A Marine Radar Dataset for Multiple Extended Target Tracking

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ABSTRACT

The marine radar remains one of the most extensively used sensor for maritime surveillance. Owing to improved technologies, it can nowadays be exploited to gain information about the extents of targets, since multiple measurements can be obtained from a single target. This paper introduces an open multitarget marine radar-based dataset subjected to a linear-time joint probabilistic data association (JPDA) filter for tracking extended targets using ellipsoidal approximations. A tailored version of the Multiplicative Error Model-Extended Kalman Filter* (MEM-EKF*) algorithm is used for estimating the orientations and kinematic properties of multiple targets recursively. Using the automatic identification system (AIS) information as ground truth, the positional errors are evaluated using the optimal sub pattern assignment (OSPA) metric and the performance of the algorithm for orientation estimation is rationally discussed with respect to the ground truth and dataset scenario. The dataset proposed is intended for comparing different algorithms for the purpose of multiple extended target tracking (METT).

Keywords: Multiple extended target tracking, ellipsoidal shapes, marine radar dataset, linear-time JPDA

1. INTRODUCTION

The past few decades have been witness to the establishment and steady growth of oceanic trade connections worldwide. To ensure safety of the goods and crew onboard, a reliable situational awareness is necessary to, for instance, provide an early detection of and avert potential collisions, detect abnormal activities such as smuggling and to maintain a constant monitoring of specific routes. The marine radar is still predominantly utilised and with improvement in sensor technologies and image processing techniques, it provides several noisy spatially distributed measurements that arise from the target(s) of interest at each observation step. The target tracking problem is, in this context, to estimate the extent (geometric shape) properties in addition to their kinematic ones simultaneously given the measurements' distribution.

In scenarios of high measurement noises, approaches of extended target tracking (ETT) have been developed where the target extent is estimated using basic geometric shapes for example, ellipses or rectangles. Most of the radar measurements acquired from generic real-world maritime environments are highly noisy, rendering it difficult to accurately model the true underlying physical extent and contour of vessels. Going by this perspective, an ellipsoidal approximation of targets aids in getting suitable insight and awareness on the traffic situation under an observation region. The random matrix approach models an extended target by its kinematic state represented by a Gaussian distribution and an extent matrix represented by a symmetric and positive definite matrix which provides an ellipsoidal approximation of the target's extent.[1,2] The approach has for instance been employed for ETT using converted X-band radar measurements that analysed extent estimation with respect to different measurement models.[3] The multiplicative error model (MEM)[4] approach models the spatial distribution of measurements from the target's surface with multiplicative noise. This is accounted for in the measurement equation by the use of a scaling factor. Targets can thus be tracked using ellipsoidal approximations,[5,6] where an ellipse is parametrised with the semi-axis lengths and orientation. In contrast to the random matrix method,

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this parameterisation permits a custom modelling of the uncertainty of each individual parameter where the state of a target of known dimension can be tracked.[6]

METT is to simultaneously estimate the number of targets, kinematic state and extent properties of each target respectively. To solve the same, multiple target tracking (MTT) algorithms have been incorporated within the random matrix framework such as the probabilistic multi-hypothesis tracking filter[7] and variants of the probabilistic data association filter.[8,9] Vivone and Braca presented an ellipsoidal METT method based on the JPDA filter, with an explicit ellipse parameters estimation[10] where the measurement vector comprises features extracted from a specific clustering approach. In addition to the data association and multi-hypothesis approaches, the random finite set (RFS) one has been applied to solve METT. Some of its recent methods include the (generalised) labelled multi-Bernoulli (LMB)[11] and the Poisson multi-Bernoulli mixture (PMBM) filters,[12] along with their respective gamma Gaussian inverse Wishart (GGIW) variants.[13,14]

In this work we introduce the MANV dataset, which is the second marine radar dataset from the German Aerospace Centre's (DLR) benchmark scenarios to be made open to the tracking and signal processing community. Furthermore, we present initial tracking results using the linear-time extended target JPDA filter[9,15] together with the tailored MEM-EKF*.[6] AIS information has been used to initialise both the kinematic and extent related information. Based on the assumptions made with regard to the radar measurements and dataset scenario, the results are presented and discussed.

The rest of the paper is organised as follows. Section 2 gives an outline of the dataset with appropriate plots. In Section 3, the target state parametrisation, the measurement model, and a summary of the approach adopted for METT are covered. Section 4 carries the tracking and evaluation results which is then followed by a conclusion.

2. MANV DATASET

The MANV (**man**oeu**v**res) dataset, depicted in Figure 1 was procured from a measurement campaign held in the Baltic sea. The dataset is one of the proposed radar-based real-world benchmark scenarios[16] that are going to be made available to the tracking community to be used for METT, but not limited to it, leaving options open for ETT and other related applications*. MANV has been regarded in particular as it contains dynamic manoeuvres that pose a challenge to tracking algorithms.

For the observation period considered, that is, from step $k = 1$ up to step $k = 1000$, the scenario consists of six known targets in total, four of which are anchored − Target 1 is the own vessel/observer − while Targets 4, 5, and 6 were buoys fitted with radar reflectors during the campaign and the other two (Targets 2 and 3 of dimension 29.04m×6.7m and 23m×6m respectively) are engaged in manoeuvres. Target 2 had a moderate speed over ground (SOG) on average, starting at about 4kn, going up to 6kn before decelerating after $k = 800$. Target 3 started at about 10kn, fluctuating down to 2kn throughout most of the period till $k = 800$, then went around 6kn towards the end.

In the radar recording of Target 1 shown in Figure 3, an unknown random vessel underway has been observed which could have been either a leisure craft or fishing vessel that was not equipped with any AIS transponder. The radar measurements arising from each target in the dataset are in fact quite dense and noisy at almost all steps. During the image processing step adopted,[6] a good proportion of clutter had already been filtered out and as resolution, a pixel unit represented 6m. The original radar measurements were extracted from radar images, individually expressed in range r^j and bearing ψ^j with respect to the own vessel whose position was retrieved from the onboard AIS. The extracted measurements occur either in clusters or may occur individually, their origins being unknown. They have been then converted to the Cartesian East North Up (ENU) coordinates (up is assumed negligible) prior to being fed to the filter in Section 3 following the standard conversion scheme.[17] A measurement vector $\mathbf{z}^j$ hence follows as

$$\begin{bmatrix} z^j_{\tilde{e}} \\ z^j_{\tilde{n}} \end{bmatrix} = \begin{bmatrix} r^j \sin(\psi^j) \\ r^j \cos(\psi^j) \end{bmatrix}. \tag{1}$$

The error between an extracted polar measurement and its true one is assumed to follow a zero-mean independent Gaussian measurement noise having standard deviations σ_r and σ_ψ are 40m of 4°.

*The dataset can be requested for by contacting the authors.

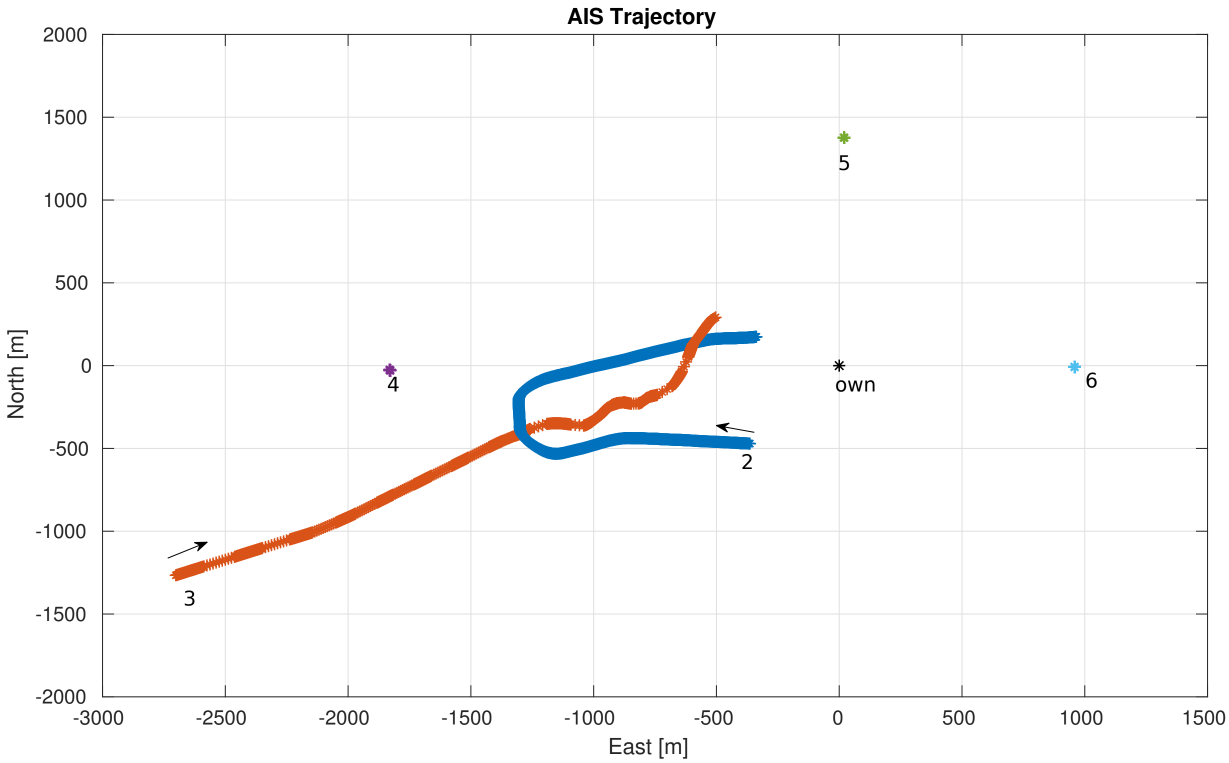

Figure 1. The plot corresponds to the AIS measurements obtained for the targets in the dataset. The targets are labelled, including the own vessel and the arrows indicate their respective courses at the beginning of their trajectories.

3. MULTIPLE EXTENDED TARGET TRACKING

At each observation step k, a set of measurements $\mathbf{Z}_k = \{\mathbf{z}_k^j\}_{j=1}^{M_k}$ becomes available. There is also a set of target states, defined $X_k = \{\mathbf{x}_k^i\}_{i=1}^{N_k}$. Formally, the METT problem is to jointly estimate the states – each individual target state comprises kinematic properties such as the position, velocity, or acceleration and the extent parameters – from the measurements.

3.1 State Model

The tailored MEM-EKF* algorithm[6] approximates the extent of a target of interest i as an ellipse with a multiplicative noise to link a measurement to its state, $\mathbf{x}_k^i$, such that $\mathbf{x}_k^i = \left[{\mathbf{r}_k^i}^T, \alpha_k^i\right]^T$, which consists of both the kinematic state vector $\mathbf{r}_k^i$ and the orientation parameter α_k^i. $[.]^T$ denotes the transpose operator. α_k^i is the property of interest from the shape parameter vector $\mathbf{p}_k^i$, visualised in Figure 2. For our adaptation, the kinematic state vector

$$\mathbf{r}_k^i = [t_{k,\tilde{e}}, t_{k,\tilde{n}}, \psi_k, \upsilon_k] \tag{2}$$

comprises the position $(t_{k,\tilde{e}}, t_{k,\tilde{n}})$ in the local Cartesian ENU coordinates, the course over ground (COG) ψ_k and the SOG υ_k. The shape parameter vector is given by

$$\mathbf{p}_k^i = [\alpha_k, l_1, l_2], \tag{3}$$

where α_k is the orientation of the ellipse taken along the ellipse's major axis, and l_1 and l_2 represent the lengths of the semi-axes of the ellipse respectively.

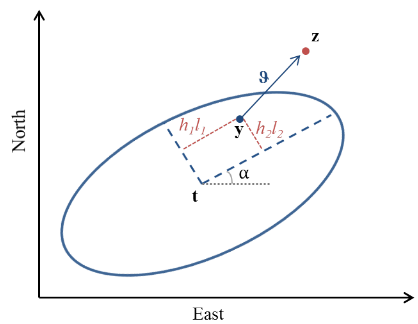

Figure 2. The adapted measurement model[5,6] where the extent is parameterised as $\mathbf{p} = [\alpha, l_1, l_2]$, showing the association of measurement $\mathbf{z}$ to source $\mathbf{y}$ with noise $\boldsymbol{\vartheta}$. $\mathbf{z}$ is related to $\mathbf{p}$ with multiplicative noise $\mathbf{h} = [h_1, h_2]^T$. The centre $\mathbf{t} = [t_{\tilde{e}}, t_{\tilde{n}}]^T$ denotes the target's position in the ENU coordinates.

3.2 Measurement Model

Each measurement $\mathbf{z}_k^j = [z_{\tilde{e},k}, z_{\tilde{n},k}]^T$ originates from a source $\mathbf{y}_k^j$ on a target's extent corrupted by an additive noise $\boldsymbol{\vartheta}_k$. The measurement model is illustrated in Figure 2. The measurement equation is given by[5]

$$\mathbf{z}_k^j = \mathbf{t}_k + \boldsymbol{\mathcal{R}}(\alpha_k) \begin{bmatrix} l_1 & 0 \\ 0 & l_2 \end{bmatrix} \begin{bmatrix} h_{k,1}^j \\ h_{k,2}^j \end{bmatrix} + \boldsymbol{\vartheta}_k \tag{4}$$

where the measurement noise is $\boldsymbol{\vartheta}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_k^j)$, the rotation matrix is $\boldsymbol{\mathcal{R}(\alpha_k)}$, and $\mathbf{h}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{C^h})$ is a multiplicative error term, where $\mathbf{C^h} = \frac{1}{4}\mathbf{I}_2$ that corresponds to the covariance of the uniform distribution an ellipse.

3.3 Dynamic Motion Model

The temporal evolution of the kinematic state of each target is based on a motion model of the following form

$$\begin{aligned} \mathbf{r}_k &= \boldsymbol{a}_k(\mathbf{r}_{k-1}, \boldsymbol{\omega}_k^{\mathbf{r}}) \\ &= \begin{bmatrix} t_{k-1,\tilde{e}} + \sin(\psi_k) \cdot \Delta T \cdot v_k \\ t_{k-1,\tilde{n}} + \cos(\psi_k) \cdot \Delta T \cdot v_k \\ \psi_k \\ v_k \end{bmatrix} + \boldsymbol{\omega}_k^{\mathbf{r}} \end{aligned} \tag{5}$$

where $\boldsymbol{\omega}_k^{\mathbf{r}} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_{\mathbf{r}}^{\boldsymbol{\omega}})$ and $\Delta T = T_k - T_{k-1}$ is the time interval, assigned 1s for the dataset. (The target index's superscript i is left out.) The evolution of the orientation parameter follows a linear model represented by

$$\alpha_k = \alpha_{k-1} + \omega_k^{\alpha} \tag{6}$$

with process noise $\omega_k^{\alpha} \sim \mathcal{N}(0, Q_{\alpha}^{\omega})$ driving the orientation.

3.4 Data Association and State Estimation

The main objective of data association is to deal with the unknown correspondence of a measurement to its respective origin, which can be either a target or clutter. Gilholm and Salmond have introduced the concept of extended targets having the possibility to be each represented by a spatial probability distribution modelled as a Poisson process.[18,19] With a Poisson model representing the underlying measurements, multiple measurements can result from a single target.[15] The same concept has been applied in this work to track the orientations and the kinematic properties of multiple targets of known ellipsoidal extents present within an observation region. The multitarget tracker employed is a linear-time JPDA filter[9] based on the aforementioned measurement model and the Poisson model. For the state estimation, the individual target states are updated following a sequential probabilistic data association (PDA) scheme described in Section III of Yang et al.'s work[9] by taking into account the marginal association probabilities.

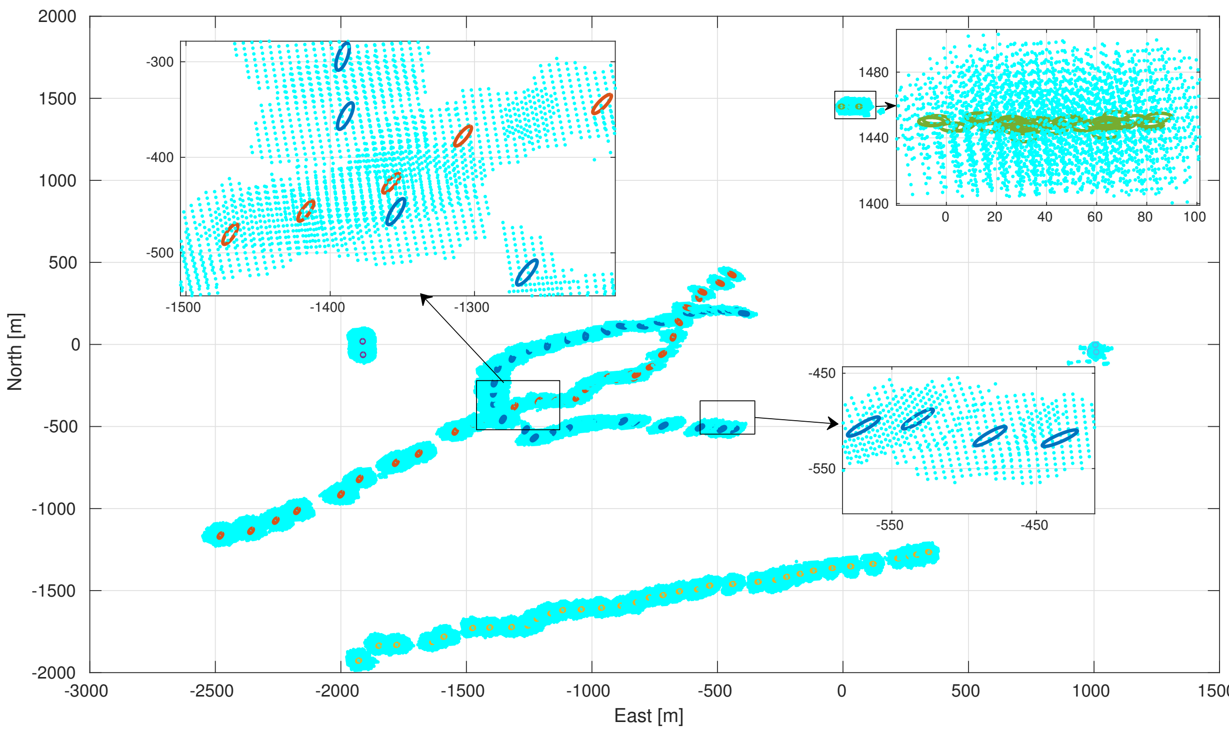

Figure 3. The radar measurements (dots) and the extent estimates (ellipses) of the targets. The estimates have been plotted at intervals of every 25 observations steps. Notice the unknown target starting from ENU coordinates $[-2000, -2000]^T$.

Table 1. Filter Parameter Settings

Parameter	Target 2	Target 3	Unknown Target	Targets 4-6
Initial orientation parameter, α_0	277°	62°	45°	50°
Initial orientation process noise variance Q_α^ω	9	25	25	16
Measurement Rate, λ	232	270	277	152, 84, 26

4. RESULTS

The linear-time JPDAF for extended targets described earlier was applied to the dataset, and the results are as shown in Figure 3. The number of targets in the scenario is assumed to be constant and known apriori for the scenario considered. We point out that this work was realised by virtue of two main assumptions. Firstly, a target of interest is not necessarily aligned along its course, which can be explained by external factors influencing vessel motion such as tide and weather conditions. Secondly, due to the limited perspective of the targets' bodies visible in the own radar's field of view, it is assumed that the targets' extents are symmetric and can be approximated using ellipses. The dynamic model adopted for every target is the one defined in (5) for simplicity.

While the track of each target was initialised based on AIS information where available – more specifically the position, COG, SOG, and dimensions, the initialisation of the unknown was based on guesses. Further target-specific parameter settings as applied are summarised in Table 1 with the predetermined rate parameter for each target given their individual measurements.

The clutter density ρ over the observation region was calculated as 8×10^{-9} and the parametric model has been used to predetermine the probability mass function of the clutter measurements. The clutter rate was taken as 5. The process noise standard deviations for the kinematic states, $\mathbf{Q}_\mathbf{r}^{\boldsymbol{\omega}}$ of all targets was $\mathrm{diag}(30, 30, 0.02, 5)$. For the validation gate, the threshold yielding to a gating probability of 0.65 was used to validate the measurements.

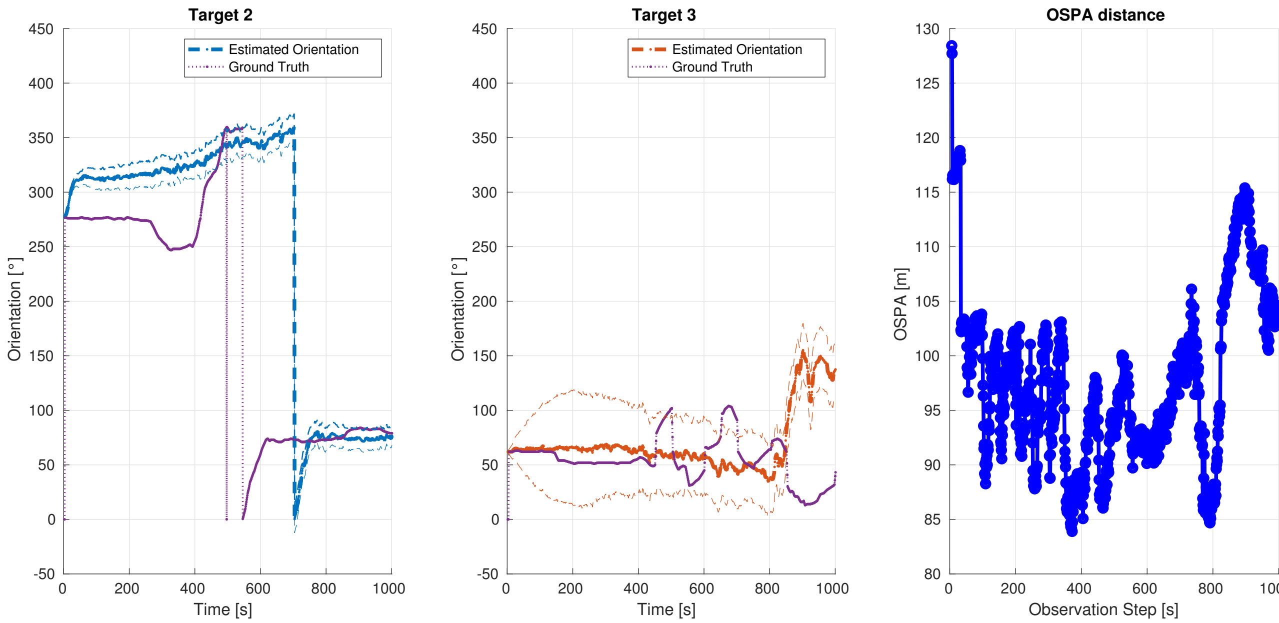

Figure 4. The estimated orientations with their corresponding standard deviations, against the AIS true heading measurements for Target 2 (left) and Target 3 (centre). (Right) The OSPA results from the kinematic state estimates evaluated against the AIS positions.

Figure 3 illustrates the extent estimates of the targets at every 25 steps along with the radar measurements displaying the rather high spreading of the measurements for farther distances with respect to the own. The results have been evaluated using the OSPA metric with AIS as ground truth as shown in Figure 4 with order setting of $p = 2$ and cut-off of $c = 150$m. The estimated orientations of the dynamic targets are also presented together with their ground truths (unavailable for the unknown one).

In Figure 4, the estimated orientations for Target 2 appear to be sensitive to the measurement spread emanating from the reflective side of the vessel due to the own's perspective. Those at the manoeuvring turns were not always well estimated, although the results do improve as the vessel gets closer to the own. Target 3's orientation estimates were rather smooth from up to $k = 450$, as observed. Later, it appears to have missed the sharper turns due to the own's perspective between $k = 450$ to $k = 750$. After $k = 800$, the target has been subjected to partial obstruction due to Target 2 which explains the estimates being off. Based on the aforementioned assumptions, a point to bring out regarding the own sensor's perspective aspect is that in highly dynamic and complex multitarget scenarios, using a single sensor will be insufficient to yield precise estimations.

5. CONCLUSION

In this paper, a JPDA filter based on the Poisson model has been employed to track the orientations of multiple targets based on a special version of the MEM-EKF* algorithm on a marine radar-based dataset. The OSPA metric was used to calculate the positional error, the vessels' estimated orientations were visualised together with the AIS-based true heading measurements of the vessels. The performance of the algorithm was fettered by the perspective of the own vessel, as expected, and seemed to be somewhat sensitive to the direction of the measurement spreads being tracked. The results would most likely be significantly improved should measurements from multiple sensors be used. In the future, we shall investigate further multiple extended target tracking algorithms using the dataset for a standard comparison.

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