Multi-Hypothesis Tracking and Fusion Techniques for Multistatic Active Sonar Systems

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Abstract – *In multistatic sonar systems data from several sensors are fused to obtain an improved tracking result compared to systems with a single source-receiver pair. Although centralised fusion leads to a theoretical optimal fusion result, distributed fusion features considerable advantages. As less data have to be passed to a fusion node, distributed fusion requires less bandwidth to transmit data as well as less computational load to process the data compared to centralised fusion.*
In this paper a distributed fusion approach is presented without performing a track-to-track association. Fusion is done by applying an additional Multi-Hypothesis Tracker to track states filtered at the single sensor stages. The presented fusion technique is applied to two distinct multistatic sonar datasets and compared to a centralised fusion approach.

Keywords: Multistatic Active Sonar, Multi-Hypothesis Tracking, Distributed Fusion, Centralised Fusion.

1 Introduction

In Anti-Submarine Warfare (ASW) modern submarines have to be detected even at long distances. This leads to a huge surveillance area where the usage of active sonar is required. When active sonar is used, scattering of acoustic energy results from objects in the water column (e.g. schools of fish or submarines) as well as from the sea bottom and the sea surface. Thus, processing of the received acoustic data, especially in shallow waters, often leads to numerous sonar contacts resulting in a high false alarm rate. Automatic detection and tracking methods aim at distinguishing false contacts from target contacts and filtering the contacts to determine a best possible estimate of the target state, e.g., its position and velocity.
Depending on the transmitted acoustic wave the localisation accuracy of the generated sonar contacts differs. Whereas Frequency-Modulated (FM) signals provide high range resolutions, the use of Continuous Wave (CW) signals leads to an additional Doppler information of the contact that can be used advantageously in the tracking stage.
Since the target strength of a cylinder-shaped submarine is aspect dependent, geometric constellations of the target and the sensors exist where a submarine is nearly stealthy, i.e., hardly detectable in the presence of noise or in an reverberation limited environment.
To improve detection and tracking performance the usage of several sensors is advantageous where the surveillance areas of the single sensors overlap and the target is detected under different aspect angles.
Data from single sensors have to be fused advantageously to provide an improved tracking output. Different fusion strategies exist, generally distinguished between centralised and distributed fusion. Whereas centralised fusion in terms of localisation accuracy leads to a theoretically optimal filtering result [1], it suffers from significant disadvantages. One of the main drawbacks of centralised fusion is the high data rate that has to be transmitted to a fusion node where contacts from different sensors are processed to form a common

track. Within distributed fusion much less data need to be transferred as tracks have already been formed from the contacts of the single sensors by local trackers. Thus, the data that have to be transmitted to the fusion node are already filtered tracks. Conventional distributed fusion techniques perform a track-to-track fusion [2] where associated tracks have to be found before they are fused to common tracks.
In the following we present a distributed fusion technique where track fusion is performed without the need to find tracks formed by single sensors corresponding to the same target. Track fusion is realised by an additional Multi-Hypothesis Tracker (MHT) that processes track states formed at local Multi-Hypothesis Trackers. Distributed fusion results are compared to centralised fusion results by means of different tracking-output performance metrics [3]. Tracking results are generated by applying the tracking and fusion algorithms to two different datasets. The first dataset contains experimental data from the sea trial SEABAR07, conducted by the NATO Undersea Research Centre (NURC). The second dataset consists of simulated data provided by the Applied Research Laboratories of the University of Texas (ARL:UT). Both datasets include sonar data from a distributed multistatic sonar scenario with one transmitting source and two receivers, separated from the source.
The structure of this paper is as follows: in section 2 the Multi-Hypothesis tracker used for local and global tracking is presented. Section 3 describes single-sensor fusion where contacts of different waveforms are fused in a centralised manner. In section 4 the approach of distributed Multi-Hypothesis fusion is presented. Tracking results gained with the presented tracking algorithms are shown and compared in section 5. Section 6 concludes the paper.

2 MHT Algorithm

Tracking using the MHT scheme as described in [4] is done in the Cartesian plane. Thus, state vectors are defined as Cartesian vectors with information on position and velocity:

$$\mathbf{x} = (x, y, \dot{x}, \dot{y})^T. \tag{1}$$

Assuming a *Nearly Constant Velocity* model, the underlying system is linear:

$$\mathbf{x}_{k+1} = \mathbf{A} \cdot \mathbf{x}_k + \mathbf{w}_k \tag{2}$$

with the system matrix $\mathbf{A}$. $\mathbf{w}$ is a Gaussian distributed random variable modelling the process noise.
The measurement vectors $\mathbf{z}$ contain information on range r and angle φ between contact and receiver.
If the signal transmitted by the sonar sensor is a CW acoustic wave, information about the Doppler can be extracted which is proportional to the range rate $\dot{r}$.

$$\mathbf{z}^{FM} = (r, \varphi)^T, \qquad \mathbf{z}^{CW} = (r, \varphi, \dot{r})^T. \tag{3}$$

The vectors $\mathbf{z}$ are nonlinearly dependent on the state vectors $\mathbf{x}$ according to the measurement function h and distorted by additive White Gaussian noise $\mathbf{v}$.

$$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k. \tag{4}$$

For track initialisation, the FM-measurement vectors $\mathbf{z}^{FM}$ are transformed into the Cartesian plane applying an Unscented Transform [5]. CW-measurements are not used for track initialisation due to their poor spatial resolution.
To process the nonlinear measurements for updating existing hypotheses, the Unscented Kalman Filter (UKF) is used applying an Unscented Transform in the filtering step where hypotheses states are transformed to $\mathbf{x}_{trans}$ to allow for an appropriate update of the hypotheses states with the measurements.
Data association is realised by applying the MHT scheme as described in [4] where the target state is represented by several different hypotheses. New hypotheses are built by associating the contacts $\mathbf{z}^j$ to already existing hypothesis states $\mathbf{x}^i$.
For every new composed hypothesis a corresponding weight is calculated according to

$$\hat{\mathrm{w}}_{k+1}^{ij} = \begin{cases} \mathrm{w}_k^i \frac{P_d}{f_c} \mathcal{N}(\mathbf{z}^j; \mathbf{x}_{trans}^i, \mathbf{S}^{ij}) & j > 0 \\ \mathrm{w}_k^i (1 - P_d) & j = 0 \end{cases}. \tag{5}$$

The weight $\hat{\mathrm{w}}^{ij}$ represents the probability that the respective hypothesis, originated by associating contact $\mathbf{z}^j$ to hypothesis $\mathbf{x}^i$, denotes the target state. The consideration of the case $j = 0$ accounts for the fact that all contacts are false alarms. For $j > 0$ the respective contacts include false alarms as well as a target contact. P_d is the probability of detection and f_c denotes the clutter density. $\mathbf{S}$ is the innovation covariance and results from the Kalman Filter update step. To assure that the calculated weights represent probabilities, the weights $\hat{\mathrm{w}}^{ij}$ have to be normalised to w^{ij} such that

$$\sum \mathrm{w}^{ij} = 1 \tag{6}$$

holds true.
To limit the number of hypotheses, gating, pruning and merging [6] are applied to the MHT algorithm. Moreover a *max-depth-width-pruning* is used where after n sonar transmissions only those m hypotheses with the strongest weights remain in the hypotheses-tree. Furthermore, sequential track extraction [7] is included in the track management of the algorithm to confirm and delete tracks.

3 Single-Sensor Data Fusion

Tracking results presented in this paper are based on seatrial and on simulated data both in a distributed multistatic scenario. In both datasets one acoustic source S and two locally separated receivers (R1 and

R2 in the simulated ARL:UT dataset and R2 and R3 in the seatrial SEABAR07 data) were used to collect data. Two different signals, FM and CW, were transmitted by the source and their echoes were recorded by the receivers. These echoes are processed to sonar contacts $\mathbf{z}^{FM}$ and $\mathbf{z}^{CW}$ with different localisation accuracies and additional Doppler information for the CW contacts $\mathbf{z}^{CW}$ as given in (3).
To take advantage of both contact information, the contacts $\mathbf{z}^{FM}$ and $\mathbf{z}^{CW}$ need to be fused. It has been shown that the additional processing of CW contacts leads to a reduction in the number of false tracks [8]. Fusion of FM- and CW-contacts is realized within the data association scheme of the MHT following a centralised fusion idea. Both contacts $\mathbf{z}^{FM}$ and $\mathbf{z}^{CW}$ are used consecutively to update the estimated hypothesis state. Thus, the update step of the UKF is performed twice.
During the prediction step, a state estimate $\mathbf{x}_k$ dependent on the sets of measurements $\mathbf{Z}_{FM}^{k-1}$ and $\mathbf{Z}_{CW}^{k-1}$,

$$\begin{aligned} \mathbf{Z}_{FM}^{k-1} &= \{\mathbf{z}_1^{FM}, \mathbf{z}_2^{FM}, \ldots, \mathbf{z}_{k-1}^{FM}\} \\ \mathbf{Z}_{CW}^{k-1} &= \{\mathbf{z}_1^{CW}, \mathbf{z}_2^{CW}, \ldots, \mathbf{z}_{k-1}^{CW}\}, \end{aligned} \tag{7}$$

is obtained using (2). $\mathbf{Z}_{FM}^{k-1}$ and $\mathbf{Z}_{CW}^{k-1}$ denote all measurements that have been processed until time $k-1$. Within the following update steps the measurements $\mathbf{z}_k^{FM}$ and $\mathbf{z}_k^{CW}$ are processed and obtain an estimated state dependent on $\mathbf{Z}_{FM}^{k}$ and $\mathbf{Z}_{CW}^{k}$, respectively. The fusion of FM and CW contacts of one source-receiver pair is illustrated in Figure 1.

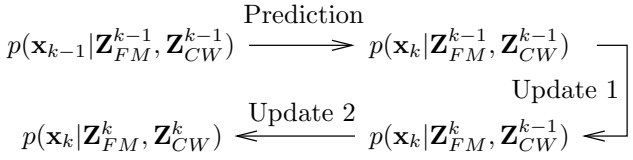


Figure 1: Scheme of fusion of different sonar signal types within one source-receiver pair.

4 Multi-Sensor Data Fusion

In both fusion methods applied to the two datasets, FM and CW contacts of the single sensors are fused such as described in section 3. Thus, in the following, contacts of one source-receiver pair fused as shown in Figure 1 are denoted simply as $\mathbf{z}_k$.

4.1 Centralised Fusion

Applying centralised data fusion within the presented Multi-Hypothesis Tracking scheme with several source-receiver pairs follows general centralised fusion architectures [9]. Sonar contacts $\mathbf{z}_k^{Ri},\ i \in \{1,2\}$ from the receivers R_i are passed consecutively to a common tracking stage, the fusion node, where tracking is performed as described in section 2. The difference of centralised multi-sensor fusion to centralised single-sensor fusion (see section 3) is the application of hypothesis reduction methods as gating, pruning and merging [6] after the processing of contacts from one source-receiver pair.
The block diagram of the centralised multisensor fusion is depicted in Figure 2.

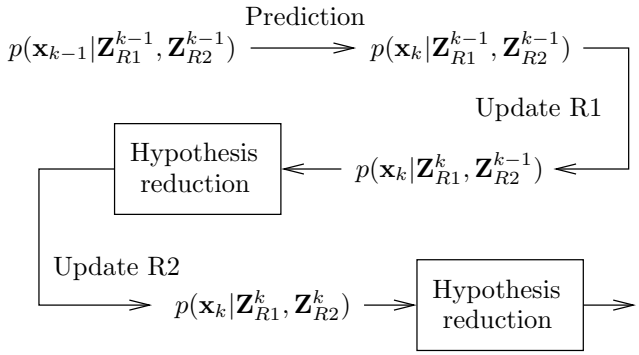


Figure 2: Scheme of centralised multi-sensor data fusion in the MHT scheme.

Without the hypothesis-reduction step following *Update R1* and *Update R2* the centralised fusion approach would be optimal [1]. Furthermore the order of processing contacts from the single sensors would not influence the tracking result. But due to processing-load restrictions a reduction in the number of hypotheses is essential.

4.2 Distributed Multi-Hypothesis Fusion

Although centralised multi-sensor data fusion is optimal in a theoretical sense, the need for distributed fusion techniques is present, for example due to limited bandwidth of the communication channel available between sensors and the fusion node. Additionally, distributed tracking is more robust against missing of contacts in single source-receiver pairs. As long as at least one local tracker provides a target track, the respective target is present at the global tracker's output.
In distributed tracking, contacts are processed at the single local tracking stages and only track states are communicated to a global tracker where filtered track data are fused.
As local tracking is done using an MHT scheme, each track state $\mathbf{x}_k^i$ is represented by a set of hypotheses with corresponding weights w^i, calculated according to (5) and (6) and representing the probability that the respective hypothesis represents the real target state. Those weighted target states of all locally extracted

tracks by all existing source-receiver pairs are passed to the global tracker where an additional MHT processes the states to fused track states $\mathbf{y}_k$.
Figure 3 shows the block-diagram of the distributed Multi-Hypothesis fusion approach exemplary for two local trackers processing contacts of receiver R1 and receiver R2, respectively. This can easily be expanded allowing additional receivers.

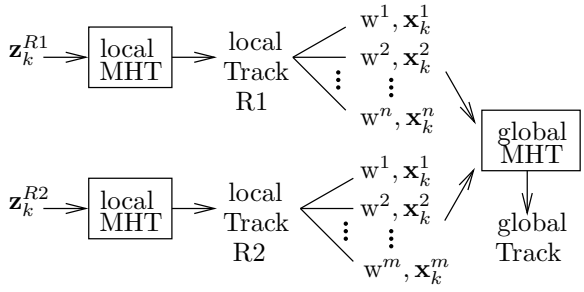


Figure 3: Scheme of distributed Multi-Hypothesis fusion exemplary for two local tracks forming one global track.

Fused tracks $\mathbf{y}_k$ are initialised by local state hypotheses $\mathbf{x}_k^i$ that could not be assigned to already existing fused tracks.
Local track state hypotheses $\mathbf{x}_k^i$ are processed as new contacts to update already existing hypotheses of the fused track states $\mathbf{y}_k$ that contain information on position and velocity similar to (1). Estimation errors $\mathbf{P}_k^i$ of track state hypotheses $\mathbf{x}_k^i$ are processed as measurement errors and are assumed to be mutually statistically independent. Thus, filtering of the hypotheses states is done by Kalman Filtering.
The corresponding measurement function h in the measurement equation (4) is now linear and can be expressed in matrix notation:

$$\mathbf{x}_k = \mathbf{H} \cdot \mathbf{y}_k + \mathbf{v}_k. \tag{8}$$

where $\mathbf{H}$ in this case denotes the identity matrix.
As track fusion is performed by applying MHT (see section 2) to track states, the fused tracks consist of hypotheses as well. For calculating the hypothesis weights a_{k+1}^{ij} of the fused track, composed of associating local state with corresponding weight $(\mathbf{x}_k^j, \mathrm{w}_k^j)$ to hypothesis $(\mathbf{y}_k^i, \mathrm{a}_k^i)$, (5) is slightly changed, in order to account for the linear measurement function and for the weights w_k^j of the local track states to:

$$\hat{\mathrm{a}}_{k+1}^{ij} = \begin{cases} \mathrm{w}_k^j \mathrm{a}_k^i \frac{P_d'}{f_c'} \mathcal{N}(\mathbf{x}^j; \mathbf{y}^i, \mathbf{S}^{ij}) & j > 0 \\ \mathrm{w}_k^j \mathrm{a}_k^i (1 - P_d) & j = 0 \end{cases} \tag{9}$$

By applying (6) the weights a_{k+1}^{ij} are normalised to represent probabilities.
The clutter density f_c' for distributed Multi-Hypothesis fusion is set smaller than f_c for single-sensor MHT because false alarms are rejected during local MHT. In contrast, the probability of detection P_d' increases for distributed Multi-Hypothesis fusion compared to P_d in local MHT.
Methods of hypotheses reduction are adapted from the MHT at local level.

5 Tracking Results

The different fusion methods have been applied to two different datasets. Tracking results are obtained with varied settings of input parameters and are analysed in terms of tracking performance metrics [3].
The ARL:UT data form a dataset where two modelled targets were injected into real seadata. The SEABAR07 dataset contains seatrial data gathered in a sonar sea experiment with one target present. In both datasets the sonar sensors used are buoy systems with a fixed source and two separate receivers operating bistatically.

5.1 SEABAR07 Run A01

In 2007, NURC conducted the seatrial SEABAR07. The geometry of run A01 which supplies the data for tracking analysis in this paper is shown in Figure 4. Two receivers, receiver R2 and receiver R3, were functional during the run. As receiver R1 was only working for a short period of time its data are not taken into account for any analysis. The position of the source S denotes the origin of the tracking coordinate plane. The true target trajectory is shown in magenta.
The run consists of 90 sonar transmissions, named pings, with an interping time of 60 seconds. During every ping a signal train consisting of an FM- and a CW- acoustic wave was transmitted.

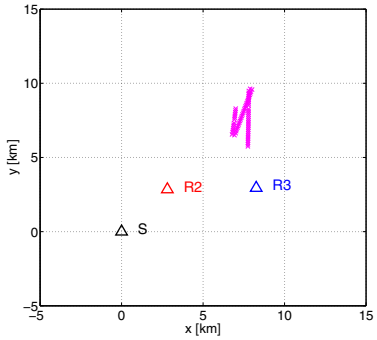


Figure 4: Run geometry of SEABAR07 run A01.

The initial set of key input tracking parameters is chosen to be:

- Maneuverability index for local and central tracker: $q = 0.01\mathrm{m}^2\mathrm{s}^{-3}$.

- Maneuverability index for distributed tracker: $q_{dist} = 0.05\mathrm{m}^2\mathrm{s}^{-3}$.
- Number of hypotheses processed by distributed fusion: $\mathrm{n}_{hypo} = 3$.

The maneuverability index q_{dist} has been chosen to be higher than q, the maneuverability index for the local as well as for the global centralised tracker, to account for the fact that local track states have already been filtered once. Filtered states, used as measurements for the global tracker, should have relatively more impact on the global filtering result than the global predicted state. Thus, the Kalman Gain factor is set respectively. The parameter n_{hypo} determines the n_{hypo} strongest hypotheses within each locally extracted track that is passed to the global fusion stage for distributed Multi-Hypothesis fusion.

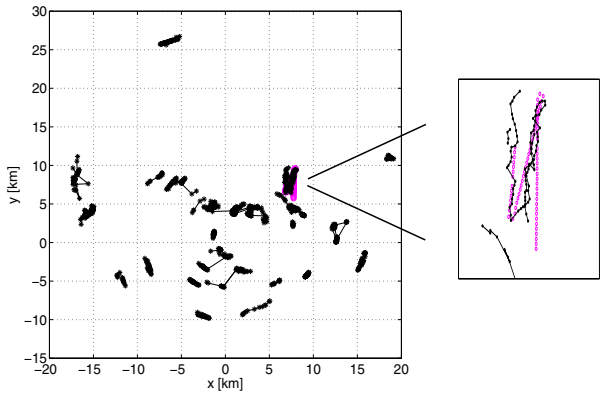


Figure 5: Tracking result of SEABAR07 A01 applying distributed Multi-Hypothesis track fusion.

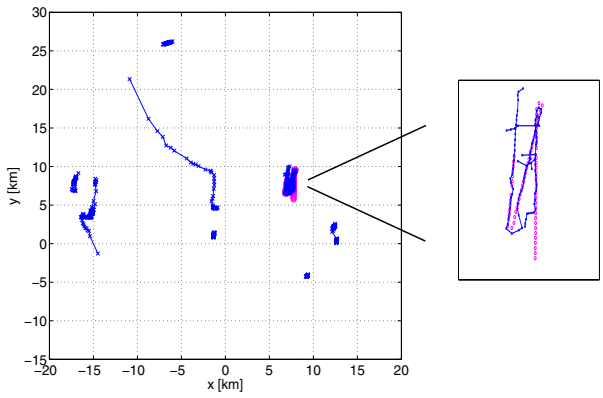


Figure 6: Centralised fusion tracking result of SEABAR07 A01 applying the centralised fusion approach.

Table 1: Tracking performance metrics for the initial key input parameter set.

	Fusion Approach	
	Distributed	Centralised
TPD	0.92	0.92
TFAR	0.92	0.13
TLE [m]	275.86	161.53
LAT [pings]	6	6
FRAG	0	0
ER	0.0065	0.0302

Tracking results obtained by applying distributed Multi-Hypothesis fusion as well as centralised fusion are shown in Figure 5 and Figure 6, respectively, where all tracks extracted during the run are shown.
From Figure 5 and Figure 6 it can be seen that distributed as well as centralised fusion extracts the true target trajectory correctly. Moreover it can be seen that applying the distributed fusion approach leads to more extracted tracks than applying centralised fusion. Table 1 summarises the tracking result by quantifying it by several tracking performance metrics [3].
As can be seen from Table 1, the track probability of detection (TPD), the ratio of the time the target is tracked to the time the target is present, is equal for both fusion approaches due to the same latency (LAT), the number of pings needed to extract the track. As more tracks are extracted when tracks are fused applying the distributed Multi-Hypothesis fusion, the track false-alarm rate (TFAR), is higher than in centralised fusion. In general, TFAR is determined pessimistically as there are five known fixed clutter points in the area of surveillance. Regarding the track localisation error (TLE), better results are obtained through centralised fusion as TLE is considerably smaller in the case of centralised fusion. In both fusion approaches the true target track is not fragmented, thus, track fragmentation (FRAG) is zero. The execution rate (ER), the ratio of processing time to run duration in centralised fusion exceeds by far ER in distributed fusion.

5.2 ARL:UT

In the ARL:UT sonar dataset two simulated targets were injected into real experimental sonar data [10], [11] which as the SEABAR07 data, have been collected by a distributed buoy sonar system. The geometry of ARL:UT data is shown in Figure 7 where the position of the source S denotes the origin of the coordinate plane. Two receivers R1 and R2 have been deployed which record the acoustic data sent every 120 seconds during 60 sonar transmissions.
The targets feature two different velocities. Target 1 is a slowly moving target travelling from east to west with a speed of approximately 2 knots, the fast mov-

ing target 2 is travelling from south-west to north-east with a speed of approximately 10 knots. Target 2 is in the blanking region of receiver R1 for a certain period during the run.

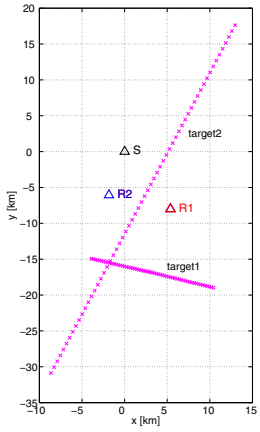
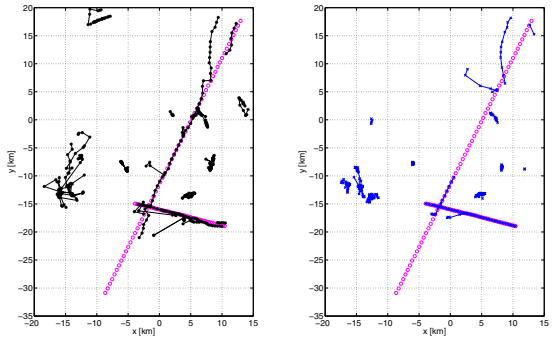


Figure 7: Geometry of ARL:UT dataset.



(a) (b)

Figure 8: Tracking results of ARL:UT. Results obtained by applying the distributed Multi-Hypothesis Fusion approach are shown in black asterisks in (a), the centralised fusion tracking result is shown in blue crosses in (b).

Applying the distributed and centralised fusion approach with the standard key input parameter set given in the previous subsection to the ARL:UT data, tracking results as shown in Figure 8(a) and Figure 8(b) are obtained. Target 1 is tracked without any fragmentation throughout the run in both fusion approaches. As target 2 doesn't form any contacts in receiver R1 within a certain period during the run, the centralised fused target track for target 2 is fragmented (see Figure 8(b)). The distributed Multi-Hypothesis fusion approach is able to track target 2 without any fragmentation as it is more robust against missing target contacts in one receiver.

Table 2: Tracking performance metrics for the initial key input parameter set.

	Fusion Approach	
	Distributed	Centralised
TPD [slow/fast]	0.92/0.77	0.95/0.38
TFAR	0.63	0.4
TLE[slow/fast]	293.79/814.03	32.11/1525.6
LAT [slow/fast]	3/12	2/13
FRAG[slow/fast]	0/0	0/1
ER	0.0014	0.0146

Table 2 summarises the tracking results obtained by the two different fusion approaches separately for the slowly moving target 1 and the fast moving target 2. Both fusion approaches yield higher quality tracks for the slowly moving target considering TPD, TLE and LAT. Target tracks obtained by the centralised tracker offer a higher track localisation accuracy. Especially for the slowly moving target the TLE of the distributed fused track is much higher than TLE of the centralised fused track. Due to the fragmentation of the fast target track in the centralised fusion approach a meaningful comparison of the single TLE cannot be made. The differences in the ER are significant. The distributed fusion approach needs much less computational load than the centralised fusion approach does.
To avoid track fragmentation for target 2, a modelling of the probability of detection P_d should be performed. As target 2 travels between source S and receiver R1 it cannot be detected during a certain period of time during the run. This information has to be used by the tracker such that contacts from receiver R1 are not expected during that period and track fragmentation is avoided.

5.3 Parameter Analysis

To analyse the influence of the depicted key input parameters, tracking results are obtained with modified parameter settings.
Varying the parameter n_{hypo} has only an impact on the distributed fusion tracking results, especially the localisation accuracy is influenced.

Table 3: Tracking performance metrics for $n_{hypo} = 2$.

	TLE [m]
SEABAR	371.49
ARL:UT slow	303.32
ARL:UT fast	827.85

Table 3 lists track localisation errors resulting by setting the parameter $n_{hypo} = 2$. A decrease of the number of hypotheses of the locally extracted tracks results in a loss of track localisation accuracy. In target tracks of both datasets TLE increases. Especially for the maneuvering target in the SEABAR07 data the difference is obvious. In this case TLE increases by approximately 100m.
The difference in track localisation accuracy for the fast and the slow target track in ARL:UT data is not as obvious as in SEABAR07 data. But again TLE increases with a decreased number $n_{hypo} = 2$.
Setting the parameter $q_{dist} = q = 0.01$ hardly influences any performance parameter apart from TLE. As expected, the track localisation accuracy for the maneuvering target in SEABAR07 data decreases. Furthermore, track fragmentation appears. For the non-maneuvering targets in the ARL:UT dataset that follow the assumptions on the target dynamics set as a *Nearly Constant Velocity* (NCV) model, a reduction of the process noise level by a decrease of q_{dist} influences the track localisation accuracy positively. The TLE decreases for both targets.

Table 4: Tracking performance metrics for $q_{dist} = 0.01$.

	TLE [m]	FRAG
SEABAR	297.13	1
ARL:UT slow	268.52	0
ARL:UT fast	794.09	0

Table 4 quantifies the influence of a decreased process noise level with $q_{dist} = 0.01$. From the analysis of the influence of the process noise it can be concluded that setting the process noise appropriately to the respective target dynamics has a crucial influence on the tracking result. Maneuvering targets are tracked more accurately with a higher level of process noise, for non-maneuvering targets the process noise should be chosen to be small when choosing NCV as assumed target dynamics.
Changing the input parameter q, the maneuverability index for the local and the centralised tracker, influences the tracking result in centralised fusion directly and in distributed fusion by a change of the hypothesis states passed to the global tracking stage. To analyse this influence, the parameter q has been set to $q = 0.05$ and tracking results are obtained applying both fusion approaches.
The localisation accuracy of the maneuvering target of SEABAR07 should increase by an increased process noise level as a maneuvering target's dynamics differs from the assumed dynamics using a NCV model.
From Table 5, that summarises the tracking results regarding the track localisation accuracy in terms of the track localisation error, it can be seen that for the centralised fusion approach, the TLE in fact decreases with an increased level of process noise. For the distributed fused track, although track localisation accuracy increases for the locally extracted tracks by increasing q, the TLE increases contrary to expectations. This happens because as the target performs the loop, the global track is formed by states of that certain target track that has a relatively high TLE at that time but is still more suitable to the global tracker at these certain points of time.

Table 5: Tracking performance metrics for $q = 0.05$.

	TLE [m]
SEABAR distributed	327.27
SEABAR centralised	155.65
ARL:UT slow distributed	291.31
ARL:UT slow centralised	32.74
ARL:UT fast distributed	401.93
ARL:UT fast centralised	628.46

Regarding the tracking results obtained by applying the algorithm with setting $q = 0.05$, to the ARL:UT dataset, the increased level of process noise hardly influences the TLE of the slowly moving target in both fusion approaches (compare Table 5 and Table 2). For the fast moving target, in the centralised as well as in the distributed fusion approach, the target track is more accurate. In Figure 8(a) it is shown that the track localisation accuracy is poor during the last part of the run for $q = 0.01$. Setting $q = 0.05$ leads to a global tracking result where the global track is formed by states of a local track that follows the true trajectory more precisely during that part of the run.
The centralised fused track follows the true target trajectory in the last part of the run more precisely as well than it is shown in Figure 8(b) for the standard key input parameters. Due to the fragmentation of the centralised fused track, a decrease of TLE during the last part of the track has great influence on the overall TLE of that track as it is shown in Table 5.
The presented results show that the levels of process noise that have to be set in the different fusion approaches have a noticeably impact on the tracking performance and, thus, should be chosen carefully.

6 Conclusions

The distributed Multi-Hypothesis track fusion approach as presented in this paper is suitable for automatic detection and tracking in a multistatic active sonar environment. Different from other distributed track fusion methods no track-to track association has to be performed, but tracks are fused using an additional MHT.
A comparison of tracking results obtained by the dis-

tributed Multi-Hypothesis fusion with a centralised fusion approach shows that although centralised fusion in general yields higher track localisation accuracies, distributed fusion has important advantages. The execution rates needed to process the multistatic sonar data centralised are many times higher than processing data in a distributed way. Moreover, whereas track fragmentation appears in centralised fusion, the distributed Multi-Hypothesis fusion tracks the target continuously as the presented approach is robust against target loss in one of the local trackers. Modelling the P_d of the single receivers appropriately is assumed to avoid track fragmentation in centralised fusion.
In our future work, the fusion approaches will be applied to further datasets to analyse the influence of single parameters in more detail. The analysis done in this paper has indicated that a special focus should be set on the level of process noise. An adaptive setting of the maneuverability index is assumed to increase tracking performance.

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