Maneuver-Adaptive Multi-Hypothesis Tracking for Active Sonar Systems

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Abstract: In undersea surveillance, active sonar systems are commonly used to detect submarines. These sonar systems allow high detection ranges, but the interaction of sound with the sea bottom may lead to a high number of false alarms as well, especially in shallow-water environments. Therefore, automatic detection and tracking procedures are needed to provide helpful assistance to sonar operators. The Multi-Hypothesis Tracking approach presented in this paper is one of these procedures. It is based on nonlinear Kalman Filtering.
In Kalman Filtering the assumption on underlying target dynamics is essential and has considerable impact on the overall tracking performance. As targets usually maneuver, their dynamics are varying and hidden. To include variable target dynamics, a Multi-Hypothesis tracking algorithm is adapted to consider target maneuvers by estimating and adjusting the process-noise level in the Kalman Filter equations. The level of process noise is determined for every track hypothesis individually based on the estimated velocities of the target. The impact on the tracking result is shown by applying the presented approach to different multistatic sonar datasets and comparing it to results gained by tracking with one global level of process noise. Tracking results are quantified by several tracking-performance metrics.

1 Introduction

Active sonar systems are used in Anti-Submarine Warfare (ASW) to detect submarines. Sonar contacts may include a high number of false alarms mainly due to the interaction of sound with the sea bottom and the sea surface, especially in shallow-water environments. To provide helpful assistance to sonar operators, automatic detection and tracking techniques are applied. Data association in the presented tracking approach is realised by Multi-Hypothesis Tracking (MHT) where a single track is represented by a set of weighted track hypotheses with the weight denoting the probability that the respective hypothesis is the true target track. The estimation of a target's state within the single hypotheses is realised by applying the Unscented Kalman Filter (UKF) [JU04]. In Kalman Filtering the assumptions on the underlying target dynamics are essential. In many tracking approaches the target's dynamics are modelled as a target travelling with a constant velocity, known as the Nearly Constant Velocity (NCV) model. Deviations of the target's behaviour from this assumption are modelled as process noise, usually set a priori and fixed. But since targets usually change their dynamic behaviour regularly, a fixed process noise does not lead to optimal tracking results. In this paper a method is proposed to estimate and adapt the level of process noise. The determination of the level of process noise is based on the estimated velocities of the track-state hypotheses. To show the impact of an adaptively chosen level of process noise the algorithm is applied to different multistatic datasets with maneuvering as well as non-maneuvering targets. If a sonar system operates in a multistatic geometry, received data can be fused appropriately to improve tracking performance. In this case a centralised fusion strategy is applied [SSH10].

2 MHT Algorithm

Tracking using the MHT scheme as described in [KKU06] is done in the Cartesian plane. Thus, state vectors $\mathbf{x}$ are defined as Cartesian vectors with information on position and velocity. Assuming a linear dependency of the subsequent states, the underlying system can be described in matrix notation:

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

with the system matrix $\mathbf{A}$, $\mathbf{w}$ is a Gaussian distributed random variable modelling the process noise (compare section 3). Sonar contacts $\mathbf{z}$ which are processed by the MHT contain information on range r, angle φ between contact and receiver and, if a Doppler can be extracted, the range rate $\dot{r}$. 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 $\mathbf{v}$. To process the nonlinear measurements for updating existing hypotheses, the UKF is used applying an Unscented Transform [JU04] in the filtering step where hypotheses states are transformed to allow for an appropriate update of the hypotheses states. To limit the number of hypotheses, gating, pruning and merging [BP99] are applied to the MHT algorithm. Furthermore, sequential track extraction [vK98] is included in the track management of the algorithm to confirm and delete tracks.

3 Dynamic Model and Process Noise

In Kalman filtering, sequential estimation of the conditional probability density function $p(\mathbf{x}_k|\mathbf{Z}^k)$ of a state $\mathbf{x}_k$ at the discrete point of time k is performed with $\mathbf{Z}^k = \{\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_k\}$ denoting all measurements processed until time k. The prediction step utilises the assumptions on target dynamics specified by the matrix $\mathbf{A}$ in (1) for linear dynamics. The random variable $\mathbf{w}_k$ models the uncertainties of the assumed target dynamics as a Gaussian distributed random variable with zero-mean and covariance matrix

$$\mathbf{Q}_k = E[\mathbf{w}_k \cdot \mathbf{w}_k^T] \tag{2}$$

with E denoting the expectation operator. The predicted state $(\hat{\mathbf{x}}_k^-, \hat{\mathbf{P}}_k^-)$ is determined by the previous state $(\hat{\mathbf{x}}_{k-1}, \hat{\mathbf{P}}_{k-1})$ and the matrices $\mathbf{A}$ and $\mathbf{Q}$, specified by the system model. Due to relatively low measurement rates used in active sonar (e.g. sampling period $T = 60$s) an appropriate estimate of the acceleration is impossible. Thus, a dynamic model that does not include any acceleration in the target state should be chosen [BSB00] and an appropriate choice for the motion model in submarine tracking is a NCV model. The covariance matrix $\mathbf{Q}$ of the discretised process noise modelling accelerations is

$$\mathbf{Q} = \begin{bmatrix} T^3/3 & 0 & T^2/2 & 0 \\ 0 & T^3/3 & 0 & T^2/2 \\ T^2/2 & 0 & T & 0 \\ 0 & T^2/2 & 0 & T \end{bmatrix} \cdot q, \tag{3}$$

with q denoting the continuous-time process noise intensity, which is derived by the auto-correlation function [BSRLK01]

$$E[\tilde{v}(t)\tilde{v}(t-\tau)] = q \cdot \delta_0(\tau). \tag{4}$$

As a guideline for the choice of the intensity of the process noise, q should be set such that changes of the target's velocity during one sampling period T are of the order

$$\Delta v_T \simeq \sqrt{qT} \Leftrightarrow q \simeq \frac{\Delta v_T^2}{T}. \tag{5}$$

These guidelines are now used for a maneuver-adaptive tracking approach. The target states $\mathbf{x}$ include velocities estimated during Kalman Filter processing. Since velocities are estimated in $x-$ and $y-$direction of the Cartesian coordinate plane separately, a level of process noise for each of these directions can be determined individually. The levels of process noise $q_x(k,N)$ and $q_y(k,N)$ are determined applying (5) as an average using the last N estimated velocities with their corresponding time stamps t based on [Sch09]

$$q_x(k,N) = \sum_{n=1}^{N} \frac{(\dot{x}_{k-(n-1)} - \dot{x}_{k-n})^2}{t_{k-(n-1)} - t_{k-n}} \cdot \frac{1}{N}, \tag{6}$$

adequately for $q_y(k,N)$.

In MHT, every track consists of several track hypotheses including the current Cartesian velocities. Thus, (6) is applied to every track hypothesis to estimate an individual level of process noise. Only tracks that have already been confirmed are subject to an adaptive estimation of process noise. Due to small association gates, a low level of process noise might lead to a missed association of a contact to a true track, especially when target maneuvers appear after a period of non-maneuvering. The MHT prevents gates from becoming such small that missed association due to starting maneuvers occur. If no contact can be associated to an already extracted track, its level of process noise is significantly increased.

4 Tracking Results

To show the influence of the presented method to adjust the level of process noise adaptively, it has been included in the MHT-tracking algorithm and applied to different datasets. Results are expressed by several tracking-performance metrics [CdT06] and compared to metrics obtained by processing the data with a fixed level of process noise. In both datasets the sonar sensors used are buoy systems with a fixed source and two separate receivers operating bistatically leading to a multistatic geometry. The multistatic processing of the data requires an appropriate data fusion. For this paper a centralised fusion strategy as presented in [SSH10] is performed.

4.1 ARL:UT

In the ARL:UT sonar dataset two simulated targets were injected into real experimental sonar data [CCL06], [LC07]. The targets feature two different, but constant velocities. Target 1 is a slowly moving target (approximately 2 knots) and target 2 is a faster moving target (approximately 10 knots). Table 1 summarises the tracking results separately for target 1 and target 2. The value for a fixed process noise level for further analysis is set to $q = q_x = q_y = 0.01\text{m}^2/\text{s}^{-3}$. If no contact can be associated to an already extracted track when applying an adaptive level of process noise, q_x and q_y are increased to $q_x = q_y = 0.1\,\text{m}^2/\text{s}^{-3}$. The value N, determining the number of preceding track hypothesis states used to calculate the q_x and q_y according to (6) is set to $N = 1$ in a first step. Both approaches yield higher quality tracks for the slowly moving target. The track probability of detection (TPD), the ratio of the time the target is tracked to the time the target is present, is higher in case of slowly moving targets. The same holds true for the track localisation error (TLE) and the latency (LAT), the number of pings needed to extract the track . Moreover, it is obvious, that for the ARL:UT data, an adaptively estimated level of process noise does not influence the tracking performance significantly. The track false alarm rate (TFAR) only increases slightly. The TLE is hardly changed for both targets. This is due to the fact that the dynamics of the target trajectories follow the assumption of targets travelling with a constant velocity precisely. In this case, filtered target states are close to optimum and cannot be improved by an adaptation of the process noise.

Table 1: Tracking performance metrics for a fixed and an adaptive level of process noise applied to the ARL:UT data.

	Process Noise q	
	Fixed	Adaptive
TPD [slow/fast]	0.95/0.77	0.95/0.77
TFAR	0.38	0.43
TLE[slow/fast]	35.10/105.54	35.13/104.79
LAT [slow/fast]	2/13	2/13

4.2 SEABAR07 Run A01

From the SEABAR07 trial, conducted by the NATO Undersea Research Center in 2007, run A01 supplies the data for this paper. During this run the target is performing maneuvers.
The positive influence of an adaptive determination of process noise on the localisation accuracy can be read from table 2, which lists certain tracking-performance metrics for comparison. The TPD is equal for both approaches. TFAR is slightly increased for the adaptive approach. Applying an adaptively estimated level of process noise influences the track localisation accuracy positively. The TLE decreases considerably.

Table 2: Tracking performance metrics for a fixed and an adaptive level of process noise applied to the SEABAR'07 data.

	Process Noise q	
	Fixed	Adaptive
TPD	0.93	0.93
TFAR	0.29	0.30
TLE [m]	155.49	110.44
LAT [pings]	5	5

5 Conclusions and Outlook

The presented approach of including an adaptively estimated level of process noise within a Nearly Constant Velocity model has potential to increase the performance of a Multi-Hypothesis Tracking algorithm. The level of process noise is determined individually for every track hypothesis by using past and current filtered target states from which a deviation in the estimated velocities is calculated. Based on the deviation, the level of process noise is derived.
Tracking results obtained for two different datasets show that results for targets which are travelling with a constant velocity are hardly influenced because there targets already follow the Nearly Constant Velocity model precisely. But besides, maneuvering targets are tracked with a higher localisation accuracy. Thus, the presented approach effects the algorithm in such a way that localisation accuracy can be improved. A higher localisation accuracy is achieved nearly without influencing the tracking quality considering further performance metrics.
In this paper the level of process noise has been determined using changes in the estimated velocities directly. A further development could be to model the level of process noise as a target state and include it in the Kalman Filtering algorithm. Thus, estimation errors would be considered and past information would be included in the estimation process. To apply the presented approach to further datasets, including moving transmitters and receivers (e.g. Low Frequency Active Sonar (LFAS) systems), and analyse the influence of certain parameters within the tracking algorithm in more detail is subject to future work.

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