# Prediction of underwater acoustic signals based on ESMD and ELM 

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#### Abstract

The local predictability of underwater acoustic signals plays an important role in underwater acoustic signal processing, as it is the basis for solving non-stationary signal detection. A prediction model of underwater acoustic signals based on extreme-point symmetric mode decomposition (ESMD) and extreme learning machine (ELM) is proposed. First, underwater acoustic signals are decomposed by ESMD to obtain a set of intrinsic model functions (IMFs). After IMFs are grouped, the training samples and forecast samples are obtained. Then, prediction model for training samples is established by using ELM to obtain the input layer, output layer weight vector and offset matrix. The trained ELM is used to predict the forecast sample to obtain component. Finally, the reconstructed IMFs and residuals are the final prediction results. The experimental results show that the proposed model is a good predictive model having better prediction accuracy and smaller error.


[Keywords : Underwater acoustic signals; Extreme-point symmetric mode decomposition; Extreme learning machine; Prediction]

## Introduction

In underwater acoustic signal processing, the ship radiation noise signal in seawater has always been one of the focuses of people's research. The ship radiation noise signal is produced by nonlinear of marine environment and hull dynamic structure and contains a large number of ship features, such as target orientation, distance and depth ${ }^{1}$. An important feature of the underwater acoustic signal is local predictability. The feature plays an important role in underwater acoustic signal processing, as it is the basis for solving non-stationary signal detection ${ }^{2}$. Volterra series theory is used to establish a nonlinear dynamic model of the underwater acoustic signal ${ }^{3,4}$. The signal is predicted by one-step prediction and multi-step prediction, for obtaining the better prediction effect. The radial basis function (RBF) neural network is used to establish the prediction model of underwater acoustic signal with better prediction effect ${ }^{5-7}$.

Empirical mode decomposition (EMD) ${ }^{8}$ is widely used in the decomposition of time series. It can decompose the signal into a number of different frequencies of the intrinsic mode functions (IMFs). But the mode mixing will appear in the process of decomposition, affecting decomposition results ${ }^{9}$. Extreme-point symmetric mode decomposition (ESMD) ${ }^{10}$ is development of the well-known HilbertHuang transform. ESMD continues the idea of empirical mode decomposition. It improves the
interpolation method of the envelope and is a better time-frequency processing method. ESMD can be used effectively in the science research and engineering applications associated with data analysis from atmospheric sciences, oceanic sciences, informatics, and so on ${ }^{11}$. Recently, the time series are usually predicted by BP neural network and RBF neural network ${ }^{12,13}$. This method has many disadvantages, such as calculation complexity, adjusted manually parameters in neural network, slow convergence rate and ease of falling into local minimum. Aiming at these disadvantages, Huang et al. proposed a singlehidden layer feed forward neural networks (SLFNs), called extreme learning machine (ELM) learning algorithm in $2006^{14}$. At present, ELM is widely used in the prediction of time series. The short-term wind is forecast by ELM ${ }^{15}$. ELM combined with fruit fly optimization algorithm (FOA) is used to forecast stock price ${ }^{16}$. Li et al. forecast wind power time series with an improved ELM, and get better results ${ }^{17}$.

In this paper, a prediction model based on ESMD and ELM is proposed in view of their advantages to predict underwater acoustic signal.

## Materials and Methods

## Extreme-point symmetric mode decomposition

ESMD is improved on the basis of EMD. The signal is decomposed by EMD to obtain a set of IMFs
and residuals. The decomposition process can be expressed as:

$$
\begin{equation*}
x(t)=\sum_{j=1}^{n} c_{j}+R \tag{1}
\end{equation*}
$$

where, $R$ is residuals, and $c_{j}$ is the IMF component. The IMF component is extracted from high frequency to low frequency. So the complex signal is smoothened.

In EMD, the enveloping outer enclosure of the signal is determined by cubic spline interpolation. However, the point of repetition of extreme points is used to be internal curve interpolation in extremepoint symmetric mode decomposition. Adjacent and equal extreme points are added as one extreme point to the signal decomposition. ESMD allows a number of residual extremes when the signal is decomposed, because those residual components can reflect the trend of data. This process can be understood as an adaptive global mean (AGM). The last remaining model is optimized by the ideal of least square method. Then the best sieving coefficient in the decomposition ${ }^{18,19}$ is determined. Compared with the EMD method, the problem of mode mixing is solved effectively.

The ESMD algorithm is as follows:
(1) Find all the local extreme points (maxima points and minima points) of the signal Y , and numerate them by $E_{i}(1 \leq i \leq n)$.
(2) Connect all the adjacent $E_{i}$ with line segments, and mark their midpoints by $F_{i}(1 \leq i \leq n-1)$.
(3) Add left and right boundary midpoint $F_{0}$ and $F_{n}$ through a certain approach.
(4) Construct $p$ interpolating curves $L_{1}, L_{2}, \mathrm{~L}, L_{p}(p \geq 1)$ with all these $\mathrm{n}+1$ midpoints, and calculate their mean value:

$$
\begin{equation*}
L^{*}=\frac{L_{1}+L_{2}+\mathrm{L}+L_{p}}{p} \tag{2}
\end{equation*}
$$

(5) Repeat the above four steps on $Y-L^{*}$ until $\left|L^{*}\right| \leq \varepsilon \quad(\varepsilon$ is a permitted error) or the sifting times attain a preset maximum number $K$, and the first mode is obtained.
(6) Repeat the above five steps on the $Y-M_{1}$ residual and get $M_{2}, M_{3} \mathrm{~L}$ until the last residual $R$ with no more than a certain number of extreme points.
(7) Change the maximum number $K$ on a finite integer interval $\left[K_{\text {min }}, K_{\text {max }}\right.$ ] and repeat the above six steps. Calculate the variance $\sigma^{2}$ of $Y-R$ and plot a figure with $\sigma / \sigma_{0}$ and $K$, where $\sigma_{0}$ is the standard deviation of $Y$.
(8) Find the number $K_{0}$ which accords with minimum $\sigma / \sigma_{0}$ on $\left[K_{\min }, K_{\max }\right]$. Then use this $K_{0}$ to repeat the previous six steps and output the whole modes. At this time, the last residual $R$ is an optimal AGM curve.

## Extreme learning machine

ELM is developed by single-hidden layer feed forward neural networks (SLFNs) ${ }^{20}$. ELM greatly improves the learning speed and generalization performance of the network and has many advantages, such as ease in selecting parameters, not falling into local minimum, and so on. In recent years, it has been widely used in time series prediction and a good predictive effect is achieved ${ }^{21}$. The structure of SLFNs is shown in Fig. 1.

For $N$ different $\operatorname{samples}\left(x_{i}, t_{i}\right)$, where $t_{i}=\left[t_{i 1}, t_{i 2}, \mathrm{~L}, t_{i n}\right]^{T} \in R^{N} \quad$ and $\quad x_{i}=\left[x_{i 1}, x_{i 2}, \mathrm{~L}, x_{i n}\right]^{T} \in R^{N}$, standard SLFNs with $R^{\circ}$ hidden layers, and activation function $g(x)$ are mathematically modeled as:

$$
\begin{equation*}
\sum_{i=1}^{\hat{N}} \beta_{i} g_{i}\left(x_{j}\right)=\sum_{i=1}^{\hat{N}} \beta_{i} g\left(w_{i} \cdot x_{j}+b_{i}\right)=o_{j}, j=1, \mathrm{~K}, N \tag{3}
\end{equation*}
$$

where $w_{i}=\left[w_{i 1}, w_{i 2}, \mathrm{~L}, w_{i n}\right]^{T}$ is the weight vector connecting the $i$ th hidden nodes and input nodes; $\beta_{i}=\left[\beta_{i 1}, \beta_{i 2}, \mathrm{~L}, \beta_{i m}\right]^{T}$ is the weight vector connecting the $i$ th hidden node and output nodes; $b_{i}$ is the


Fig. 1 - The structure of SLFNs
threshold of the $i$ th hidden node, and $o_{j}$ is output value of the node.

The standard SLFNs with Kohidden nodes and activation function $g(x)$ can approximate these $N$ samples with zero error that is $\sum_{j=1}^{N}\left\|o_{j}-t_{j}\right\|=0$, there exist $\beta_{i}, w_{i}$ and $b_{i}$ such that
$\sum_{i=1}^{N} \beta_{i} g\left(w_{i} \cdot x_{j}+b_{i}\right)=t_{j}, j=1, \mathrm{~K}, \stackrel{\vdots}{N}$
The above formula can be expressed as a matrix:
$H \beta=T$
where
$H\left(w_{1}, \mathrm{~K}, w_{{\underset{N}{N}}}, b_{1}, \mathrm{~K}, b_{\dot{N}_{N}}, x_{1}, \mathrm{~K}, x_{N}\right)=$
$\left[\begin{array}{ccc}g\left(w_{1} \cdot x_{1}+b_{1}\right) & \mathrm{L} & g\left(w_{N_{N}} \cdot x_{1}+b_{\text {N }_{N}}\right) \\ \mathrm{M} & \mathrm{L} & \mathrm{M} \\ g\left(w_{1} \cdot x_{N}+b_{1}\right) & \mathrm{L} & g\left(w_{\dot{N}_{N}} \cdot x_{N}+b_{N_{N}}\right)\end{array}\right]_{N \times N}$
$\beta=\left[\begin{array}{c}\beta_{1}^{T} \\ \mathrm{M} \\ \beta_{-}^{T} \\ N_{N}\end{array}\right] \quad T=\left[\begin{array}{c}t_{1}^{T} \\ \mathrm{M} \\ t_{N}^{T}\end{array}\right]$
The hidden layer matrix $H$ is a definite matrix, so training SLFNs is equivalent to solving the least squares solution $\hat{\beta}$ which makes $H \beta=T^{13}$ :
$\hat{\beta}=\min _{\beta}\left\|T\left(a_{1}, \mathrm{~L}, a_{N}, b_{1}, \mathrm{~L}, b_{N}\right) \beta-T\right\|$
The above formula is written as a matrix ${ }^{13}$ :
$\hat{\beta}=H^{+} T$
where $H^{+}$is the Moore-Penrose generalized inverse of matrix $H$.
The algorithm of ELM is as follows:
(1) Randomly initializate the input layer weight $w_{i}$ and bias $b_{i}$.
(2) Calculate the hidden layer matrix $H$.
(3) Calculate the output layer weight vector $\beta$.

## Prediction model of ESMD-ELM

First, the signal is decomposed by ESMD to obtain a set of IMFs. After IMFs are grouped, the training
samples and forecast samples are obtained. Then, prediction model for training samples is established by using ELM to obtain the input layer, output layer weight vector and offset matrix. The trained ELM is used to predict the forecast sample to obtain component. Finally, the reconstructed IMFs and residuals are the final prediction results. The block diagram of ESMD-ELM prediction model is shown in Fig. 2. The algorithm of ESMD-ELM is as follows:
(1) Load the original data, decompose the data by ESMD, and obtain IMFs and residuals.
(2) Divide the data of each IMF component and residual into training samples and test samples, and residual into training and test sample establish the ELM prediction model.
(3) Determine the number of input layers, output layers and hidden layers of the ELM model.
(4) The established ELM model is used to predict each component. The reconstructed IMFs and residuals are the final prediction results.

## Results and Discussion

In this paper, normalized pre-treatment ship radiated noise signal is adopted. Its sample rate and length is 20 kHz and 2048 points, respectively. Onethousand points are randomly selected as experimental data, and its time domain waveform is shown in Fig. 3.

The underwater acoustic signal is decomposed by the ESMD software developed by Wang et al. ${ }^{22}$. The minimum number of residual modal points and the maximum number of iterations are 4 and 40 , respectively. The minimum number of shifts for the


Fig. 2 - The block diagram of ESMD-ELM prediction model
output of the minimum variance ratio is calculated as four. ESMD is performed at the best number of sieving coefficient. The results of ESMD are shown in Figure 4.

Seven IMFs components and one remainder are obtained by ESMD. IMF1-IMF3 preserves the high frequency components of the original underwater acoustic signal. IMF7 and R are low frequency components. The remainder R represents the global optimal AGM curve.

The IMF1-IMF7 and residuals were predicted by ELM prediction model. The number of nodes in the input layer is 5 , the number of nodes in the hidden layer is 15 , and the number of nodes in the output layer is 1 . The first five values of each component are used to predict the sixth value. One thousand data can


Fig. 3 - The time domain waveform of underwater acoustic signal


Fig. 4 - The results of ESMD
be divided into 990 sets of data, where the former 800 sets of data are used as the test data, and the latter 190 sets of data are used as the forecast data. Activation function $g(x)$ is radial basis function. The prediction results are accumulated to give final prediction results, which are shown in Figure 5.

It can be seen from Figure 5 that the fitting degree of the actual value and the predictive value is higher. Figure 6 shows the comparison results of BP neural network prediction model and ELM neural network prediction model under the same conditions.

To verify the prediction result, the RMS error (RMSE) and mean absolute error (MAE) are used to estimate the result of prediction model. RMS error can be used to measure the deviation between the observed value and the true value, which reflects the


Fig. 5 - The prediction results of ESMD-ELM


Fig. 6 - The prediction results of BP and ELM

| Table 1-Error comparison of RMSE and MAE in three models |  |  |
| :--- | :---: | :---: |
| Model name | RMSE | MAE |
| BP | 0.0956 | 0.00756 |
| ELM | 0.0524 | 0.00270 |
| ESMD-ELM | 0.0308 | 0.000953 |

discrete degree of the data. The mean absolute error can reflect the actual situation of the prediction error.

The RMS error (RMSE) is

$$
\begin{equation*}
R M S E=\sqrt{\frac{1}{N} \sum_{i=1}^{N}\left(Y_{p r e d}-Y_{r e a l}\right)^{2}} \tag{10}
\end{equation*}
$$

The mean absolute error (MAE) is

$$
\begin{equation*}
M A E=\frac{1}{N} \sum_{i=1}^{N}\left|Y_{p r e d}-Y_{r e a l}\right| \tag{11}
\end{equation*}
$$

where $Y_{\text {pred }}$ is forecast data, and $Y_{\text {real }}$ is original data. Compared with the three models, the RMS error and the mean absolute error of each model are shown in Table 1.

As shown in Table 1, the RMSE and MAE of the BP neural network prediction model are 0.0956 and 0.00756 , respectively, and the RMSE and MAE of the ELM prediction model are 0.0524 and 0.00270 respectively, which shows that the ELM neural network has better accuracy than the BP neural network. The RMSE and MAE of ESMD-ELM prediction model are 0.0308 and 0.000953 respectively, which further improves the prediction precision and reduces the prediction error. Therefore, the model with ESMD and ELM neural network proposed in this paper is a better prediction model.

## Conclusion

In this paper, a hybrid prediction model of extreme-point symmetric mode decomposition and extreme learning machine is proposed to predict the underwater acoustic signal. Extreme-point symmetric mode decomposition can effectively eliminate the aliasing phenomenon when the underwater acoustic signal is decomposed. Compared with the traditional BP neural network, the extreme learning machine chooses the weights of the hidden layer randomly in the process of determining the network parameters, reduces the adjustment time of the network parameters, has strong non-linear learning ability, and
can be better fitting the underwater acoustic signal. The experimental results show that the proposed method can effectively predict the underwater acoustic signal.

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