A MULTI-DIRECTIONAL MOTION INTERACTING FUSION MODEL FOR DIVER TRACKING

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Abstract:

According to the diver motion characteristics, which are low speed and rapid change of direction, a multi-directional motion model is presented. Then the motion model is introduced into an interacting multiple model method, while the time-varying motion model transition probability was corrected according to current measurements. Firstly, the predictive state was obtained by a multi-directional motion model. Secondly, the parallel Kalman filters were applied to estimate multi-directional state. Finally, the interactive fusion processing for estimations from multi-directional motion model was conducted to implement diver state estimation. The method was verified by both simulation and experiment. The results show that the proposed method has higher tracking accuracy and superior adaptability than conventional interactive multiple model algorithm based on single direction motion model. The proposed method is effective for diver tracking.

1 Introduction

The diver with asymmetric characteristics has become the principal factor threatening security in the underwater domain. So, many substantial efforts to detect divers have been done by a lot of countries and organizations [1,2]. The motion models of underwater vehicles such as steering model, constant velocity model and constant acceleration model have been currently applied to diver tracking [3,4]. In comparison with underwater vehicle, diver's motion has characteristics of maneuvering. For maneuvering target tracking, the motion models matched with the target's actual motion are to be primarily established [5]. Recently, the conventional motion model for maneuvering target tracking includes a switching model, multiple model and interactive multiple model. The switching model applies the maneuver detection to implement switching between a maneuvering motion model and non-maneuvering motion model [6,7]. The multiple model method yields weighted summation from state estimation by the set motion model set. Shalom proposed the interacting multiple model (IMM) method which has excellent precision and robustness for high-maneuvering target tracking [8-11].

The motion model set must be set up according to motion characteristics of a specific moving target. Maneuvering target tracking is implemented by using IMM method for building on these motion models. Julien Burlet proposed the adaptive

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interactive multiple model tracking method for pedestrian and car tracking. The multi-directional motion model set is established on analysis of the target motion characteristics in this approach [12,13]. J. Wang proposed an adaptive neural dynamics model for omni-directional mobile robot tracking to tackle the speed jump problem [14].
The characteristics of diver motion are discussed in this paper. And the multi-directional motion model according to motion characteristics is also established for the specific target tracking. Finally, the multi-directional motion model is introduced into IMM for diver state estimation. In IMM, the motion model transition probability is corrected in real-time according to current measurements. Simulation verification is conducted in this paper. The proposed algorithm was also presented for diver detection process using experimental data processing. The diver state estimation was compared with IMM based on single-direction motion model. The results reveal that the multi-directional model for interactive fusion tracking methods represents better diver's motion behavior and estimates more accurate state than the conventional IMM based on single-directional motion model.

2 Diver tracking based on multi-directional motion fusion model

2.1 The motion characteristic of diver

In comparison with underwater vehicles including mechanical devices, the diver cannot move on the planned path due to the lack of navigation equipment. Generally, the motion characteristics of divers are as follows [8]:
(1) The movement speed is low. It is about 0.5 m/s.
(2) The fluctuation of speed amplitude is not obvious in adjacent sample time.
(3) Divers movement direction is uncertain due to underwater visibility.
(4) The divers move only at a certain water depth because of the limitation of the human physiological structure.
(5) The diver track is zigzag with general consistent direction and local variable direction.
According to the characteristics of diver movement mentioned above, it is difficult to represent divers' underwater motion utilizing a single direction motion model. This paper presents a multi-directional motion model on grounds of the above characteristics for diver tracking.

2.2 Multi-directional motion model

According to the diver motion feature about low velocity and frequent direction change, the assumptions are made as follows:
(1) The divers move in a state of uniform motion in a straight line in inter-sample time;
(2) The divers move in a two-dimensional plane ignoring the depth information.
According to divers' movement feature and above assumptions, a multi-directional motion model set with sixteen constant velocity motion models is established to describe diver movement, as shown in Figure 1. The red circle represents the current location of the diver. V_y indicates the current velocity direction in target state estimation. The motion model in each direction is composed of two constant velocity movements.

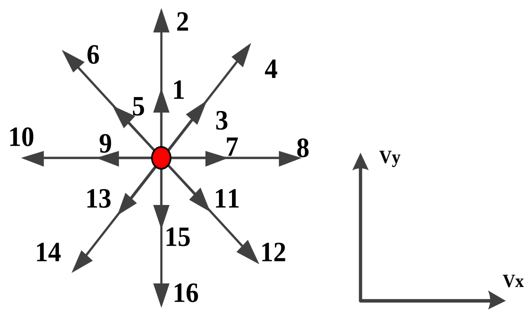

Figure 1. The diagram of multi-directional motion model.

2.3 The IMM based on multi-directional motion model

The essence of IMM algorithm is employed to present the probability weight summation method based on the state estimation results from multiple motion models. The advantage of IMM is its ability to rapidly adapt to target maneuvers.
Supposing that there are sixteen motion models in multi-directional model set denoted as $m_1, m_2, \cdots, m_{16}$ for underwater moving diver state estimation, and

that $\pi_{ij} = P\{m(k) = j \mid m(k-1) = i\}$ we represent motion model transition probability of motion model i at time $k-1$ to motion model j at time k. The motion transition probability matrix is initialized by the uniform distributed random number. Generally, multiple motion models switch according to a homogeneous Markov chain by meeting a given state transition matrix. Generally, the artificially fixed motion (model) transition probability matrix reduces the estimation accuracy. In literature [15], a time-varying transition probability model is corrected in real-time according to the current measurements as:

$$\pi_{ij}(k) = \frac{\pi_{ij}(k-1)\exp\left[\mu_j(k) - \mu_j(k-1)\right]}{\sum_{j=1}^{16}\pi_{ij}(k-1)\exp\left[\mu_j(k) - \mu_j(k-1)\right]}, \quad (1)$$

where $\pi_{ij}(k)$ denotes the transition probability from motion model i to motion model j at time k, $\mu_j(k)$ denotes that the probability of motion model j is effective at time k.

As shown in the above equation, since the elements of j^{th} column in motion model transition matrix increase according to the motion model j probability increments, the motion model will share a larger proportion in next interactive process.

Each motion model generates state estimation respectively by filter algorithm, while the input to filter algorithm is the mixture value of the sixteen filter output at the previous time step. Finally, diver state estimation is the weighted summation from all filters output. Figure 2 shows the flow diagram of multi-directional motion interactive fusion method for diver tracking.

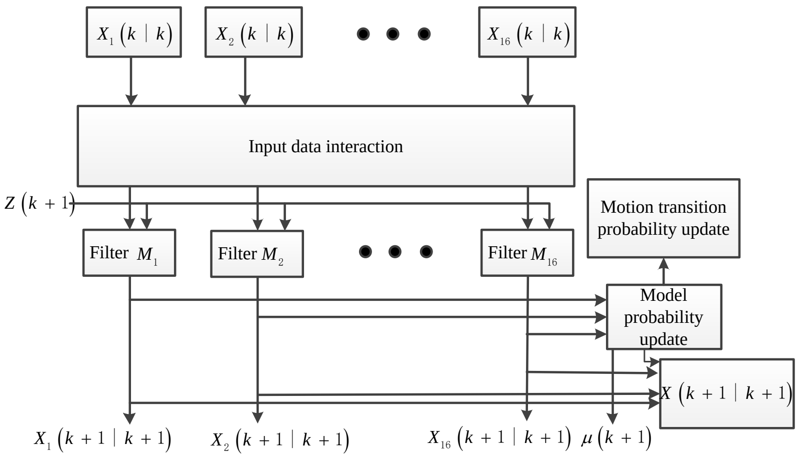

Figure 2. Principle block diagram of multi-directional motion interacting fusion model.

The IMM is a recursive algorithm structure including input data interaction, filter estimation, model probability update and output data interaction. The calculation process is described as follows:

Step 1: Input data interaction

The mixing probabilities for predicting the process is calculated as

$$\mu_{ij}(k+1 \mid k) = \pi_{ij}\mu_i(k) / \mu_j(k+1 \mid k). \quad (2)$$

Normalization constant factors can be calculated as

$$\mu_j(k+1 \mid k) = \sum_{i=1}^{16}\pi_{ij}\mu_i(k). \quad (3)$$

Finally, the input data interaction at time $k+1$ is calculated as

$$X_j^0(k+1) = \sum_{i=1}^{16}\mu_{ij}(k+1 \mid k)X_i(k), \quad (4)$$

and

$$P_j^0\left(k+1\right) = \sum_{i=1}^{16}\left\{\begin{array}{l}\mu_{ij}\left(k+1\mid k\right)\times \\ \left[\begin{array}{l}P_i\left(k\right)+ \\ \left(X_i\left(k\right)-X_j^0\left(k+1\right)\right) \\ \left(X_i\left(k\right)-X_j^0\left(k+1\right)\right)^T\end{array}\right]\end{array}\right\}, \quad (5)$$

where $j=1,2,\cdots,16$, $X_i\left(k\right)$ is target state estimation according to the motion model i at time k while $P_i\left(k\right)$ denotes corresponding covariance estimation.

Step 2: Filter estimation

Based on sixteen multi-directional motion models and the valid diver measurement $z\left(k+1\right)$ from the active sonar, the model conditioned target state $X_j\left(k+1\right)$ and covariance $P_j\left(k+1\right)$ for motion model j at time $k+1$ are calculated via parallel Kalman filter.

Step 3: Model probability and transition matrix update

The model probability update is conducted by likelihood function based on the filter estimation through step 2. The likelihood function of the motion model j is calculated as

$$L_j\left(k+1\right) = N\left(\tilde{z}_{k+1}^j, 0, S_{k+1}^j\right),\ j = 1,2,\cdots,16, \quad (6)$$

where $\tilde{z}_{k+1}^j$ is the innovation of the motion model j at time $k+1$ while S_{k+1}^j is the corresponding covariance, $N\left(x,\mu,\sigma^2\right)$ denotes that random variable x obeys the normal distribution and its mean and variance are μ and σ^2, respectively.

The probability of the model j at time $k+1$ is updated as

$$\mu_j(k+1) = \frac{\mu_j(k+1\mid k)L_j(k+1)}{\sum_{i=1}^{16}\mu_i(k+1\mid k)L_i(k+1)},\ j = 1,2,\cdots,16 \quad (7)$$

Finally, the transition matrix is updated according to Equation (1).

Step 4: State estimation and covariance fusion

According to the updated model probability, the state estimation and associated covariance are fused according to

$$X\left(k+1\right) = \sum_{j=1}^{16}\mu_j\left(k+1\right)X_j\left(k+1\right), \quad (8)$$

and

$$P\left(k+1\right) = \sum_{j=1}^{16}\left\{\begin{array}{l}\mu_j\left(k+1\right) \\ \left[\begin{array}{l}P_j\left(k+1\right)+ \\ \left(X_j\left(k+1\right)-X\left(k+1\right)\right) \\ \left(X_j\left(k+1\right)-X\left(k+1\right)\right)^T\end{array}\right]\end{array}\right\}. \quad (9)$$

The combined state estimation is the probability weighted summation of all results obtained from the multi-directional motion models.

The method mentioned above differs from general IMM estimator so that the motion model set is composed of multi-direction motion models and time-varying motion model transition matrix.

3 Simulation and results

To evaluate effect of the proposed method, the simulation analysis was executed to compare the performance of IMM algorithm with multi-directional motion model set and single direction motion model respectively for diver tracking with Monte Carlo simulations.

3.1 Simulation scenario

The target is assumed to move in the 2-D plane of the Cartesian coordinate. Simulation data is obtained with the independent movement direction across time to generate target track with low velocity and high direction change rate. The target state vector is $X = \left[x, y, v_x, v_y\right]$ representing position and velocity in Cartesian coordinate system. Table 1 illustrates the simulation parameters with values and specifications.

Table 1. Simulation parameters

Parameter	Value	Specification
X_0	(-40 m, 40 m, 1 m/s, 0 m/s)	Target initial state
σ_r	0.1 m	Distance resolution
σ_θ	2.0°	Angle resolution
T	1 s	Sampling period
t	100 s	Sampling range
S_0	(0 m, 0 m)	Sonar position

3.2 Simulation results and analysis

The simulation data is processed with IMM method based on the proposed multi-directional motion model and the single direction model. Figure 3 illustrates the state estimation results.

The root mean square error (RMSE) of each state component was chosen as the measure of estimation performance from different methods. The RMSE after M times Monte Carlo simulation at time k is defined as

$$RMSE = \frac{1}{M}\sum_{m=1}^{M}\left[\left(\hat{x}_{km} - x_k\right)^2 + \left(\hat{y}_{km} - y_k\right)^2\right], \quad (10)$$

where $\left(x_k, y_k\right)$ denotes the real position of target at time k, while $\left(\hat{x}_{km}, \hat{y}_{km}\right)$ denotes the estimated position in the m^{th} Monte Carlo simulation at time k.

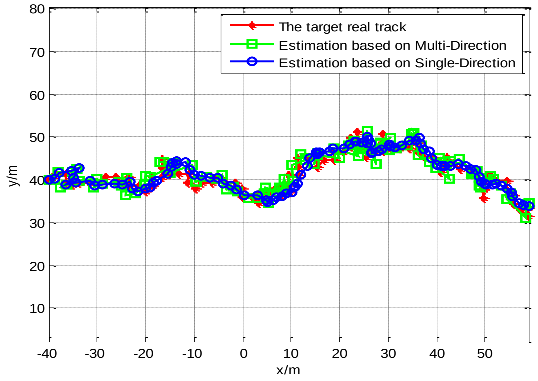

Figure 3. Target tracking simulation results.

The RMSE results from IMM method with the multi-directional model and singledirection model are obtained after 100 times Monte Carlo simulation, as shown in Figure 4.

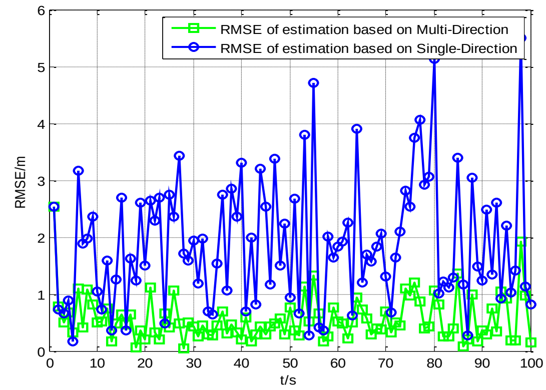

Figure 4. The RMSE of estimation from the two IMM methods.

Simulation results demonstrate that the proposed algorithm yields robust and high accuracy target state estimation in comparison with the IMM based on single-direction motion models. The reason is that the proposed motion model can more effectively describe the target movement with low speed and high direction change rate.

4 Experimental data process

4.1 Experimental setup

The realistic experiment of diver detection in multistatic system was conducted in offshore waters of the South China Sea in April 2013 by Institute of

Acoustics, Chinese Academy of Sciences. The multistatic system for diver detection was set up through reconstruction of multiple anti-diver sonars, as illustrated in Figure 5. The multistatic system consists of a transmitter sonar node denoted as S1 and two receiver sonar nodes denoted as R1&R2. The red area is the coverage area of sonar S1 . The two blue areas are the coverage area of sonar R1&R2.The green line indicates the small target position observed by GPS. Besides transmitting the signal, the transmitter node S1 also listed reflected sound signals from the target together with the receiver node R1&R2 in the experiment. The time synchronization for all sonar nodes was implemented by means of the trigger signal from GPS.

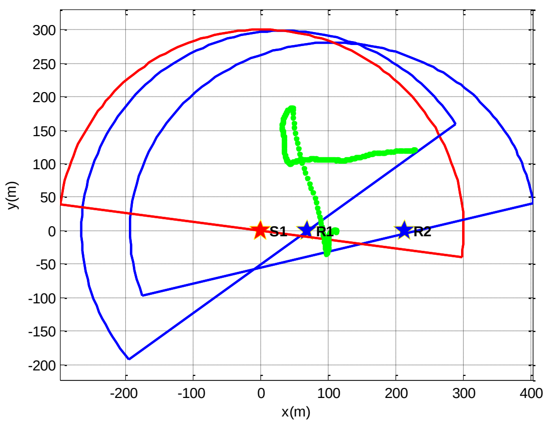

Figure 5. Ground truth plot and sonar layout for the realistic experiment.

4.2 Experimental data processing results

The diver was detected in multistatic sonar system, so the multistatic fused measurements are served as the observation for target state update process.

The diver state estimation for moving diver detection data in multistatic sonar system by the two different motion models is shown in Figure 6. Figure 7 illustrates the estimation error calculated using the formula 10.

Figures 6 and 7 show that the proposed method depicts more accurate and robust target state estimation in comparison with IMM based on the single direction motion model method. The estimation error based on single direction motion method is significantly increased when diver maneuvers.

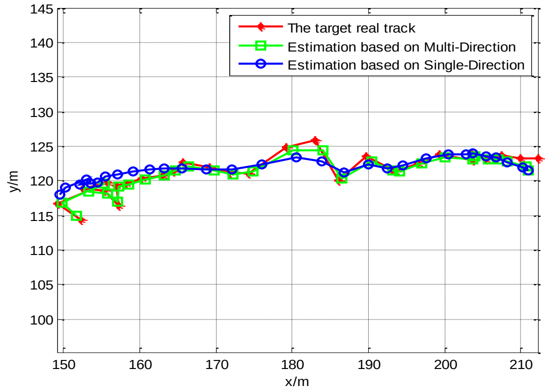

Figure 6. Divers state estimation by various motion model.

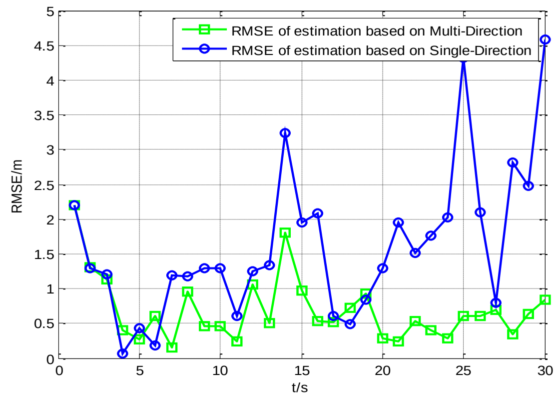

Figure 7. The RMSE for estimation results.

5 Conclusion

Aiming at solving the moving diver tracking problem, the diver motion characteristics of low speed and high direction change rate are analyzed in this paper. According to the specific motion characteristics, the multi-directional motion model has been designed to describe the movement of the diver. Then the proposed motion model is introduced into the IMM algorithm for diver tracking. And the simulation analysis and moving diver detection experimental data processing by the multi-directional motion interactive fusion model are also presented comparing with the IMM method based on the single direction motion model. The results indicate that the fusion method based on multi-directional motion models yield more accurate and robust target state estimation. Therefore, we can conclude that the proposed method has remarkable tracking performance for diver tracking.

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