A Hybrid Deep Sea Navigation System of LBL/DR Integration Based on UKF and PSO-SVM

LIU Ben¹,², LIU Kaizhou¹, WANG Yanyan¹,², ZHAO Yang¹, CUI Shengguo¹, WANG Xiaohui¹
(1. State Key Laboratory of Robotics, Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang 110016, China; 2. University of Chinese Academy of Sciences, Beijing 100049, China)

Abstract: In order to improve the navigation accuracy of human occupied vehicle (HOV) precisely and efficiently, an innovative hybrid approach based on unscented Kalman filter (UKF) and support vector machine (SVM) is proposed to fuse integrated navigation data. HOV is generally equipped with long baseline (LBL) acoustic positioning system and dead reckoning (DR) as an integrated navigation system. UKF is adopted to estimate the state of the dynamic model because of its good performance in filtering nonlinear problems. An accurate and stable filtering result can be obtained when both LBL and DR are online. At the same time, SVM is utilized to train DR information with the result when LBL outrages, and the particle swarm optimization (PSO) algorithm is employed for SVM parameters optimization. Therefore, the integrated navigation system can maintain a good performance when the LBL is off-line. Simulation results with the real navigation data of Jiaolong HOV show that the methodology proposed here is able to meet the needs of HOV application.

Keywords: unscented Kalman filter (UKF); particle swarm optimization (PSO); support vector machine (SVM); deep sea navigation system; human occupied vehicle (HOV)

1 Introduction

HOV is an efficient kind of deep sea vehicles to exploit the deep ocean. HOV plays an important role in many fields such as oceanic biology, oceanic geography, and oceanic chemistry. Jiaolong, which is the first deep-sea HOV of China, has surveyed undersea world successfully for several times in ocean. Real time information about HOV position greatly helps object location and motion control. HOV is required to employ better navigation due to the increasing demand for safety and precise operation[1-2]. The features of Jiaolong are detailed in Tab.1.

<table>
<thead>
<tr>
<th>attribute</th>
<th>specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>size</td>
<td>8.2 m × 3.2 m × 3.4 m (L × W × H)</td>
</tr>
<tr>
<td>tonnage</td>
<td>22,000 kg</td>
</tr>
<tr>
<td>speed</td>
<td>1 kn, maximum speed is 2.5 kn</td>
</tr>
<tr>
<td>thruster</td>
<td>4 vector thrusters, 2 rotation thrusters, 1 bow horizontal thruster</td>
</tr>
<tr>
<td>acoustic system</td>
<td>DVL, USBL, LBL, side-scan sonar, imaging sonar, obstacle avoidance sonars</td>
</tr>
<tr>
<td>navigation system</td>
<td>DVL, USBL, LBL, FOG, depth gauge</td>
</tr>
</tbody>
</table>

1.1 Underwater navigation system

The navigation system is critical for submerge situations, such as bottom operation, rising to surface from a deep hazardous underwater environment. For different situations, the information obtained from sensors can be quite different. For example, the navigation system is only able to make use of the position information from the long baseline (LBL) system and the attitude information from fibre optic gyroscope (FOG) during the submergence phase and rising-to-surface phase. Once Jiaolong dives to the bottom, the Doppler velocity log (DVL), LBL, and FOG can all be used in navigation system. The DVL gives the velocity of HOV, LBL is an acoustic locating system which can give the position of HOV, and FOG gives the attitude information of HOV. Fig.1 shows the original navigation system of Jiaolong in bottom working stage. This paper focuses on the bottom situation and aims to develop an improved hybrid underwater navigation system based on DVL, LBL, and FOG etc.

LBL system is widely used in various underwater navigation applications for its capability of providing accurate position information. Nevertheless, the LBL...
system has some shortcomings, such as low update frequency and many outliers.\textsuperscript{[3-4]}

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{Fig1.pdf}
\caption{Navigation system of Jiaolong}
\end{figure}

The DR method is generally utilized to compute the track map of HOV. However, the accuracy of DR suffers from integration drift, and the accuracy of micro-electrical measurement units degrades sharply, which will lead to large position errors of HOV computed by DR.\textsuperscript{[5]} LBL/DR integrated navigation system is a modern navigation system for underwater vehicles, which combines the accuracy of the LBL and the stability of the DR.

\subsection{1.2 Classical fusion approach}

The Kalman filter (KF) has been widely used in the area of navigation and is capable of estimating the information in multivariable stochastic process as it is recursive in time domain.\textsuperscript{[6]} Using KF and DR, errors can be filtered out and accurate positions can be obtained when LBL system is online. KF can be used to gain a comprehensive navigation solution by weighting the measurements from LBL system and DR, respectively. However, the KF directly used in nonlinear system is not as effective as that used in linear system, so the extended Kalman filter (EKF) was developed for nonlinear systems. KF became the subject of a wide range of applications in underwater navigation. However, EKF may introduce large errors in the process of linearization because of the approximations, and then become biased in the estimation process.\textsuperscript{[6-7]} Unlike EKF, UKF adopts unscented transformation instead of linearizing nonlinear function. The UT (unscented transformation) algorithm introduces errors in estimating the mean and covariance at the third and higher order terms in the Taylor series. UKF can gain more precise estimation results and reduce the computational burden.

When LBL system is off-line, there is only DR available, which results in bad navigation performance. Therefore, it is important to establish a well-trained model to predict the position information. Nowadays, several methods have been reported for the classification or regression in various fields. Artificial neural networks (ANNs) have been pervasively adopted and are able to achieve acceptable results in many applications.\textsuperscript{[8]} However, it has disadvantages, such as local minimum problem, which probably leads to low prediction accuracy. As a consequence, it is not guaranteed for all the models to converge to optimal solutions.\textsuperscript{[9]} Support vector machine (SVM) is an effective mathematical method in prediction, and this technique has been greatly developed in the past decades. Comparing with ANN, SVM can provide more accurate results.\textsuperscript{[10]} Therefore, SVM is chosen to be trained and offer prediction, and the PSO algorithm is adopted to search and determine the parameters of SVM.

In this paper, a novel scheme using UKF and SVM regression algorithm is proposed to improve the LBL/DR system.

\section{Basic algorithm}

In this section, the UKF algorithm is stated in detail. Also, the particle swarm optimized SVM is introduced specially.

\subsection{2.1 Unscented Kalman filter}

In this paper, the model of LBL/DR is shown as follows. State vector is defined as: $X = [x, h, j, u, v, r]$, where $x, h, j$ are the north position, east position and heading, in the navigation frame, $u, v$ are the forward velocity and starboard velocity in the vehicle reference frame, and $r$ is the angular velocity. A first-order kinematic model is used here. The process model is defined as:

$$
\begin{align}
    x_{k+1} &= x_k + \sin(j_k + N_{1}^v) \times (u_k + N_{2}^v) + \\
    &\quad \cos(j_k + N_{1}^v) \times (u_k + N_{3}^v) + \\
    h_{k+1} &= h_k + \cos(j_k + N_{1}^v) \times (u_k + N_{2}^v) - \\
    &\quad \sin(j_k + N_{1}^v) \times (u_k + N_{3}^v) + \\
    j_{k+1} &= j_k + (r_k + N_{4}^v) \times Dt \\
    u_{k+1} &= u_{k+1} + N_{5}^v \\
    v_{k+1} &= v_{k+1} + N_{6}^v \\
    r_{k+1} &= r_{k+1} + N_{7}^v
\end{align}
$$

\text{(1)}
where $N^v$ is process noise. And the observation model is defined as:

$$Y = X + N^v$$ (2)

where $N^v$ is observation noise, and $k = 1, 2, \cdots, \infty$ represents the time.

The UKF based on UT has a good performance in filtering nonlinear dynamic model. The procedure for implementing the UKF can be summarized as shown in Fig.2.

![Fig.2 The operation of UKF](image)

2.2 SVM&PSO algorithm

As a successful computation and regression technique, SVM has been applied to various areas of science and engineering\[10-11\]. The SVM regression algorithm is used here to improve the accuracy of the DR-only navigation solution during LBL system outages.

Given a training set $\{x_i, y_i\}_{i=1}^N$, the SVM model for nonlinear function estimation has the following representation in the feature space:

$$y(x) = w^T \psi(x) + b$$ (3)

The nonlinear function $\psi$ maps the input space to a higher dimensional feature space. And the parameter $b$ is a bias value.

The support vector regression solves an optimization problem:

$$\min \frac{1}{2}||w||^2 + C \sum_{i=0}^{\infty} (\xi_i + \xi_i^*)$$ (4)

$$\begin{cases}
y_i - (w, x_i) - b \leq \epsilon_i + \xi_i^*
y_i - (w, x_i) + b \geq -\epsilon_i + \xi_i^*
\end{cases}
$$

$$\xi_i, \xi_i^* \geq 0, \quad i = 1, \cdots, l$$

where $\xi_i$ is the upper training error ($\xi_i^*$ is the lower) subject to the $\epsilon$ insensitive tube. The cost of error $C$ and the width of the tube $\epsilon$ have a major impact on the regression quality. By minimizing the training error and the regularization term, SVM avoids underfitting and overfitting successfully\[11\].

There are several kernel functions used in SVM, and the most universal RBF (radial basis function) kernel is chosen as the kernel function of the SVM in this paper:

$$K(x, x_i) = \exp\left(-\frac{||x - x_i||^2}{2\delta^2}\right)$$ (5)

When using RBF kernels, the parameters $\delta$ and penalty factor $C$ of SVM need to be chosen. Their optimal combination should be determined before SVM is trained due to their great influence on the performance of SVM model. In this paper, PSO algorithm is adopted to make final optimized selection of these two tuning parameters and will be detailed in next part.

In literatures [12-13], the basic PSO theory has been detailed. PSO can perform continuous codification, which is ideal for search of optimal SVM hyperparameters. What’s more, it has the potential of adaptive control and flexibility, which is very meaningful for solving optimization problems.

3 The proposed methodology

In this section, a hybrid UKF/SVM method is designed. The integrated navigation system consists of two parts. One is hybrid UKF/SVM system, and the other one is the PSO-SVM based prediction when LBL system is unavailable. The progress of the dynamic system will be described in subsequent parts.

Although the LBL system suffers from low update rate and outliers, it can gain precise position information. Liu introduced a method which used UKF to fuse the measurements of LBL/DR system\[1\] and detailed that the UKF method is applicable to approximate the real position of HOV by fusing LBL/DR. When the LBL system is available, DR data including velocities and heading angles etc, and the LBL localization information are fused together with the model presented in section 2.1. Thus the HOV can attain a solution (A), which is precise and reliable in practice. Meanwhile, the SVM will learn to establish a reasonable model from both the DR information and filtered position data (FPD). What’s more, the PSO will ensure SVM perform well by searching for the best parameter configurations. Fig.3 shows the PSO-SVM/UKF hybrid methodology in details. As shown in Fig.4, the data of DR will be imput-
ed to the SVM regression model when the LBL system ceases to work. Concurrently, the model will output a series of corresponding prediction value which can be trusted as approximately real error between DR position information and real position information of Jiaolong. And the prediction error will be applied to DR solutions so that the navigation system will stay stable in such a situation without the LBL.

where \( \mathbf{x} \) is the initial state, \( \mathbf{P}_x \) is the initial covariance matrix, \( \mathbf{R}_s \) is the process noise covariance matrix and \( \mathbf{R}_u \) is the observation noise covariance matrix.

![Diagram](image)

Fig.3 The configuration of the PSO-SVM/UKF hybrid methodology

![Diagram](image)

Fig.4 The configuration of the PSO-SVM

4 Application and experiment results

Previous sections have detailed the methodology proposed in the paper, including the fusion techniques for navigation and the SVM regression. Here in order to assess the performance of the proposed method, the approach will be experimented with field test data. As mentioned above, the data used here comes from one of the trials of Jiaolong, which were conducted under about 3867 m deep seabed.

4.1 Real data fusion in UKF

The settings of UKF are as follows:

\[
\mathbf{x} = [0, 0, 3.392, 1.19, 0.0864, 0]^T
\]

\[
\mathbf{P}_x = \text{diag} \{1, 1, 1e-4, 1e-4, 1e-4, 1e-4\}
\]

\[
\mathbf{R}_s = \text{diag} \{5e-7, 5e-7, 1e-7, 1e-7, 1e-3, 1e-6\}
\]

\[
\mathbf{R}_u = \text{diag} \{1e-8, 1e-8, 0.3e-6, 0.5, 1e-6\}
\]

In Fig.5~Fig.7, the variations of the track map of Jiaolong are presented separately. It is obvious that the tendency of the three lines reveals a significant fact that
the DR-only system has a large drift error with time going by; the LBL system can give precise position information, while it also suffers from too many outliers. Then we can see that the track map becomes smoother and have less outliers after UKF filtering.

4.2 The PSO-SVM based prediction during LBL outrages

Here a part of Jiaolong trial navigation data is chosen that is about 2 min and includes 100 points. The data is divided into two groups; one group is treated as training data, which consists of 50 points. And the other one is chosen as the test group. The HOV running state are summarized here. The front and lateral velocities are in range of [0.65 m/s, 1.13 m/s] and [0.14 m/s, 0.5 m/s], respectively. The heading angle is from 0° to 180°.

In this section, the training data is processed by PSO algorithm firstly. And the original settings of PSO are:

\[ c_1 = 1.5, \quad c_2 = 1.7, \quad w = 1, \quad V_{\text{max}} = 60, \quad \text{popsize} = 20, \quad \text{max} \text{gen} = 100 \]

where \( c_1, c_2 \) represents the local and global learning ability, respectively, \( w \) is the inertia weight, \( V_{\text{max}} \) is maximum speed of particle, \( \text{popsize} \) means the population size of particle, and \( \text{max} \text{gen} \) is maximal number of evolution generations.

\[ \text{E}_1 = \max \{|e_1|, |e_2|, \cdots, |e_n|\}, \quad (6) \]

To verify the performance of PSO-SVM, max absolute error \( (\text{E}_1) \) and mean absolute error \( (\text{E}_2) \) are defined separately,

\[ \text{E}_1 = \max \{|e_1|, |e_2|, \cdots, |e_n|\}, \]

\[ \text{E}_2 = \frac{1}{n}\sum_{i=1}^{n}|e_i| \]

After the model is established, we can use the test data as input to verify the reliability of the model. As shown clearly in Fig.9, Fig.10 and Tab.2, the position error of DR system is large and it cannot meet the needs of precise navigation of HOV during LBL system outrages. On the contrary, the compensation model of PSO-SVM and ANN both can estimate the position error. Also, it is obvious that the PSO-SVM has a better performance than ANN in reducing the error.
\[ E_2 = \sum_{i=1}^{n} |e_i| \times \frac{1}{n} \]  

(7)

where \( e_i \) represents the error of predicting position and the real position. Variable \( n \) represents the number of navigation position data for tests.

In order to demonstrate the robustness and applicability of the methodology detailed above. We then implement it with field data which were collected from another deep-sea trial. In this trial, the running states of HOV is stated as follows. The front and lateral velocities are in range of \([0.46 \text{ m/s}, 1.27 \text{ m/s}]\) and \([0.1 \text{ m/s}, 0.47 \text{ m/s}]\) respectively. The heading angle is from 0° to 180°. The training set includes 50 points, leaving 150 points as test set. Here the initial settings are completely as same as the previous test. The penalty factor \( C \) and the kernel function \( \delta \) of DR-SVM are set as same as the DR-PSO-SVM in the first test. The parameters of DR-PSO-SVM in the second experiment are optimized and set to be \( C = 0.1, \delta = 7.4433 \).

The results of the second test can be seen in Fig.11, Fig.12 and Tab.3. We can see that the ANN model can make compensation for the position error to some extent, while the performance of ANN becomes worse and inaccurate with the time going by. Because the DR-SVM cannot adjust its parameters \((C, \delta)\) according to the changed navigation data, it cannot provide a stable compensation for the position error. It will even become divergent and unbelievable after a long time. Due to the parameter optimization of PSO, the DR-PSO-SVM is more adaptive to different situations. It can make a good estimation of the error of DR and performs well.

![Graph](image1)

**Fig.11** Comparison of east position errors in the second test

![Graph](image2)

**Fig.12** Comparison of north position errors in the second test

**Tab.3** Comparison of errors among different methods in the second test

<table>
<thead>
<tr>
<th>method</th>
<th>( \varepsilon_{1 \text{east}} )</th>
<th>( \varepsilon_{2 \text{east}} / \text{m} )</th>
<th>( \varepsilon_{1 \text{north}} )</th>
<th>( \varepsilon_{2 \text{north}} / \text{m} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO-SVM</td>
<td>1.233</td>
<td>0.450</td>
<td>6.975</td>
<td>2.555</td>
</tr>
<tr>
<td>SVM-only</td>
<td>1.354</td>
<td>0.603</td>
<td>12.493</td>
<td>4.054</td>
</tr>
<tr>
<td>BP-NN</td>
<td>1.519</td>
<td>0.613</td>
<td>5.759</td>
<td>3.724</td>
</tr>
<tr>
<td>DR-only</td>
<td>4.829</td>
<td>4.081</td>
<td>17.528</td>
<td>4.062</td>
</tr>
<tr>
<td>DR-PSO-SVM</td>
<td>1.233</td>
<td>0.450</td>
<td>6.975</td>
<td>2.555</td>
</tr>
</tbody>
</table>

5 Conclusion

In this paper, a method using UKF to fuse the LBL/DR system information is proposed when the LBL system is available. To accomplish the navigation solution when LBL system is off-line, a regression algorithm is introduced, which employs the SVM in data training process and obtains the model to predict the position data in case of LBL system outage. Also, the PSO method is used here to select the best configuration of SVM parameters, which would make the method proposed more adaptive and applicable.

Numerical experiments based on real data of Jiaolong show that the UKF method is efficient in fusing the navigation data and Jiaolong can obtain precise and stable position information by UKF. The results of simulation experiment show the good performance of PSO-SVM proposed here than other algorithms. Since the method above is able to access the accurate navigation information in different situations, it enables the researchers to use the methodology in the underwater vehicles like Jiaolong when they need to construct a precise and stable navigation system due to its high accuracy.

References


About Authors:

LIU Ben (1990 –), male, graduate students. His research interests include the navigation and control of underwater vehicles.

LIU Kaizhou (1976 –), male, ph.D, Professor. His research interests include robot control, system simulation, and virtual reality.

WANG Yanyan (1986 –), female, ph.D. candidate. Her research interests include trajectory planning of robots.