Method for Underwater Target Tracking Based on an Interacting Multiple Model

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Abstract  According to the requirements of real-time performance and reliability in underwater maneuvering target tracking as well as clarifying motion features of the underwater target, an interacting multiple model algorithm based on fuzzy logic inference (FIMM) is proposed. Maneuvering patterns of the target are represented by model sets, including the constant velocity model (CA), the Singer model, and the nearly constant speed horizontal-turn model (HT) in FIMM technology. The simulation results show that compared to conventional IMM, the reliability and real-time performance of underwater target tracking can be improved by FIMM algorithm.

Keywords  underwater target; tracking; interacting multiple model; fuzzy logic inference

Introduction

The unmanned underwater vehicle (UUV), e.g., underwater robot, sonar, submarine, etc., can complete various underwater engineering missions such as scientific exploration, submarine searching, salvage, underwater archeology, shipwreck refloation, and so on[1]. To accomplish the aforementioned functions, one of the many difficult problems associated with the underwater vehicle (or target) is the issue of target tracking. Many tracking methods have been developed for solving the above problem, e.g., Kalman filtering, α-β-γ filtering[2], and particle filtering[3]. These algorithms can satisfy the requirements of target tracking and positioning under certain tracking precision and calculation complexities. However, these vehicles, which are affected by ocean currents and surf, are different from space probes, lighter-than-air vehicles, aerostats, and ground or sea surface vehicles. They have a slow movement velocity and weak maneuvering performance. Meanwhile, considering the requirements of reliability and real-time tracking, in this paper, the interacting multiple model (IMM) technology[4] is introduced to deal with the tracking and positioning problems of underwater vehicles. This method can be suited for the maneuvering patterns of underwater targets through fuzzy logic inference to accomplish adaptive transformation among the sub models.

1  Fuzzy logic inference-based IMM algorithm

In IMM technology[4-6], it is assumed that the plant states can be described by a finite number of models
and each model corresponds to one of the input levels of the maneuvering states. Meanwhile, only one model matches the real motion state of the underwater target at a certain moment.

The transfer matrix of the IMM model is set to $\pi = \{\pi_{ij}\}$; the initial probability of model $i$ is $\mu_i(k^{-1}/k^{-1})$, and one of the sampling periods of IMM algorithm is described by $\text{IMM} \left[ M_k, M_{k+1} \right]$, where $\text{M}_k$ is the number of model sets at time $k$.

The conventional IMM algorithm utilizes fixed model sets at all tracking times. For underwater targets, their maneuvering states can be described by a finite number of models. Usually, because underwater large vehicles have slow motion velocity and weak maneuvering capability, their motion patterns can be expressed by the conventional constant velocity model (CV), Singer model, and the nearly constant speed horizontal turn model (HT)[5].

By reason of the continuous motion of the targets, it is difficult to describe the idiographic motion pattern with the aforementioned maneuvering models. Usually, a large number of models are utilized to cover the possible maneuvering states of the target. Therefore, the covering probability is increased as the number of filter models rises, which adds to calculation workload. Meanwhile, the discrepancy among the different models results in unnecessary simultaneous interference among the models, which reduces the real-time capability of target tracking. Accordingly, the IMM filtering algorithm is combined with fuzzy logic inference in this paper, which achieves the purpose of adaptive transforming of patterns through automatically adjusting certain parameters in the model sets. Consequently, the proposed technology decreases the mismatching errors between the tracking models and the maneuvering patterns and reduces the need to introduce new motion models again.

The main steps in the fuzzy tracking algorithm in this paper are given as follows: ① Determine the prediction error and change of error; ② Fuzzificate and quantitate the prediction error and the change of error; ③ Calculate the fuzzy value according to fuzzy control rules; ④ Transform the fuzzy control value to the exact value, that is, do defuzzification[7]; ⑤ Adaptively modify the bandwidth of the system variables[8]; ⑥ Accomplish state tracking of the underwater target by IMM technology.

Step 1 Determine two input variables and one output variable of the fuzzy inference system. According to prediction error, the input variables are defined as

$$e(k) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} e_i^2(k)}$$

$$\Delta e(k) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \Delta e_i^2(k)}$$

where $k$ is the count $k$ step of the filtering process; $n$ is the number of coordinate dimensions of the error vector; $e_i$ is the difference between the measurement and the predication value of underwater targets at time $k$, and $\Delta e_i = e_i^*(k) - e_i(k-1)$.

The values of $e_{\text{max}}(k)$ and $\Delta e_{\text{max}}(k)$ change with the motion velocity of the target because the motion velocity of the target is time-varying. In order to avoid having the input variable exceeding the definition domain (e.g., being larger than 1), the input variables $e'(k)$ and $\Delta e'(k)$ are confined to the definition domain $X$ through the normalized process[9], and the domain is set to $[0 \ 1]$.

Step 2 Classify the domain defined above, and accomplish fuzzificating and quantitating of the input variables. Although the uncertainty performance of variables can be more accurately described with more fuzzy classification, this method results in a greater complication for the fuzzy control rules. Considering the special conditions of underwater vehicles, the input variables $e'(k)$ and $\Delta e'(k)$ are classified into four orders, i.e., positive big (PB), positive middle (PM), positive small (PS), and zero (ZO).

Step 3 The membership function is determined by the maneuvering characteristic of the underwater target. Because of the continuity of underwater large target motion in fluid, it is difficult for an underwater vehicle to have sudden changes in a highly dynamic flying vehicle. Accordingly, the membership function can be represented by a fuzzy distribution function with a middle value characteristic such as a rectangle distribution function, norm distribution function, trapezoid distribution function, ridge distribution function, Cauchy distribution function, and so on[7].
To analyze the problem conveniently, in this paper the trapezoid distribution function is utilized to describe the membership function illustrated in Fig. 1.

The output variable is a self-adjusting system noise variance $Q(k)$, which has a large variety range. In order to reduce the number of fuzzy classifications, and further to decrease the complexity of the fuzzy control rules, i.e., to improve the real-time performance of the algorithm, the output variable $Q(k)$ is divided by 100. Thereby, the range of the output variable is confined to [0 3]. Then the definition domain of $Q(k)$ is divided into six levels labeled in linguistic terms as extremely large positive (EP), very large positive (VP), large positive (LP), medium positive (MP), small positive (SP), and zero (ZE). The specific membership function of the output variable is defined by triangular functions shown in Fig. 2.

The boundary of the fuzzy set is defined as a left open-set (or right open-set), which can assure at least one model being available. The fuzzy rules can be defined with the input and output variables defined above. Otherwise, the fuzzy rules can be determined by field data simulation, experiential evaluation of experts\cite{8}, and modern stochastic approximation theory, such as genetic algorithm\cite{10}. In this paper, the fuzzy rules are obtained by using experiential evaluation of defense experts in reference [8].

**Step 4-5**  Fig. 3 demonstrates the kernel part of the fuzzy interacting multiple models (FIMM), where self-adjusting variable bandwidth (SAVB) is the adaptive variable bandwidth of the maneuvering target via the amplitude of system noise variance. Therefore, according to any prediction error $e'(k)$ and the error change $\Delta e'(k)$, the system noise bandwidth is adapted by fuzzy rules. Further, the gain matrix of Kalman filtering is indirectly adapted.

The system can obtain the acceleration estimation of underwater target $a(k)$ through the above fuzzy Kalman filtering, and the estimation is regarded as the input for the IMM filtering system.

**Step 6**  The precision tracking and positioning of the underwater target is accomplished by the above processes.

## 2 Experiment and analysis

Three-dimensional positions of the vehicle can be determined through azimuth angles, elevation angles, ranges, Doppler frequency shifts, and radial velocities measured by the sonar system\cite{11}. The measurement precision of Doppler frequency shift is small and a little frequency shift error can incur a large positioning error, which makes it difficult to satisfy the requirement of precision positioning. In this paper, the passive positioning method using azimuth angles (or elevation angles) and ranges is discussed in detail in the following simulation.

In voluminous time, the underwater vehicle moves at constant velocity along a constant course angle, and maintains a straight-line while sailing at a certain depth up to the water surface. Meanwhile, only under special conditions does the vehicle maneuver with less acceleration or other motion. As in the above-motioned analyses, to enhance the real-time performance of target tracking, a limited number of models are selected. System noise variances of sub
filters are adaptively adjusted through fuzzy logic inference, which can achieve the purpose that the covering probability of the target maneuvering pattern is increased by a finite number of models. The above technology is propitious to the improvement of real-time performance of underwater target tacking. In this paper, the motion patterns of underwater vehicles are classified as follows[5].

The first sort of pattern is the non-maneuvering model, i.e., the constant velocity mode, which can be accurately described by the existing constant velocity model (CA) without any modification, and its state vector is \( X_c = (x, v_x, y, v_y) \). The second sort of pattern is the Singer model related to time with state vector \( X_S = (x, v_x, y, v_y, a_x, a_y) \). In the third sort of pattern, considering that an underwater large vehicle usually turns in a certain depth plane, the maneuvering model of the target is described by the HT model, whose state vector is \( X_T = (x, y, h, \omega, s) \), where \( h \) is the course angle; \( \omega \) is the turn speed, and \( s \) is the motion velocity of the target.

Note that the above three states models are defined in different coordinates (i.e., Cartesian and turn model coordinates). Accordingly, during mixing data simulation, the states vectors and covariance matrix must be transformed to the unification coordinates in order to conveniently resolve the renewal process of the states. Where the sates vector of the Singer model related to time is transformed to \( X_{TC} = (x, v_x, a_x, y, v_y, a_y) \), the covariance matrix of the HT model is transformed to \( P_{TC} = AP_T A^T \).

To explain the problem conveniently, the underwater target and the passive sonar station are assumed to maneuver in the same depth plane. That is, the target and sonar station are in the same two-dimension plane. Firstly, as Fig.4 illustrates, the earth-fixed inertia coordinate system is established and the coordinate origin is the sonar station. Therefore, the measurement equation of the passive sonar is represented as

\[
Y(k) = CX(k) + V(k)
\]

where \( Y(k) = [R(k), \beta(k)]^T \) is the measurement vector; \( R = \sqrt{x^2 + y^2} \) is the range, and \( \beta = \tan^{-1}(y/x) \) is the azimuth angle. \( C \) is the measurement matrix, and \( V(k) \) is the measurement noise, which is assumed to be a Gaussian white noise with zero mean value.

Then, comparing with the conventional IMM, the effectiveness of the proposed FIMM algorithm is testified by Monte Carlo simulation of over 500 runs. The simulation parameters of the underwater target trajectory are described as follows.

The total simulation duration is 150 seconds and the sampling period is 1 s. Within 1~79 s, 90~109 s, and 121~150s, the target maneuvers in a straight-line motion at constant velocity. At 80~89 s and 110~120 s, the vehicle maneuvers in a semicircular motion with a rotating speed of 5.6 deg/s and -2.8 deg/s, respectively. The initial position of the target is \( x_0 = 10 \) km and \( y_0 = 5 \) km. Meanwhile, the initial velocity is \( v_{x0} = -18 \) m/s and \( v_{y0} = -5 \) m/s.

The process noises of the coordinate component, velocity component, and acceleration are independent, with root mean squares (RMS) of 50 m, 5 m/s, and 2.5 m/s\(^2\), respectively. The model probability \( \mu \) is [1 0 0]. For an IMM system performance which is very robust to the choice of transition matrix probabilities and where calculation results affected by the probability scale [0.80 0.95] are negligible[5], the Markovian transition matrix probability \( \pi \) for different IMM algorithms is selected as follows

\[
\pi_{ij} = \begin{cases} 0.9, & i = j \\ 0.1/(N-1), & i \neq j \end{cases}
\]

where \( N \) is the number of models.

Measurements of the noise variances of the sensor distances and azimuth angles are \( \sigma_{a} = 25 \) m and \( \sigma_{\beta} = 0.01 \) rad, respectively. The initial states estimation \( \overline{X}(3) \) and covariance \( \overline{P}(3) \) are achieved by three-point startup technology[6].

Compared to the traditional IMM method, Fig. 5 demonstrates the part simulation results of the proposed FIMM algorithm in this paper, where Fig.5(a)
depicts the tracking RMS of the $X$ coordinate and Fig.5(b) shows the tracking RMS of $X$ velocity.

Fig.5 illustrates that FIMM algorithm and the conventional IMM method can track the maneuvering of the target when the target moves in a straight-line motion with constant velocity. However, the precision of FIMM is superior to that of IMM, which is demonstrated by the error curve of the $X$ coordinate tracking shown in Fig.5(a). When an underwater target maneuvers at constant speed horizontal turns, the tracking precision of FIMM is enhanced to 50%, in contrast to that of the conventional IMM method. It is obvious that in order to achieve the above tracking precision of the FIMM algorithm, the conventional IMM method must increase the number of motion models or modify the system statistical parameters, which increases the calculating complexity. Consequently, the real-time performance of the IMM algorithm is inferior to that of the FIMM technology, and the tracked underwater vehicle is likely to unlock.

3 Conclusions

From the above simulation analysis, it is concluded that an FIMM algorithm can effectively describe different motion patterns of underwater targets only through utilizing a lesser number of models, which reduces the mismatching error between filtering models and the maneuvering patterns of the target. Meanwhile, compared to conventional IMM technology, the proposed method can track the motion patterns of the target with high precision by on-line fuzzy control, which makes it unnecessary to introduce more sub models. Accordingly, the calculation workload of the FIMM algorithm is decreased. Further, the presented IMM method can satisfy the requirements of real-time and reliability of underwater target tracking.

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