Letter

A Feature-Aided Multiple Model Algorithm for Maneuvering Target Tracking

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Dear Editor,

This letter deals with the tracking problem for non-cooperative maneuvering targets based on the underwater sensor networks. Considering the acoustic intensity feature of underwater targets, a feature-aided multi-model tracking method for maneuvering targets is proposed. Specifically, at each node, direction of arrival (DOA) estimation and model selection is performed, and information is fused in the central node where multi-model-based tracking is realized to closely monitor the target. Simulation results show that our proposed method is capable of rapidly responding to model switching and significantly improve the accuracy of maneuvering target tracking.

The underwater non-cooperative maneuvering target is one of the principal factors that impact marine security. In underwater acoustic sensor networks (UASNs), passive detection nodes are typically used for long-term detection and tracking of targets due to the challenge of recharging and replacing them. At a passive node, vector hydrophones, hydrophone arrays and other devices collect the acoustic signals exposed by targets in the ocean. The direction and some feature information of the target are picked out by signal processing methods, such as compressed sensing (CS) [1], [2], multiple signal classification (MUSIC) [3] and estimation with the sparse representation [4]. Based on the DOA estimation on existing nodes, the measurement of the target position can be obtained by multi-node fusion [5]. However, the localization is inaccurate, and it is necessary to employ appropriate filters to mitigate errors when tracking a moving target.

Estimating the correct motion model of the target is a crucial issue in the commonly used Kalman filter. However, because of the uncertainties and variations in the behavior of the maneuvering targets, divergence often occurs. To follow the changes in target state, multiple model (MM) based methods are frequently utilized [6], [7]. In particular, the interacting multiple model (IMM) algorithm is regarded as one of the most effective methods. It involves a set of multiple models that describe the dynamic system and it is assumed that the jumps between different models are subject to a Markov process [8]. The weighted probabilities of different motion models are regulated by system evolution and interaction between models [9]. The designation of the Markov transition probability matrix in the IMM are fixed, which relies on sufficient prior knowledge and may be irrational sometimes. To deal with this problem, many adaptive IMM algorithms were proposed to achieve better treatment [10], [11]. Since the adjustment of the matrix is driven by error, it takes some time to respond to the model transition which will cause obvious delay, and the adjustment is not effective and stable enough.

In addition, the sound exposed by targets in water was studied and summarized [12]. Based on underwater acoustics research, models about sound propagation and interfering phenomena were also proposed [13]. Some institutions have successfully collected underwater acoustic sounds at the harbor or in the ocean, which are usually generated by moving underwater target. These studies have inspired us to improve target tracking performance with signal features.

Considering the relationship between acoustic signals and target movement, we propose a feature-aided multi-node (FAMM) maneuvering target tracking method. Specifically, we investigate the intensity of acoustic signals exposed by underwater targets. In the UWSNs, a switching strategy is proposed to select a possible tracking model at each passive node. Multiple nodes are integrated to track an underwater maneuvering target and multiple models are fused driven by both tracking error and the target feature. The method is designed to track specific types of underwater targets with some degree of maneuverability. Information from multiple nodes are fused efficiently. The model selection is more correct and the tracking accuracy is improved as a result.

Problem statement and basic models: In the critical oceanic region, invading non-cooperative targets, such as submarines, automatic underwater vehicles and ships, cause huge threats and require close attention. These targets exhibit some maneuverability in a 3-dimensional (3D) Cartesian coordinate, where their motion state may vary, but changes are usually infrequent and not rapid [14]. Furthermore, the speed and acceleration of these targets are relatively low and the movement patterns are not very complicated. Therefore, we employ the most commonly used models of constant velocity (CV), constant acceleration (CA) and constant turn (CT) to describe their motion. The motion state of a target at time k is denoted as

$$\boldsymbol{X}_k = \begin{bmatrix} x_k & \dot{x}_k & \ddot{x}_k & y_k & \dot{y}_k & \ddot{y}_k & z_k & \dot{z}_k & \ddot{z}_k \end{bmatrix}^T \tag{1}$$

where $\boldsymbol{p} = (x_k, y_k, z_k)$ is the position, $\boldsymbol{v} = (\dot{x}_k, \dot{y}_k, \dot{z}_k)$ is the velocity, and $\boldsymbol{a} = (\ddot{x}_k, \ddot{y}_k, \ddot{z}_k)$ is the acceleration of the target.

For a moving target, the state equation is given as $\boldsymbol{X}_k = \boldsymbol{F} \times \boldsymbol{X}_{k-1} + \boldsymbol{Q}_k$, where $\boldsymbol{F}$ is the transition matrix, which of CV, CA and CT models are shown in [15]. $\boldsymbol{Q}_k$ is the variance of movement error, subject to Gaussian distribution.

A typical USWN with M passive nodes is shown in Fig. **S1**. In each tracking period t from time $k-1$ to k, the received average signal energy is denoted as $P_m(k)$. When $P_m(k)$ is greater than the background noise intensity threshold $E_{\min}$, it is considered that a target is observed by node m. Additionally, observations at node m include the features of the frequency and direction of targets, denoted as $f_{k,m}$ and $\Theta_{k,m} = [\alpha_{k,m}, \phi_{k,m}]$, respectively. Here, α_m and ϕ_m represent the azimuth and elevation of the target, respectively.

Based on the direction observations obtained from multiple nodes, the position of a target is determined with the directly least square positioning method in the operation center. Detailed computation refers to Section 2 in [5]. Thus, the linear position measurement equation of a target in the central node is expressed as $\boldsymbol{Z}_k = \boldsymbol{H}\boldsymbol{X}_k$.

Feature-aided motion model selection: The intensity feature reflects the movement of the target, especially when the motion state changes significantly. Therefore, the signal intensity feature of underwater targets is studied and we propose a FAMM method to improve the tracking performances.

In each passive node, the motion model of the target is judged by the received signals. The intensity of the received acoustic signal is mainly influenced by two major factors: the noise generated by the target and the loss in the propagation path.

Mechanical noise and hydrodynamic noise are dominant types of

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sound exposed by underwater targets. Generated intensity P_E is primarily determined by the steady part of mechanical noise which comes from the engine operation, which can be expressed as $P_E = a+b|\boldsymbol{v}|$. The lost signal intensity from the target to the sensor is the path loss, which includes the absorption loss $P_A(R,f) = 10\log(\alpha(f))\times R$ and the spreading loss $P_S(R) = c\times 10\log(R\times 10^{-3})$, where R [km] is the distance, $\alpha(f)$ is the absorption coefficient, and the diffusion coefficient $c = 1$. Detailed explainations about these models are given in Appendix.

In this way, we obtain the following formula for the intensity of sound received by a passive node from the underwater target as

$$P_{\text{total}} = P_E - P_S - P_A + Q_c = a + b|\boldsymbol{v}| - \log R - 10\log(\alpha(f))\times R + Q_c \quad (2)$$

where Q_c is the random noise of background in the target-free case.

The average intensity $P_m(k)$ during a tracking period t is regarded as the intensity feature of a target. Fig. S2 in Appendix displays the sound collected by an actual hydrophone when a ship passes by. The variation in $P_m(k)$ can reflect the movement of the target during the tracking period of 1 s.

Based on the movement and signal feature of underwater targets, the motion of an underwater maneuvering target jump between two states: the constant motion state and the constant acceleration motion state, where the constant motion state includes CV and CT models. The details of the model switch and selection strategy are as follows:

State 1: The target is assumed to be in the CV model initially. From $k-1$ to k, the change of received sound intensity is

$$\begin{aligned}\Delta P_k &= P(k) - P(k-1)\\ &= b(v_k - v_{k-1}) + \log\left(\frac{R_{k-1}}{R_k}\right) + 10\log(\alpha(f))(R_{k-1} - R_k) + q_c \quad (3)\end{aligned}$$

where the noise $q_c = 2Q_c$. For the frequency usually below 1 kHz, the second to last term is negligible. Thus, ΔP_k is primarily related to the acceleration of the target. When the target continues to move at a constant speed, the acceleration is approximately 0 and the variation is small. ΔP_k is mainly affected by the change in distance. The maximum level of the change is defined as $P_{\max} = \left|\log\left(\frac{R_k - v_k t}{R_k}\right)\right| + q_c$, which can be estimated from the predicted state at time k.

Define Condition 1: $|\Delta P_k| < \eta_1 \times P_{\max}$. When Condition 1 is satisfied, the target is considered to maintain in CV state.

If the state of the target switch from CV to CA, the acceleration will change abruptly, and $|\Delta P_k|$ will increase significantly. At time k, the rate of change is denoted as $\ddot{P} = |\Delta P_k - \Delta P_k| \propto |a_k - a_{k-1}|$.

Thus, changes in acceleration also lead to abrupt changes in ΔP_k and $\ddot{P}$. We define Condition 2: $(|\Delta P_k| > \eta_2 \times P_{\max})\&(\ddot{P} > \eta_3 \times P_{\max})$. When Condition 2 is satisfied, the tracking model switches from CV to CA, and the state jumps to State 2.

If the motion state of the target goes from CV to CT, there is no abrupt change in acceleration, but some variation in $|\Delta P_k|$. Thus, when neither Condition 1 nor Condition 2 is satisfied, the model is transformed to CT.

State 2: The target is considered to be in the CA model.

Define Condition 3: $|\Delta P_k| > \eta_2 P_{\max}$. If Condition 3 is not satisfied, the motion state returns to State 1, and the model is returned to CV. Otherwise, State 2 will be retained and the CA model will be used.

To sum up, the state transformation and model selection diagram is shown in Fig. S3 in Appendix. In this letter, we set $\eta_1 = 1.2$, $\eta_2 = 1.8$ and $\eta_3 = 2$ for typical scenarios. Details about the selection of parameters are explained in Appendix.

Multiple nodes fusion and target tracking: In an UWSN, the state estimation of the target based on a single node is not always reliable, and the confidence levels of different nodes may vary. In the central node, the probabilities of multiple models are estimated using a combination of features and errors to improve tracking accuracy. The feature-based estimation is obtained by fusing information from multiple nodes. Specifically, the information matrix is denoted as $\boldsymbol{\Omega} = \left\{w_j^m\right\}_{j=1,2,3}^{m=1,2,\ldots,M}$, where each row represents a CV, CA, or CT model, and a column represents the node m, w_j^m is a binary variable and $w_j^m = 1$ indicates that node m believes that the target is in jth motion model. At time k, the node closer to the target will be more trusted and the confidence level of node m is defined as

$$\sigma_m = 1/\sqrt{(x_m - \hat{x})^2 + (y_m - \hat{y})^2 + (z_m - \hat{z})^2}. \quad (4)$$

Therefore, the intensity feature-based probability of a motion model is calculated by $u_{f,j}^{(C)} = \sum_{m=1}^{M} \omega_j^m \times \sigma_m$. After normalization, $u_{f,j}(k) = u_{f,j}^{(C)} / \sum_{j=1}^{3} u_{f,j}^{(C)}$.

In addition, the model probability estimated from the tracking error is u_j, and $u_j(k|k-1) = \frac{\Lambda_j(k-1)u_j(k-1)}{C(k-1)}$, where $C(k-1) = \sum_{j=1}^{3} \Lambda_j(k-1)$ $u_j(k-1)$ and $\Lambda_j(k-1)$ is the likelihood function. Initially, $u_j = \frac{1}{3}$.

Combining the estimation results from feature and error information, the model probability is calculated by $\hat{u}_{0,j}(k) = \beta_1 u_{f,j}(k) + \beta_2 u_j$ $(k|k-1)$. When the feature and the error play an equally important role in the estimation, $\beta_1 = \beta_2 = 0.5$, which can be adjusted based on the detection error in practice.

Based on the model probability, the input of the tracking filter at time k is $\hat{\boldsymbol{X}}(k-1|k-1) = \sum_{j=1}^{3} \hat{\boldsymbol{X}}_j(k-1|k-1)\hat{u}_{0,j}(k)$, where $\hat{\boldsymbol{X}}_j$ is the state estimation from filter j. Correspondingly, the covariance is $\boldsymbol{P}(k-1$ $|\, k-1) = \sum_{j=1}^{3}[\boldsymbol{P}_j(k-1\,|\,k-1) + \tilde{\boldsymbol{X}}_j(k-1\,|\,k-1)\tilde{\boldsymbol{X}}_j'(k-1\,|\,k-1)]\hat{u}_{0,j}(k)$ where $\tilde{\boldsymbol{X}}_j(k-1|k-1) = \hat{\boldsymbol{X}}_i(k-1|k-1) - \hat{\boldsymbol{X}}(k-1|k-1)$.

In each model, the tracking is carried out with the standard Kalman filter and detailed calculation refers to [16]. In the jth filter, the likelihood function is calculated by $\Lambda_j(k) = \exp\left\{-\frac{1}{2}\left[\varepsilon_j^T(k)\boldsymbol{S}_i^{-1}(k)\varepsilon_j(k)\right]\right\} / \sqrt{|2\pi \boldsymbol{S}_j(k)|}$, which reflects the deviation between measurements and predictions in each filter.

Using the tracking results from multiple filters, the weight of multiple models is once updated as $u_j(k) = \Lambda_j(k)\hat{u}_{0,j}(k)/C_0(k)$.

Finally, the output target state at time k is denoted by $\boldsymbol{X}(k) = \sum_{j=1}^{3}$ $\hat{\boldsymbol{X}}_j(k|k)u_j(k)$, which is also the input state of time $k+1$. The flow chart of the whole tracking method is shown in Fig. S4 in Appendix.

Simulation example: Monte Carlo experiments are conducted in a 3D scenario on a computer with the Microsoft Windows 10 System using the software MATLAB R2021b. When a non-cooperative target invades the ocean region, it is assumed that four nodes in the UWSN can continuously detect the target together. The positions of these nodes are (−400 m, −400 m, 0 m), (−350 m, 700 m, 10 m), (800 m, −300 m, 5 m) and (700 m, 600 m, 0 m). The motion state of the non-cooperative maneuvering target transforms among CV, CA and CT models during the period of 150 s, and the initial state of the target is (−350, 3, 0, −350, 2, 0, 80, 0, 0). In the simulation, the motion model changes every 20 seconds, and the movement error $Q = 10^{-3}$. The position, velocity, and acceleration on the x-axis of the target in an experiment are shown in Fig. 1, where grey lines represent the moment when the motion state of the target changes.

In the simulation, the detected signal frequency is 200 Hz. According to the research [17], the average errors of DOA estimations are set as 0.5 rad and the measurement variance is approximately 10 m. The turning speed of the CT model is set as 0.5 rad/s. When the target is similar to the moving destroyer, parameters a and b of the

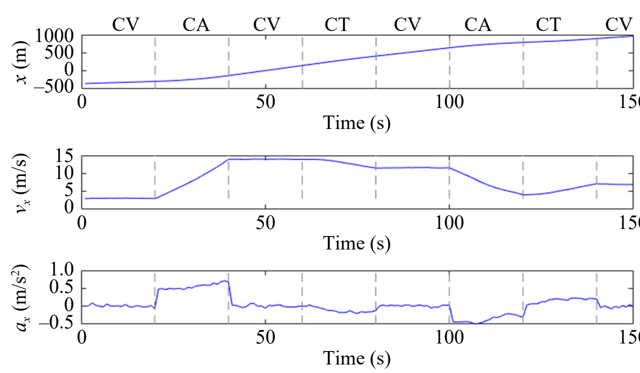

Fig. 1. Real target state on the x-axis.

intensity model are set as 80 dB and 3 dB/m/s, and $Q_c = 0.2$ [18]. The feature of the signal intensity received by a node is displayed in Fig. S5 in Appendix, from which each node estimates the possible motion model that the target may follow.

In the central node, 100 tracking experiments are conducted with different methods and the root means square error (RMSE) is used to illustrate the results. In Fig. 2, the tracking results of our proposed FAMM algorithm are compared with several algorithms: the best multi-model (BMM) [6], the original IMM [7], the adaptive IMM (AIMM) [10] and another adaptive IMM methods [11]. Specific steps of these algorithms can be found in these references.

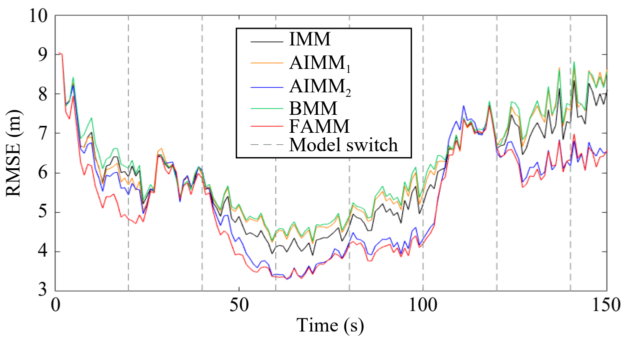

Fig. 2. RMSE of tracking with different methods.

Fig. 2 shows that our algorithm achieves the most accurate tracking results among these methods. The BMM selects only one model based on error but the model judgement is often wrong. The IMM relies on error and the state transition probability, but its Markov transition probability matrix is fixed, which requires sufficient prior information and history data of target motion. In addition, it ignores the irrationality of the transition matrix designation, which make it difficult to adapt to different targets and environments. Adaptive methods can dynamically regulate the matrix between different models. However, the first AIMM only works well for two models, but not for three models or more. The other AIMM improves the tracking accuracy effectively but still has some problems in timely model switching.

In contrast, our proposed algorithm achieves the smallest error during both stable tracking and model switching periods. To demonstrate the improvement, we list the specific percentage of error reduction compared to localization and the second AIMM algorithms in Table 1. The table shows that our filter significantly reduces positioning error, and achieves better results than the AIMM in all states, especially during the model switching process. Besides, the computation time and communication burden do not increase significantly. Other 4 methods do not consider multiple nodes with different confidence levels. In practice, the FAMM method can adjust according to the application environment and obtain better effect for target of interest.

Table 1. Comparision of Accuracy Improvement

Comparison (%)	Model switch	CV	CA	CT
With position	44.15	42.23	35.87	45.96
With AIMM$_2$	18.07	4.12	3.09	1.18

Conclusion: In this letter, we investigate the correlation between the intensity feature of underwater acoustic signals received by passive nodes and the motion of underwater targets. A feature-assisted multi-model maneuvering target tracking method is proposed based on a multi-node underwater sensor network. Feature information is used to predict the tracking model and the tracking error is combined to adjust the probability of multiple models in the center. Precise target tracking is realized in the center based on the multi-model Kalman filter. Compared to the IMM-based algorithm, our FAMM method avoids reliance on motion state transition information. Moreover, the algorithm exhibits advantages in information fusion among different nodes. Simulation results show that the proposed algorithm improves tracking accuracy in both the model transition and stable processes. In summary, the proposed FAMM is effective to track non-cooperative maneuvering target in underwater environments.

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Appendix: Supplementary material of this letter can be found in links https://doi.org/10.57760/sciencedb.10840.

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