Sensor deviation anomaly trend prediction based on phase space reconstruction and Support Vector Regression

Han Renjie\textsuperscript{1,a}, Song Dong\textsuperscript{2,b*}, Li Yujie\textsuperscript{3,c}

\textsuperscript{1}School of Civil Aviation, Northwestern Polytechnic University, Xi’an, Shanxi, China
\textsuperscript{2}School of Civil Aviation, Northwestern Polytechnic University, Xi’an, Shanxi, China
\textsuperscript{3}School of Civil Aviation, Northwestern Polytechnic University, Xi’an, Shanxi, China
\textsuperscript{a}email: jonaasy@163.com, \textsuperscript{b}email: songdong@nwpu.edu.cn, \textsuperscript{c}email: 15929325817@163.com

Abstract Ship combat systems are developing in the direction of integration and intelligence, and the integration also brings problems such as difficulty in predicting abnormal sensor trends in combat systems. The failure characteristics of sensors in combat systems are highly secretive, and it is difficult to detect and deal with system equipment failures by relying on empirical qualitative or single-indicator testing methods. In order to safeguard the ship's combat capability and make reasonable maintenance decisions, it is important to study more accurate prediction methods. This article proposes a method for predicting sensor deviation anomaly trends based on phase space reconstruction and Support Vector Regression(SVR), taking sensors in naval combat systems as typical research objects. Firstly, a phase space reconstruction is performed on the sensor deviation time series data to increase the accuracy of subsequent prediction; then a SVR prediction model is built, and the model is trained and optimised using the reconstructed data; finally, the constructed prediction model is compared with the regular SVR model and BP neural network model to verify that the constructed model has higher prediction accuracy.

1. Introduction

With the rapid development of computer technology and network technology, many sensor devices are being used in naval systems. Due to the highly secretive nature of naval sensors and the complexity of fault associations, it is difficult to select fault characteristics for fault prediction based on manual experience, which can no longer meet the requirements of the modern maritime battlefield with its complex environment, fast pace of combat, high intensity, high attrition and the need to quickly restore combat effectiveness. Through comprehensive training and learning of the sensor's massive historical and real-time data and fault anomaly information, the working condition of the combat system equipment can be analysed and the anomaly trend of the equipment can be predicted.

In this article, the anomaly trend prediction is aimed at sensors in naval combat systems, and the detection deviation sequence is investigated using the sensor's detection deviation at distance as a characteristic parameter. In the life cycle of the sensor, with the accumulation of use time, the detection deviation of the sensor will gradually expand from the normal fluctuation range until it exceeds the failure threshold of the sensor detection deviation and leads to failure. The sensor deviation data is a sequence of actual values ordered sequentially in time, which satisfies the relevant...
characteristics of time-series data, and can therefore be used to predict abnormal trends in sensor deviation data.

This article is organized as follows. In the Theory chapter, the phase space reconstruction of sensor deviation sequences is introduced. In the Methods chapter, sensor deviation anomaly prediction model is described. Moreover, model parameters selection and evaluation indicators are given. The Results chapter summarizes the experiment’s outcome and compares them with the regular SVR model and BP neural network. Conclusion summarizes the article and illustrates the implications for practice.

2. Theory

There are various methods for predicting sensor bias, such as the empirical formula method, the decreasing curve method, the growth curve method and the grey method. These traditional prediction methods involve building a subjective model of the data series and then calculating and predicting based on the subjective model. With the development of chaos science, it is not necessary to build a subjective model in advance, but to make forecasts directly based on the objective laws calculated by the data series itself, which avoids artificial subjectivity in forecasting and improves forecasting accuracy. The prerequisite for applying chaos time series analysis to forecasting is the identification of the nature of the series.

At present, the phase space reconstruction method has become the most noticed method of identifying the properties of time series. The key of this method is how to determine the reconstruction parameters—embedding dimension and time delay.

In this article, the C-C method is chosen to calculate both the time delay and the embedding dimension. The algorithm is implemented as follows:

For a time series \( x = \{x_i | i = 1, 2, ..., N\} \), define the correlation integral as shown in equation (1):

\[
C(m, N, r, \tau) = \frac{2}{M(M-1)} \sum_{1 \leq i < j \leq M} \theta(r - d_{ij})
\]

(1)

In the formula, the distance between any two points in phase space is denoted as \( d_{ij} = \|x_i - x_j\| \). The scale is defined as \( r > 0 \). The points of the reconstructed phase space based on the values of the delay time \( \tau \) and the embedding dimension \( m \) are defined as \( x_i \). Typically, after decomposing a time series into \( t \) mutually disjoint subsequences, the statistic for each subsequence is then defined as:

\[
S(m, N, r, t) = \frac{1}{t} \sum_{i=1}^{t} \left[ C_1(m, N/t, r, t) - C_m^1(1, N/t, r, t) \right]
\]

(2)

According to the results of a mathematical statistical study by Brock et al, the three statistics are calculated as follows:

\[
\bar{S}(t) = \frac{1}{16} \sum_{m=2}^{4} \sum_{r=4}^{4} S(m, r, t)
\]

(3)

\[
\Delta \bar{S}(t) = \frac{1}{4} \sum_{m=2}^{4} \Delta S(m, t)
\]

(4)

\[
S_{cor}(t) = \Delta \bar{S}(t) + \bar{S}(t)
\]

(5)

In the formula, the first minimal value of \( \Delta \bar{S}(t) \) corresponds to the delay time \( t \), the minimum value of \( S_{cor}(t) \) corresponds to the embedding window length of the time series \( tw \), the embedding dimension \( m \) is then calculated from \( tw = (m - 1)t \).

Based on the above algorithm, this article performs a parametric solution for the sensor deviation time series, and the results are shown in Figure 1:
Figure 1 Selection of phase space reconstruction parameters

As can be seen from Figure 1, the minimum value of $S_{cor}(t)$ corresponds to the time of 18, the first minimal value of $\Delta S(t)$ corresponds to the delay time $t$ of 2, then the embedding dimension can be calculated as $m = 10$.

3. Methods
This section examines trend prediction analysis techniques for sensor anomalies. The actual problem of predicting anomalous trends in sensor deviation can be summarised as a regression problem. The SVR model is built by phase space reconstruction of the sensor detection deviation timing data, and the prediction model can be determined by training and optimisation.

3.1. Predictive model building
Based on phase space reconstruction theory, the time sequence of sensor deviations of length $n$ is $\{x(t), t = 0, 1, 2, \ldots, n\}$. The state transfer transformations in the m-dimensional phase space is:

$$X_{i,t} = F(x)$$  \hspace{1cm} (6)

where $X_i$ is the i-th phase point in phase space, $t$ is the delay time, and there is:

$$X_i = (x_i, \cdots, x_{i+(m-1)t})$$  \hspace{1cm} (7)

Thus the expansion of equation (6) can be expressed as follows:

$$(x_{i+1}, \cdots, x_{i+(m-1)t}) = F(x_i, \cdots, x_{i+(m-1)t})$$  \hspace{1cm} (8)

In summary, the input and output of the sensor bias prediction model based on phase space reconstruction is shown in equation (9) and (10):

$$input = \begin{bmatrix}
X_1 &= (x_1, x_{1+t}, \cdots, x_{1+(m-1)t})^T \\
X_2 &= (x_2, x_{2+t}, \cdots, x_{2+(m-1)t})^T \\
\cdots \\
X_n &= (x_n, x_{n+t}, \cdots, x_{n+(m-1)t})^T
\end{bmatrix}$$  \hspace{1cm} (9)
\[ \text{output} = \begin{cases} Y_1 = x_1(t - 1) + 1 \\ Y_2 = x_2(t - 1) + 1 \\ \vdots \\ Y_n = x_n(t - 1) + 1 \end{cases} \quad (10) \]

3.2. Model prediction process

Based on the construction of the SVR model, the overall prediction process of the SVR model based on phase space reconstruction is established. It mainly consists of three parts: the model input module, the optimisation module and the performance evaluation module. A block diagram of the sensor bias prediction based on phase space reconstruction and SVR is shown in Figure 2.

![Block diagram of sensor bias prediction](image)

3.3. Model parameters selection

This article uses \(\varepsilon-SVR\) model and a radial basis kernel function for regression analysis of non-linear problems. The parameters that need to be trained for this process are the penalty factor \(C\), the kernel function parameters \(\gamma\) and the insensitivity coefficient \(\varepsilon\).

Different combinations of model parameters correspond to different model performance. A wide range of parameter grid searches are required to obtain the optimal parameters for the prediction model. The parameters are exhaustively enumerated in a certain parameter interval at a certain step length, and then the k-fold cross validation is applied to check the goodness of each parameter and select the pair with the best (relative) results. In cross-validation, the training data is randomly divided into \(k\) subsets of equal size, of which \(k-1\) subsets are used as training samples to obtain a support vector regression machine model, which is used to predict the subsets that do not participate in training and calculate the mean squared error. The mean squared error of the \(k\) predictions is taken as the performance metric and the percentage of correctly predicted data is calculated, the closer the value to 1, the higher the prediction accuracy.
3.4. Model evaluation indicators
Commonly used evaluation indicators for models are Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and similarity (e.g. Coefficient of Equality (EC)).

The MSE is equal to the square root of the sum of the squares of the errors between the predicted and measured values, averaged over time. The MSE not only characterises the magnitude of the errors, but also the degree of dispersion and concentration of the error distribution. The average absolute value of the error between the predicted and measured values is characterised by the MAE; the smaller the value of the MAE, the higher the accuracy of the results. MAPE is a measure of the extent to which the predicted value deviates from the measured value; a larger MAPE value means that the difference is greater. The coefficient of equality, EC, is a measure of the agreement between the predicted and actual values and takes a value between 0 and 1. The closer the EC value is to 1, the more similar it is. Usually if $EC > 0.9$, then the prediction model is predicting better.

4. Results
The SVR-based prediction model experiments are divided into two main parts: model training and model testing. In the experiments of this article, the sensor deviation time series data are first reconstructed using the phase space reconstruction technique, followed by the reconstructed data as the model sample data, of which 75% is used as the training set and the remaining 25% as the test set.

In order to judge whether the constructed prediction model is effective, it is necessary to demonstrate whether the model can reach convergence quickly during the training process, and thus a learning curve is introduced to judge the degree of convergence of the model training. In the training process, the learning curve for distance deviation anomaly trend prediction based on SVR model was obtained as shown in Figure 3.

![Learning curve for distance deviation anomaly trend prediction based on SVR model](image)

As can be seen from Figure 3, the learning curve as a whole shows a decreasing trend, i.e. as the size of the training sample data continues to increase, the corresponding MSE error becomes smaller and smaller. When the training sample data size exceeds 300, the model 10-fold cross-validation MSE error rapidly drops to a very low level and the model training converges rapidly. At this point the optimal parameters for model optimisation are obtained: penalty factor $C = 10$, kernel function parameters $\gamma = 0.001$, and insensitivity coefficient $\varepsilon = 1.0$.

Prediction experiments with the above optimal parameters. The prediction model constructed in this article is compared with the regular SVR model and the BP neural network model, which are shown in Figure 4.
Figure 4 Comparison of different model forecasts

The prediction results of the three models were evaluated separately by applying the prediction model evaluation indicators proposed, and the results were obtained as shown in Table 1.

| Model                | MSE      | MAE   | MAPE  | EC   |
|----------------------|----------|-------|-------|------|
| BP neural network    | 20.19    | 3.20  | 0.16  | 0.92 |
| Regular SVR          | 20.21    | 3.20  | 0.15  | 0.92 |
| SVR (phase-space)    | 17.08    | 2.26  | 0.12  | 0.93 |

As can be seen from Table 1, the phase space reconstruction-based SVR model in this article takes the smallest values of MSE, MAE and MAPE, and the largest values of EC. Compared with the BP neural network prediction model and the regular SVR prediction model, the model constructed in this article has advantages in all performance indexes and has good prediction performance, which can predict the change of the anomaly trend of the real-time sensor detection deviation more accurately.

5. Conclusion

A sensor deviation anomaly trend prediction method based on phase space reconstruction and SVR is proposed for the current problem that sensor deviation anomaly prediction is difficult to be performed and the accuracy is insufficient. Firstly, the phase space reconstruction is performed on the sensor deviation time series data. Then the support vector regression prediction model is established, and the model is trained and optimized using the reconstructed data. Finally, the prediction output is compared with the regular SVR and BP neural network method, and the results show that the method has higher prediction accuracy.

References

[1] Anguo Zhang, Zheng Xu. (2020) Chaotic time series prediction using phase space reconstruction based conceptor network. Cognitive Neurodynamics, 14: 1-9.
[2] Chang Jincai, Wang Zhihang, Zhu Qingyu, Wang Zhao, Li Jin. (2020) SVR Prediction Algorithm for Crack Propagation of Aviation Aluminum Alloy. Journal of Mathematics, 2020: 1-12.
[3] Hou Yue, Li Haiyan. (2014) Chaotic time series prediction for tent mapping based on BP neural network optimized glowworm swarm optimization. In: 2014 International Conference on Advances in Materials Science and Information Technologies in Industry(AMSITI 2014). Xi’an. pp. 183-187.
[4] J.A.K. Suykens & J. Vandewalle. (1999). Least Squares Support Vector Machine Classifiers. Neural Processing Letters. 9: 293-300.