Performance evaluation of underwater target tracking using data fusion on acoustic and electromagnetic data

Leif Persson, Eva Dalberg, Andris Lauberts & Ron K. Lennartsson
FOI, Swedish Defence Research Agency
SE-164 90 Stockholm, Sweden
Email: leifp, eva.dalberg, andris, ron.lennartsson@foi.se

Abstract—Underwater passive acoustic target tracking is challenging in littoral environments. One way to mitigate the difficulties is to add non-acoustic sensors and use data fusion. The topic of this paper is how to evaluate, in an objective way, the performance of data fusion in this application. Different performance measures are discussed. The performance measures are applied on data from a trial where one acoustic and one electric source were towed by a ship, simulating an underwater target. The trial was performed in a very shallow water littoral environment. Data were recorded using a passive acoustic horizontal line-array and an array of underwater electric sensors. The results show that there is a risk of degraded performance after fusion, if the data from the sensors have very different quality. In order to reduce this risk, it is crucial to reliably evaluate the quality of each estimate at all times.

Keywords: Data Fusion, Performance Measures, Tracking, Kalman Filtering, Underwater Surveillance.

I. INTRODUCTION

There is an increasing interest for sensor networks in littoral surveillance systems. This is natural since a network of sensors has many advantages given that their full potential is utilised. A network can be optimised depending on the surveillance needs, taking into account the surrounding environment, and that it can be scalable over time. The actual configuration will, however, in many practical situations be restricted by the number and types of affordable sensors. A natural way of making the most out of the available resources is to fuse data from the sensor nodes in the network, see e.g. [1].

One important application for underwater surveillance networks is tracking of underwater targets. In this case, information fusion means using a tracking algorithm on data from distributed sensors, where each sensor gives some kind of information about the target track [2]. The sensors can also be placed on a platform, such as a submarine [3]. Some sensors may only extract the range or the bearing of the target, while other sensors can estimate these parameters simultaneously. In most cases, the performance of the nodes in the network will not be the same. There may be parts of the target track where several sensors have overlapping information, as well as parts having no information at all. This means that the fusion process must be able to handle a dynamic number of sensors, delivering different types of information, affected by uncertainties or errors to a varying degree.

How then, will we be able to assess the performance of a specific algorithm, or a specific network configuration? We have previously addressed the question whether adding information from electrode arrays can improve tracking of underwater targets in littoral environments [4]. In this paper we discuss some measures of performance that can be used in order to achieve an objective evaluation of different tracks. Our goal has been to quantify whether there is a performance gain or not when fusing the information from a passive acoustic array with information from an passive electrode array, compared to the individual estimates.

A. Outline of this paper

We begin by introducing our ideas on how to evaluate the performance of a tracking algorithm in Section II. Then we present the data, the sensors, and their performance in Sections III-V. The Kalman filter is briefly introduced in Section VI. The results are discussed in Section VII, followed by the conclusions in Section VIII.

II. MEASURES OF PERFORMANCE

Our focus is on performance measures that can be used for objective evaluation of the tracking performance. This is a topic that has been discussed in e.g. [5].

The sensor data have been complemented with DGPS-information of the positions of the sources. This means that we could compare the resulting track with ground truth. We have also looked at the spatial overlap between the GPS-track and the reconstructed track. The fragmentation rate of the track, i.e. if there are large irregularities in the track, has also been investigated.

Operationally, ground truth is not known, and thus there is a need for assessment of whether a track should be relied upon or not [6]. One problem is to assess the output from the tracking filter itself, and how to judge the quality of the resulting track. Another problem is how to establish the reliability of the information from each sensor delivering data to the tracking filter. Solving the latter problem is important for deciding whether fusion should be used or not. If one sensor outperforms the other substantially, the quality of the fused track may be lower than the quality of the track based on information from the best sensor only.
III. THE DATA

In this work we have treated two types of sensors; i) one passive acoustic horizontal line array, and ii) one long-base line electrode line-array. These sensors have very different detection ranges against underwater targets.

A field trial was performed in August 2004 in the Stockholm archipelago. The acoustic array, consisting of 31 elements with 1.5 m spacing, placed on the sea-floor. The electric field sensors, 8 electrode pairs, were configured as a straight array, spanning a length of 1500 m. In Fig. 1 a schematic overview of the sensors used is displayed. The electric field sensors, 8 electrode pairs, were configured as a straight array, spanning a length of 1500 m. In Fig. 1 a schematic overview of the sensors used is displayed. The electric field localisation algorithm uses Cartesian coordinates; range and bearing toward the centre of the acoustic array have also been calculated and both coordinate systems are used in this paper.

One acoustic and one electric source were towed simultaneously from a ship at a speed of 3-4 knots. The ship positions were recorded using a DGPS system. Further details can be found in [7]. The track analysed in this report had a total length of 6 km, and the water depth was approximately 40 m during the track.

IV. ACOUSTIC TARGET LOCALISATION

Passive localisation of underwater targets in shallow water is a difficult task and has received considerable attention in the literature see e.g. [8]. If the sound propagation medium becomes nonstationary, systematic errors are observed [9]. Here, we estimate the target bearing by beamforming and target range by estimation of the wavefront curvature.

A. Bearing estimation

The temporal and spatial structure of the received wave field is of importance for target bearing estimation. The direction-of-arrival of wavefronts generated by sound sources is an important parameter in passive underwater surveillance. The bearing estimation scheme for an array system is an optimisation for enhanced target tracking based on the given limitation in directivity, resolution and beamwidth.

The model is based on the assumption that a source signal $x(t)$ generates a wave field at bearing $\theta$ relative to an array of $M$ sensors. In a first approximation the received wave field consists of the source signals attenuated with $\alpha_m$, and then delayed with $\tau_m(\theta)$ at sensor $m$ as,

$$x_m(t) = \alpha_m x(t - \tau_m(\theta)) + \phi_m(t). \quad (1)$$

The weights $\alpha_m$ can for simplicity be set to unity and the time delays $\tau_m(\theta)$ equal $\theta(r_m - r_n)/v$, where $v$ is the propagation velocity of the received wavefront and $r_m - r_n$ is the radius vector difference between sensor $m$ and $n$.

The received signal power is given by

$$R_{xx} = R_{ss} + R_{nn} \quad (2)$$

where the signal power of $x(t)$ in Eq. 1 is for the array represented by $R_{ss}$ and $R_{nn}$ represents the additive ambient noise.

The steering vector is introduced as

$$C(\theta) = [1, e^{j2\pi f(1)d/v\sin(\theta)}, ..., e^{j2\pi f(M-1)d/v\sin(\theta)}]^t \quad (3)$$

where $f$ is the frequency, $d$ the sensor spacing and $M$ the number of sensors in the line array. If this vector is applied on the data $R_{xx}$ as

$$P(\theta) = C^H(\theta) R_{xx} C(\theta), \quad (4)$$

we have the beamformer used for bearing tracking of targets and in conjunction with the range estimation. The acoustical signal-to-noise ratio in the beamspace $P(\theta)$ is the relation between the target power represented by $R_{ss}$ to the isotropic power in the off target directions in $R_{nn}$. Also, since we have a line array, a left and right ambiguity occur. However, the given a priori information solves that problem.

B. Range estimation

For a passive acoustic sonar system the estimation of the target range is difficult. However, it is beneficial to have a range estimate in many tactical situations. We use the wavefront information in the target direction $\theta$ to estimate the range. The sensor positions in the array need to be fairly accurately known, otherwise a large bias can occur for wavefront ranging methods [9].

As soon as a target is detected a track based on bearings from Eq. 4 will be established. Most bearing estimation methods make the assumption that the source is far-field and therefore the spherical wavefront appears planar at the array. This is a strong assumption for a bounded wave propagation media, such as shallow waters, however it gives a fairly accurate bearing estimate. This bearing estimate is used for a refined calculation of the shape of the wavefront, e.g. [8] and [10]. The inter-element cross-correlations in the array is used for the wavefront curvature estimation. This shape is compared to a wavefront model and translated to a range. An
iteration scheme is used for finding the maximum beampower in the target bearing. The final target bearing is estimated from the updated delays using the final wavefront shape. Simultaneously, the wavefront is shaped given different delays $\tau_m(\theta)$ with the constraint of steering at the target bearing $\theta$. The delays for the maximum output beampower are used for the shape of the wavefront in the final range estimate.

C. Localisation performance

The performance of the acoustic range and bearing algorithms are in terms of position errors is displayed in Fig. 2 (bearing) and in Fig. 3 (range). The main part of the tails in the range error distribution is due to a low SNR regime.

V. RANGE AND BEARING ESTIMATES USING ELECTRODE SENSORS

Source localisation is performed on data from an electrode array, using a matched field processing technique. Source localisation is performed on data from an array of underwater electric field sensors using a matched field processing technique. The analysis is performed in three steps. First, the time-series recorded by each sensor in the array is grouped into a sequence of data windows. Then a detector is applied, requiring detection in at least $N$ sensors. Finally, an estimate of the source position is made. The difference between the measured and calculated (using a forward model) amplitudes is minimised. Optimisation is performed of the heading and the position of the source (i.e. they are the estimates). All other parameters in the model were kept fixed.

This localisation method is essentially similar to the one used in our previous work [4]. The most important changes to the methodology used earlier is the added requirement of detection before an estimate of the source position is performed. In addition, an arbitrary orientation of each sensor is now allowed.

A. Electric field amplitudes, data and model estimates

The electric field amplitudes were calculated assuming a narrow band source. Data windows of 5 seconds were used. The noise level was calculated from 30-minute recording immediately prior to the measured track with a towed source. The detection threshold was chosen to be 3 dB above the level containing 90% of the noise samples.

The Nlayer 2.0 [11] forward model allows a stratification in the environmental parameters vertically, but no variation horizontally. The environment was modelled using parameters estimated from dedicated environment assessment studies performed at the measurement site, see [12] for an overview of this topic.

B. Source position estimates

The minimisation problem is ill posed and prone to local optima. To avoid these, the minimisation algorithm is restarted with new initial values $M$ times and the solution with smallest residual between the data and the forward model among the ensuing $M$ results is chosen. The final solution in each step is then used as the starting value for the next step. The number of restarts depends on whether the source was detected in the previous step or not. If there was no detection in that step, $M = 100$, otherwise $M = 25$ in order to save computation time.

Since the sensors measure the E-field in one dimension only, and the sensors are arranged along the cable in a straight line, the array is plagued by a left-right ambiguity. In operational systems this ambiguity may be handled in two ways, either by adding sensors off the symmetry line, or by allowing two hypothesis of the source position in the ensuing tracking algorithm. Here, only the positions on the correct side of the array have been used in the tracking algorithms.

C. Localisation performance

The performance of the localisation algorithm in terms of the positioning errors depend on the SNR in the individual sensors. Requiring a high SNR will, however, decrease the detection range. As expected, the overall performance will be a compromise between early detection and accurate positioning. The current choice of using at least 4 sensors for the electric sensors with at least 3 dB SNR results in position errors summarised in Fig. 2 for the bearing and in Fig. 3 for the range. The detection range is in the electric case just below 1 km.

VI. THE KALMAN FILTER

Tracking is performed using a linear Kalman filter, see e.g. [13]. The code is adopted from an implementation given by [14]. The target is treated as a single, isolated object. Thus, apart from a possible disturbance from distant passing by objects, the association problem is not an issue here. The bearing and range are estimated each second with the acoustic system and every 5 seconds with the electrode system. Observations
(surpassing given error thresholds) collected from acoustic and electromagnetic sensors are treated as independent data sources. In case of an actual observation, the Kalman filter parameters are updated and a new state vector (position and velocity) is predicted. In case of no observation, the velocity elements of the system matrix are multiplied by a factor 0.999, making the (blind) tracking slow down until possibly catching a new observation. The filter output is updated every second.

The covariance position elements are set individually for the electric and acoustic estimates, with fixed values equalling their mean absolute deviations from the GPS track. The fused track is based on data from both sensor systems with the same covariances as used for the individual tracks.

In our data, the acoustic array detects the source through the whole track, although the signal is masked at some times by disturbances. The electric source is detected by the electrode array less than half the track. This means that we do not have continuous information from the electrode array.

VII. RESULTS

Results after applying the Kalman filter on data from i) acoustic sensors only, ii) electric field sensors only and iii) all data combined have been compared.

A. Comparisons with GPS, mean and standard deviations

We have compared the output from the Kalman filter with the GPS-information using,

- the absolute euclidian distance between the GPS-position and the Kalman filter output

For each entity we have calculated the difference between the GPS-data and the output from the Kalman filters along the track. The mean and standard deviation of that difference is used as a performance measure.

Fig. 4 compares the mean and standard deviations of the errors after Kalman filtering. The results have been normalised using the mean and standard deviation from the fused track. This makes it easy to identify whether fusion improves the tracking performance. After normalisation, a mean value larger than one means that fusion improves the tracking performance, since the quotient of the errors before and after fusion is larger than one. Similarly, a value smaller than one means that the performance is decreased after fusion. A similar argument is valid for the standard deviations.

Also shown in Fig. 4, the mean errors are smaller after fusion for the north coordinate, bearing and distance. However, the mean east coordinate error and the mean range error is smaller when using the individual tracks compared to the fused track. In all cases, except for the distance error, the standard deviation of the errors are smaller for the fused track compared to individual tracks.

The main improvements of fusion is in Cartesian coordinates in the north component and in cylindrical coordinates in the bearing. If the application requires the smallest possible absolute error, using fusion is the best choice, since both the mean and the standard deviation of the error is smaller for the fused track, in general.
B. Comparisons with GPS, fractions of time with enough accuracy

In some applications it may be enough to know the position of the target within some pre-defined accuracy. We have looked into what fraction of time the estimated track is within +/-100 m from the GPS-position or within +/-10 degrees from the true bearing. This is shown in Fig. 5, for the same five parameters used in the previous section.

In Cartesian coordinates the track based on information from the electric sensors has a larger time-fraction within these errors than the track based on information from the acoustic array. The difference is so large that the fused track is less good than the track based only on the electric field data. The time-fraction of the range is improved by fusion. Looking at the time-fraction of the bearing the fused track and the acoustic track are comparable, and much better than the electric track.

C. Spatial overlap

In section B we compared the tracks from the Kalman filter with the GPS-information at each time. However, it can be relevant to look at the overall shape of the track, regardless if the filter by some reason (e.g. systematic or due to timing uncertainties) is lagging behind or running ahead of the GPS-track.

We divided the area covering the track geometry in squares, marking all squares laying on the GPS-track with a different colour. Also, a similar scheme was carried out for the Kalman filter tracks. To enable comparisons of the spatial distributions of the filtered tracks with the GPS-track, we counted the number of overlapping segments divided by the total number of segments on the GPS-track.

Four different sizes of the squares were used; 10x10 m, 50x50 m, 100x100 m and 200x200 m. The results for the three Kalman filter tracks are summarised in Table I.

For all resolutions, the track with the largest spatial overlap with the GPS-track is the one based on data from electric sensors only, followed by the fused track. The latter case is displayed in Fig. 6 at a resolution of 50x50 m and in Fig. 7 at a resolution of 200x200 m.

D. Track fragmentation

Tracks may also be plagued by fragmentation, i.e. discontinuities. A fragmented track may intuitively indicate that the tracker has problems finding the true track. We have used the following parameters trying to quantify how fragmented a track is. The track has been divided into segments, where a new segment is defined to start whenever the jump between two sequential track-points is larger than 50 m.

- the fraction (measured in time) of the track with segments shorter than 30 seconds
- the fraction of the track where the segments are longer than 300 seconds
- the number of jumps larger than 50 m

The results are shown in Table II. When the Kalman filter has been applied to acoustic data only, the track is less fragmented and contains longer segments, compared with the track when it is applied to data from the electrode sensors. However, the acoustic track has more long jumps.
Fig. 7. The GPS-track (blue), and the fused track (yellow) and overlapping parts of these tracks (brown). The spatial resolution is in this case 200x200 m.

TABLE II

<table>
<thead>
<tr>
<th>Track Fragmentation</th>
<th>Acoustic</th>
<th>Electric field</th>
<th>Fused</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraction short tracks (&lt; 30 sec)</td>
<td>0.56</td>
<td>0.67</td>
<td>0.5</td>
</tr>
<tr>
<td>Fraction long tracks (&gt; 300 sec)</td>
<td>0.44</td>
<td>0.16</td>
<td>0.38</td>
</tr>
<tr>
<td>Jumps &gt; 14 m</td>
<td>8</td>
<td>5</td>
<td>7</td>
</tr>
</tbody>
</table>

and the electric field tracks are very different, and the fused track has actually more long jumps and a smaller fraction of long segments than the best individual track. However, the fused track is less fragmented than the individual tracks.

E. SNR

Fusion has the potential of increasing the tracking performance, but as is commonly known, if the performance of one of the sensor systems is significantly worse than the others, it may degrade the fused track performance [13]. This general conclusion has been verified in this work. Thus, it is essential for any fusion scheme to have a quality estimate of each sensor at all times, so that the data may be rejected in case of low credibility.

One of the most straight-forward indicators of how the information in a sensor should be valued is the signal-to-noise ratio (SNR), since a large signal indicates that the source is close to the sensor. In many cases the source localisation algorithms will be more accurate for large SNR.

In Fig. 8 the beamspace SNR in the acoustic array is displayed. The time interval between 1700 and 2800 s is a difficult part with low SNR regime. Especially, the range estimate has poor performance in this region.

In Fig. 9 the correlation between SNR in the electrode sensors and the tracking quality.

VIII. CONCLUSIONS

This example shows how difficult it is, even for one single trial, to give a decisive answer to the question of whether the tracking performance is improved by using data fusion. There are some conclusions that we can draw, even from this limited material:

- Fusion has the potential of increasing the tracking performance, but as is commonly known, if the performance of one of the sensor systems is significantly worse than the others, it may degrade the fused track performance [13].
- This general conclusion has been verified in this work. Thus, it is essential for any fusion scheme to have a quality estimate of each sensor at all times, so that the data may be rejected in case of low credibility.
- One of the most straight-forward indicators of how the information in a sensor should be valued is the signal-to-noise ratio (SNR), since a large signal indicates that the source is close to the sensor. In many cases the source localisation algorithms will be more accurate for large SNR.
- In Fig. 8 the beamspace SNR in the acoustic array is displayed. The time interval between 1700 and 2800 s is a difficult part with low SNR regime. Especially, the range estimate has poor performance in this region.
- Fig. 9 shows that there is a correlation between time-windows with good SNR in the electrode sensors, and smaller tracking errors. The Kalman filter track shown is the one based on the electric sensor information only. This figure also shows that there are large parts of the track where the SNR is below threshold, which means that the sensors give no information of the source position at all. For those positions, the track is thus extrapolated from the previously given data, making the performance measure questionable in these parts.

This example shows how difficult it is, even for one single trial, to give a decisive answer to the question of whether the tracking performance is improved by using data fusion. There are some conclusions that we can draw, even from this limited material:
large differences in the performance of the position estimates pose a large risk of reduced performance for the fused track
it is crucial to have reliable knowledge of the performance of each sensor system estimates at all times, so that the correct decision whether to use the system data can be made
the application will decide what should be put behind the label “good performance” and these requirements will have to be quantitatively clear in order to set thresholds and other parameters right
position estimates from one sensor system can be useful even if it does not provide information throughout the whole track

There are many questions that can be answered by Monte Carlo simulations and by analytic performance analysis, e.g. what performance will be reached by using fusion on multi-sensor systems with unequal estimate performance. However, that can be done only by some simplified assumption on what the probability density function of the measurement vector in each sensor system will look like. Reality is often more complicated and we suggest using simulations and analytic studies together with analysis of a larger sample of data in order to gain further insights into when and how fusion can and should be used for multi-sensor underwater surveillance.

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REFERENCES


