMM-MSPDA filter was tested with both asynchronous sensor measurement updates. The trajectory obtained from this fusion process is shown in Fig. 2c. As can also be seen in Table 1, the filter being conditioned on radar image data only can not compete in terms of accuracy to filtered AIS position data. However, while the filter running on low rate AIS messages is introducing a large position error during the second turn maneuver (at label T_2 in Fig. 2b) due to missing AIS messages radar can still be used for tracking as it provides continues measurement updates. By fusing both sensors the filtered trajectory overpasses smoothly the lack of AIS messages during the turn maneuver, while it is mainly following AIS updates otherwise. In this particular case, the maximum error in the estimated target position was drastically reduced from nearly 236 m to below 56 m.

In Table 1 prominent statistics for the three different filters are listed stressing the performance improvement from the proposed IMM-MSPDA filter in terms of maximum and RMS error. It is not surprising that the σ-value of the error distribution, i.e., the value which bounds 68.27 % of the errors, is increasing for the fused process compared to the filtered trajectory conditioned on AIS data only. Due to the high rate radar measurements more uncertainty is inferred to the filter in times where AIS messages would actually suffice.

Table 1: Statistics of the horizontal position error for the three different filters.

	mean	σ (68.27 %)	RMSE	max.
IMM-PDA AIS only	9.6 m	3.2 m	36.9 m	235.7 m
IMM-PDA Radar only	18.3 m	19.1 m	22.3 m	75.8 m
IMM-MSPDA	8.9 m	7.1 m	14.8 m	55.6 m

4. CONCLUSION

In this work, an IMM-MSPDA framework was utilized to exploit the complementary nature of radar and AIS sensors in a loosely-coupled data fusion architecture. The overall aim is to provide a more robust picture of the traffic situation in the vicinity of a particular vessel, resilient to AIS faults or anomalies. Based on real-world measurements the benefits of the proposed scheme could be visualized for cases of missing or insufficient AIS message updates. In future work this framework will be extended for multiple target tracking including track initialization based on candidate extraction from radar.

5. REFERENCES

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