An Efficient Positioning and Tracking Algorithm for AUV in Underwater Environment

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Abstract

Autonomous underwater vehicle (AUV) research has focused on tracking, positioning, precise guidance, return to dock, and other tasks. The AUV called a robotic fish has become a hot research topic in several areas, including for intelligent education, civil and military uses. In the nonlinear tracking analysis of the robotic fish, it was found that the interval Kalman filtering algorithm contains all possible filtered results but that the range is wide and relatively conservative, and the interval data vector is uncertain. This paper proposes an optimized algorithm for suboptimal interval Kalman filtering. The suboptimal interval Kalman filtering scheme uses the interval inverse matrix with its lowest inverse. This proposed method provides a more approximate nonlinear state equation and measurement equation than does the standard interval Kalman filtering, increases the accuracy of the nominal dynamic system model, and improves the speed and precision of the tracking system. Monte-Carlo simulation results show that the optimal trajectory of the suboptimal interval Kalman filtering algorithm is better than that of both the interval Kalman filtering method and the standard filtering method.

Key Words: AUV, Kalman Filtering, Suboptimal Interval Kalman Filtering, Robotic Fish Tracking, Monte-Carlo Simulation

1. Introduction

An autonomous underwater vehicle (AUV) includes smart devices, a submerged underwater vehicle and a robot [1]. Both at home and abroad, AUV-based research is focused mainly on the thruster, material, power and its supply, path planning, obstacle avoidance, cruise, tracking, remote fault diagnosis and repair, dock and others [2].

The robotic fish is a kind of underwater vehicle that possesses a long submersion time, is large-scale, can navigate complex terrain, produces little noise, is easy to camouflage and conceal, and can adapt to high pollution and high radiation. In recent years, robotic fish have been rapidly deployed and utilized in the fields of archaeology, military, undersea exploration, pipeline inspection, pollution monitoring, and intelligent teaching, among many others [3]

The main task of robotic fish tracking is to obtain the motion parameters, such as the number, position, velocity and acceleration of the tracked object, by using sensors [4]. The purpose is to realize the control, guidance, obstacle avoidance and rapid escape of the robotic fish through precise tracking.

Currently, the common algorithms are based on image processing and tracking technology and include the multi hypothesis tracker [5], probabilistic data association filtering [6] and Kalman filtering [7]. Relative to other underwater vehicles, although the structure of the robotic fish model is simple, it is capable of storing only a small amount of data. It has high nonlinear trajectory

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and control accuracy requirements. However, it is particularly suitable for computer vision, wireless sensor networks and underwater vehicle simulation research [8]. The most commonly used nonlinear tracking method is Kalman filtering. It is carried out in the vicinity of the Taylor linear prediction, which can finally obtain a linearized observation equation.

There are many target tracking methods based on Kalman filtering. These methods include limit Kalman filtering (LKF), unscented Kalman filtering (UKF) [9], extended Kalman filtering (EKF) [10,11], central difference Kalman filtering (CDKF) [12], wavelet Kalman filtering (WKF) [13], interval Kalman filtering (IKF) [14] and particle Kalman filtering (PKF) [15].

UKF and CDKF can be classified as sigma filter (SPKF) target tracking methods. SPKF is used to construct the weight set, which can estimate the mean and covariance of the state by adjusting the sample points. In addition, the UKF and CDKF algorithms require manually adjusted parameters to provide accurate estimates. Therefore, they are currently in the theoretical stages. EKF and LKF belong to linear or approximately linear processing, which have the disadvantages of low precision and large error. Virtual noise will have some influence on the real-time estimations, which makes EKF and LKF unsuitable for underwater applications. IKF was first introduced by GM Siouris et al. [16] to research tracking algorithms for ballistic missile and other flying objects. A Motwani et al. [17] researched the guidance and navigation of aquatic unmanned vehicles. Daniel Clark et al. [18] creatively introduced PKF into the multi object tracking of sonar images.

Compared with the IKF tracking algorithm, the suboptimal interval Kalman filtering (SIKF) proposed in this paper has the following advantages.

(a) SIKF is a correction of Kalman filtering (IKF) of the interval system. The linear model is used to estimate the parameters of the system to compensate for the linear error of the observation equation and reduce the influence of the observation error.

(b) The structure of the perception layer of robotic fish is improved. This paper puts forward a three-dimensional path (vertical depth $Z$, around $X$ and the level of stealth $Y$) tracking design mod to ensure that the requirements of the Kalman filtering algorithm are met for the state data source accuracy.

(c) The robustness and accuracy of the filter are better than those of other passive target tracking algorithms.

(d) The application of the inverse matrix of the dynamic estimation makes the nonlinear processes of the underwater virtual noise and the state trajectory closer to the real track.

(e) By learning from the tracking advantages of the PKF target filter, SIKF is particularly suitable for underwater target tracking research for vehicles such as robotic fish. It can improve miniaturization, increase intelligence, provide wide applications, ensure privacy, and improve guidance and docking.

2. Model and Algorithm Flow

2.1 Target Tracking Model

We consider robotic fish to possess low visual resolution in diminished underwater light. We have considered increasing the infrared sensors in the eyes, mouth, dorsal fin, and pelvic fins, referencing the Kalman filtering algorithm, using the spatial mesh method [19] and realizing 3D path robotic fish tracking [20]. Figure 1 gives the design of the structural model of the robotic fish avoidance sensor. The six sensor signal vectors are $S_{ml}$ (left ventral), $S_{mr}$ (right ventral), $S_{mf}$ (mouth), $S_{mb}$ (dorsal), $S_{mlf}$ (left eye) and $S_{mr}$ (right eye). The three vertical layers are the horizontal bottom layer (mouth and ventral), the middle layer (left and right eyes) and the top layer (dorsal fin). For a more convenient calculation, we set the bottom level with the vertical section at an angle $\beta$ equal to $45^\circ$. The linear velocity of the robot fish is $v$.

![Figure 1. Distribution of the sensor nodes.](image-url)
declination of gyro N’s compass is θ. Maya 3D modelling [21] of the tracked target is shown in Figure 2.

The sensor data acquisition system includes the water level sensor, the sonar system, the power system, the negative pressure pump, the power supply system and the wireless sensor network communication system. The basis of control system is to realize submerged underwater target tracking.

2.2 Calculator Circuit and Recursive Formulation

The interval Kalman filtering method estimates the current value of the target acquisition control signal according to the previous estimated vector and the most recently observed vector. The state equation and the given algorithm are used to estimate the state variables. The state variables are transformed into the target state model and path to realize target tracking, guidance and control. The algorithm includes filter gain and filter estimation, as shown in Figure 3.

Given the initial values of $\hat{X}(0)$ and $P_0$, according to the measurement of the $K$ moments $Y_k$ with $|\Delta R_k|$ instead of $R_k$, we can get the state estimation at $K$ moment by recursive computation. The recursive modelling method of $\hat{X}_k$ is shown in Figure 4.

2.3 Algorithm Flow

The algorithm’s flow is shown in Figure 5. The main
steps of the flow chart are as follows.
(a) Initialize the parameters, including the state vector, trace, control input, the depth of the target, the dimension of the number, and the number of iterations.
(b) Initialize the starting position of the object vector (including depth, latitude and longitude coordinates) and the velocity in each parameter interval.
(c) The definition of the convergence of each vector is calculated, including the error covariance, the covariance probability, the Kalman filtering gain, the filtering error estimation covariance, the estimation error and the error covariance matrix.
(d) Update the position and velocity of each vector.
(e) Calculate the definition of the convergence of each monomer vector and iteratively search for the lowest inverse of the interval matrix to replace the existing single matrix inverse. Compare the results with the other values.
(f) Determine whether the value of the convergence of each vector is consistent with the observed values.
(g) Execute the (d) to (f) loop until the preset accuracy requirements are met and the number of preset iterations of the experimental is reached.
(h) Output the mean error, variance, and standard deviation of the error. Draw the mean value of the estimated error’s curve.

3. Interval Kalman Algorithm and Optimization

3.1 Interval Kalman Algorithm
To simplify target tracking, we consider the determined depth $Z$ along axes $X$ and $Y$ to the time interval domain measurement considering [22]. We assume that $x$, $T$, $u$ are state vectors of $K$ moments, trace and control inputs, respectively. The state equation [23] for robotic fish along the $X$ axis can be described as follows.

$$X(k + 1) = [x(k) \quad \hat{x}(k)]^T, \quad \Phi = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}, \quad \Gamma = \frac{1}{2} T^2, \quad W(k) = u$$

The observed equation can be expressed as:

$$Z(k) = C(k)X(k) + \nu(k)$$

In the formula, $C(k) = [1 \quad 0]$, $\nu(k)$ is the zero mean noise sequence and the variance is known. To predict the target track, we can solve for the following [25]:

$$\hat{X}(k | k - 1) = \Phi \hat{X}(k - 1 | k - 1)$$

In this formula, the filtering estimation and stochastic expectation should be satisfied such that

$$\hat{X}(k | k - 1) = E[X(k) \mid Z^{k-1}]$$

The results show that the observation value of the front $K - 1$ interval reflects the estimation of the current state. Through the experimental data correction, the predicted error covariance probability [26] can be expressed as

$$P_{\hat{X}}(k | k - 1) = \Phi P_{\hat{X}}(k - 1 | k - 1) \Phi^T + \Gamma Q(k - 1) \Gamma^T$$

We obtain the filter iterative expression as follows [27]:

$$\hat{X}(k | k) = \hat{X}(k | k - 1) + K(k)[Z(k) - C(k)\hat{X}(k | k - 1)]$$

Here, $k(k)$ is Kalman filtering gain. The estimated covariance of the filter error is

$$P_{\hat{X}}(k | k) = [I - K(k)C(k)]P_{\hat{X}}(k | k - 1)$$

By means of a simple system simulation, we can illustrate the time function curve of the prior valuation covariance and the Kalman gain, which converge to a stable value.

When filtering is measured, the initial value is specified. Due to the existence of uncertainty and discreteness in the underwater tracking of robotic fish, measurement cannot set the initial state. We can use the first few observations to establish the estimated initial state of the actual measurement. Here, the first two observations are used to estimate [28]:

$$\hat{X}(2 | 2) = [z_1(2) \quad z_2(2) - z_1(1)]/T$$

Then, the estimation error should be
The error covariance matrix should be

\[
\hat{X}(2 \mid 2) = \left[ -v_x(2) \frac{T}{2} \sigma_v \frac{T}{2} \right] \frac{T}{\sigma_v^2 / T} + \frac{v_x(1)}{T} \frac{v_x(2)}{T} \right]^{-T}
\]

The error covariance matrix should be

\[
P_{\hat{X}}(2 \mid 2) = \begin{bmatrix} \sigma_v^2 / T & \sigma_v \frac{T}{T} \\ \sigma_v / T & 2\sigma_v^2 / T \end{bmatrix}
\]

3.2 Suboptimal Interval Kalman Algorithm Optimization

The time, depth, speed, and terrain in underwater operations are diverse and uncertain. With the passage of time, some system parameters change or are adjusted. At this time, the interval Kalman filtering algorithm cannot be directly applied to estimate the recursive data using \( \{v_k\} \) and get the best estimate \( \{x_k\} \) from the unknown state vector \( \{x_k\} \). In this case, it is necessary to address the uncertainty and robustness of Kalman filtering [29].

In this framework, the original interval system of the proposed algorithm is improved and optimized by the Kalman filter. By using the interval matrix and the rational interval function of the interval system, an improved interval Kalman filtering algorithm is proposed. The master process is

\[
\tilde{x}_0 = E(x'_0)
\]
\[
\tilde{x}_k = A'_k x'_k + G'_k [v'_k - C'_k A'_k x'_k]
\]

The slave process is

\[
P_0 = Var(x'_0)
\]
\[
P'_k = Var(x'_k)
\]

\[
M_{k+1} = A_{k+1} P_{k+1} [A_{k+1} - B_{k+1} Q_{k+1} B_{k+1}^T]^{-1}
\]
\[
G'_k = M'_{k+1} C'_k - [C'_{k+1} M'_{k+1} - R_k]^{-1}
\]
\[
P'_k = [I - G'_k C'_k] M'_{k+1} [I - G'_k C'_k]^{-1} + [G'_k R_k G'_k]^T
\]

The interval matrix replaces the lowest inverse [30] and keeps all other values unchanged. Set \( C_k \) as the centre point of \( C'_k \) (or the interval matrix of the nominal value) and \( M_{k-1} \) as the centre point of \( M'_k \). Then, we have

\[
C_k = C_k + \Delta C_k \quad M_{k-1} = M_{k-1} + \Delta M_{k-1}
\]

\[
[C'_{k+1}] [C'_{k+1}]^{-1} + [\Delta C_k] [M_{k-1} + \Delta M_{k-1}] [\Delta C_k]^{-1}
\]

\[
= [C_k M_{k-1} C'_k + \Delta C_k R_k]
\]

where

\[
\Delta R_k = C_k M_{k-1} [\Delta C_k]^{-1} + C_k [\Delta M_{k-1}] [\Delta C_k]^{-1} + [\Delta C_k] [M_{k-1} [\Delta C_k]^{-1} + [\Delta C_k] [\Delta M_{k-1}] [\Delta C_k]^{-1}
\]

Let \( \Delta R_k \) be replaced by its upper bound \( |\Delta R_k| \), which consists of the upper bound of \( |\Delta R_k| = [r_k(i, j), r_k(i, j)] \). Then, we obtain

\[
|\Delta R_k| = |r_k(i, j), r_k(i, j)| \geq 0
\]

When the perturbation matrix \( \Delta C_k = 0 \), we use the common matrix \( |\Delta R_k| \) inverse interval matrix inversion \( [C_k M_{k-1} C'_k + \Delta R_k]^{-1} \) to replace \( [C'_k M_{k-1} C'_k + \Delta R_k]^{-1} \). This simplifies the inversion while retaining the same precision for the interval system measurement equation and the nominal model. The biggest possible interference has been considered. Therefore, \( |\Delta R_k| = R_k \) is able to use the system, given the stability of the numerical inverse as the best solution.

To summarize, by replacing \( |\Delta R_k| \) with \( \Delta R_k \), the suboptimal interval Kalman filtering algorithm is obtained. The master process is

\[
\tilde{x}_0 = E(x'_0)
\]

\[
\tilde{x}_k = A'_k \tilde{x}_k + G'_k [v'_k - C'_k A'_k \tilde{x}_k]
\]

\[
P_0 = Var(x'_0)
\]

\[
P'_k = Var(x'_k)
\]
The slave process is

\[ \hat{x}_k^i = A_k^i \hat{x}_{k-1}^i + G_k^i [v_k^i - C_k^i A_k^i \hat{x}_{k-1}^i] \quad k = 1, 2, \ldots \]  

(24)

The simulation experiment and analysis

To verify the accuracy of the suboptimal Kalman filtering algorithm, the experimental environment’s trajectory is as follows.

In \([0, 400]\), we move along the \(Y\) axis to submerge. The initial \(v\) is set to -15 m/s, and the initial address coordinates are \([2000, 10000]\). In \([401, 600]\), we move along the \(X\) axis of 90° to accelerate and steer. The acceleration is 0.0625 m/s\(^2\), which is set to zero when steering. In \([601, 610]\), we move along a uniform straight line. In \([611, 660]\), we begin a 90° turn, and the acceleration is set to 0.25 m/s\(^2\). After completing the turn, the acceleration is reduced to zero, and we move along a uniform straight for a period of time. The set of relevant parameters is shown in Table 1.

We set the tracking scanning gap period to 2 seconds. The \(X\) and \(Y\) direction are the independent observations, and the observed noise is the standard deviation for 100 metres. By using the Monte-Carlo simulation method, the iterative mean calculates the mean, and the variance of the estimate is expressed as

\[ \bar{\sigma}_i(k) = \frac{1}{M} \sum_{i=1}^{M} [x_i(k) - \hat{x}_i(k | k)] \]  

(29)

The standard deviation of the error is

\[ \sigma_i = \sqrt{\frac{1}{M} \sum_{i=1}^{M} [x_i(k) - \hat{x}_i(k | k)]^2 - \bar{\sigma}_i^2(k)} \]  

(30)

Here, \(M\) is the Monte-Carlo simulation iteration number [31], and \(k\) is the sample number. When the number of simulations increases, the experimental results are closer to the actual results, but the simulation speed will slow down. In the simulation experiment, set \(M\) as 100. To further study the interval Kalman filtering algorithm for the track verification of robotic fish, the simulation of the uniform motion of the system is carried out after 660 seconds. The simulation experiment will produce the real track of the robotic fish, the suboptimal interval Kalman filtering estimation and the final output. This will facilitate comparisons among the real track, the observed track and the filtering estimated track. For the given Monte-Carlo simulation times, the average and standard deviation of the estimated error is plotted along the \(X\) and \(Y\) axes with an increase in sampling points.

First, the real track of the robot fish is given. It can be clearly seen from Figure 7 that the true path of the robot fish is along the \(-Y\) axis after two turns to the destination. The suboptimal interval Kalman filtering is estimated from the \(X\) axis direction of the filtered estimated tracks and the theoretical tracks, as shown in Figure 8.

The estimated track and the theoretical track on the \(Y\) axis are shown in Figure 9. The observed value and the theoretical track are compared. It is shown in Figure 10.

The output of the \(X\) and \(Y\) direction of the theoretical track and suboptimal interval Kalman filtering estimation in the rectangular coordinate system [32] are shown in Figure 11.

<table>
<thead>
<tr>
<th>Table 1. Initial state and tracking of targets</th>
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<tr>
<td>Target</td>
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<td>--------</td>
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<tr>
<td>Target 1</td>
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<tr>
<td>Target 2</td>
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<td>Target 3</td>
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<td>Target 4</td>
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<td>Target 5</td>
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From the figure, we can find the measured observations and estimates based on the suboptimal interval Kalman filtering algorithm. Their errors can be eliminated from start to end using the thread dynamic relative position. In the tracking process, the data were improved by the algorithm. It significantly improves the relative positional accuracy in the time domain. The simulation results of the mean error curve based on the suboptimal interval Kalman filtering along the $X$ and $Y$ directions are shown in Figures 12 and 13.

The standard deviation curves corresponding to the $X$ and $Y$ axes are shown in Figures 14 and 15. In the robotic fish tracking experiments, the simulation data and
observed real data are given. This includes a comparison between the interval Kalman filtering and the suboptimal interval Kalman filtering, as shown in Figures 16 and 17.

The comparison between the sonar simulation data and the real data error of the robotic fish tracking algorithm is shown in Table 2.

From a comparison of the simulated standard deviation curve and the tracked sonar data, the estimated state of the algorithm is basically the same as that of the measured data. This means that the measurement vector is equivalent to the filtering estimation. After the start of the parade, the state estimation error immediately converges, and there is no large oscillation of the results from the curve and the iterative data. The estimated state tends to be smooth. Since the standard Kalman filter on the simulation of virtual noise and observation noise is a fixed value, we do not make corresponding adjustments to the filter error; thus, the filtering accuracy is lower. Using interval Kalman filtering estimation, the real-time dynamic estimation corrects for the noise variance. Concurrently, the system model of linear error compensation improves the filtering accuracy. The suboptimal Kalman filtering method for the nonlinear model is not a simple linear approximation but is the inverse interval matrix instead of the lowest inverse matrix. That is considered the biggest noise. Therefore, it is reasonable to address the relationship of the nonlinear process model between noise and state trajectory such that the filtered estimated course and speed are close to the real observation. This is one of the most accurate methods in the Kalman filtering
experiment and is worthy of further study, discussion, popularization and application.

5. Conclusions

This paper uses robotic fish as the underwater tracking target. We obtain the master-slave process state equation and measurement equation [33] from the filtering structure design, the filtering estimation and the error of the algorithm. We calculate the variance and covariance of the optimized matrix and inverse matrix. We present the suboptimal Kalman filtering calculation circuit, flow chart and algorithm steps. From the Monte-Carlo simulation of the iterative results, the suboptimal interval Kalman filtering algorithm has a better performance for robotic fish tracking. It can effectively suppress the noise from the environment. It can both track the position of the underwater vehicle and play a positive guiding role in precise guidance, return recovery, computer vision, intelligent simulation systems and the research and practice of teaching.

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