Hindawi
International Journal of Antennas and Propagation
Volume 2017, Article ID 6458954, 10 pages
https://doi.org/10.1155/2017/6458954

Research Article

Performance Assessment and Prediction for Superheterodyne Receivers Based on Mahalanobis Distance and Time Sequence Analysis

Jinwen Sun,[1,2,3] Chen Lu,[2,3] Manxi Wang,[1] Hang Yuan,[2,3] and Le Qi[2,3]

[1] *State Key Laboratory of Complex Electromagnetic Environment Effects on Electronics and Information System, No. 33, 085 Mailbox, Luoyang, Henan, China*
[2] *School of Reliability and Systems Engineering, Beihang University, Beijing, China*
[3] *Science & Technology on Reliability and Environmental Engineering Laboratory, Beijing, China*

Correspondence should be addressed to Le Qi; qixiaole@buaa.edu.cn

Received 28 February 2017; Revised 28 April 2017; Accepted 23 May 2017; Published 2 July 2017

Academic Editor: Ana Alejos

The superheterodyne receiver is a typical device widely used in electronics and information systems. Thus effective performance assessment and prediction for superheterodyne receiver are necessary for its preventative maintenance. A scheme of performance assessment and prediction based on Mahalanobis distance and time sequence analysis is proposed in this paper. First, a state observer based on radial basis function (RBF) neural network is designed to monitor the superheterodyne receiver and generate the estimated output. The residual error can be calculated by the actual and estimated output. Second, time-domain features of the residual error are then extracted; after that, the Mahalanobis distance measurement is utilized to obtain the health confidence value which represents the performance assessment result of the most recent state. Furthermore, an Elman neural network based time sequence analysis approach is adopted to forecast the future performance of the superheterodyne receiver system. The results of simulation experiments demonstrate the robustness and effectiveness of the proposed performance assessment and prediction method.

1. Introduction

The superheterodyne receiver is one of the most successful forms of radio used in electronics and information systems. With good sensitivity, frequency stability, and selectivity, superheterodyne receivers can translate high-frequency signals to lower frequency signals to make high-quality voice and signals [1]. While modern devices use various radio-receiver designs, the superheterodyne receiver remains one of the most successful ones due to its typicality and extensibility. Moreover, it always plays a key role in an information system. In many cases, a superheterodyne receiver's performance determines the performance of the whole upper system to great extent. Therefore, serious performance degradation assessment and prediction should be carried out to prevent unexpected failures of superheterodyne receivers that might lead to failure of the whole information system. It provides a judgement for the receiver's health condition, which helps make decisions on maintenance actions. Hence, performance prediction is essential for the preventative maintenance and key to prevention of system breakdown.

Although superheterodyne receivers are widely used, studies on their performance assessment and prediction have been rarely exploited. Only a few studies for some specific receivers have been investigated in the field of fault diagnosis and prognostics. Middleton proposed canonical non-Gaussian noise models for measurement and prediction of receiver performance in real interference environments [2]. Wu et al. used a k-means classifier based method to implement hybrid radar emitter recognition [3]. Furthermore, artificial neural networks and Markov chain are also widely used for classification based on observed signals [4, 5]. However, most of these studies just put emphasis on fault diagnosis but ignored the importance of performance assessment and

prediction for receivers. To bridge this gap, performance assessment and prediction approaches using system input and output signals for superheterodyne receivers are targeted in this study.

In order to evaluate the performance degradation degree of the superheterodyne receiver system, at the first step, a state observer is usually established to estimate the system output [6, 7]. Specifically, radial basis function (RBF) neural network has relatively high convergence speed and can approximate to any nonlinear functions [8]. It has been proved that RBF neural network is an effective fault observer to generate residual error [7]. The residual error contains a large amount of state information of the system, which can be used to extract features for performance assessment of the system. To further analyze the signals of superheterodyne receiver and to extract features, techniques such as time-domain analysis are extensively applied by processing the residual error. Then the performance degradation degree is usually assessed by calculating the overlap or distance between the real-time features and the baseline features in the feature space. Shi et al. introduced Self-Organizing Map (SOM) based method for performance degradation assessment with good robustness [9]. However, distortion occurred when the high-dimensional data was mapped into low-dimensional data by using SOM. On the other hand, distance measurement approach such as Mahalanobis distance has been proved a useful way to rapidly assess the performance degradation of many nonstationary systems [10]. Thus Mahalanobis distance measurement is accepted as the key performance assessment method.

As for the constantly updated performance prediction, many time-series analysis methods such as ARMA model and the Kalman filter are widely used for prediction of complicated system [11]. But the ARMA needs a large amount of historical data and is suitable for stationary signal, and the Kalman filter needs to establish accurate state equations. For nonlinear systems' performance prediction, artificial neural networks and support vector machine (SVM) are more suitable [12]. A simulation study based on artificial neural network was proposed for nonlinear time-series forecasting by Zhang et al. [13], and an available capacity computation model relying on artificial neural network was elaborated for battery life prediction by Chan et al. [14]. However, the convergence rate of prediction is rather slow, while the amount of training data is rather huge. Elman neural network is a kind of dynamic neural network, which shows good calculation rate and precision in performance prediction via dynamic historical data [11]. Considering the nonlinear time-invariant features of superheterodyne receivers, Elman neural network is employed for performance prediction in this study.

To solve the aforementioned problems, a method that combines Mahalanobis distance and Elman neural network is proposed in this study in order to realize the accurate performance assessment and prediction, which is beneficial in terms of improving the system's operation reliability. Our original contributions are summarized as follows.

Firstly, a performance feature extraction method based on RBF observer is proposed for superheterodyne receiver system. Based on the extracted features, the health confidence value which reflects the performance of the system is then calculated by the Mahalanobis space.

Secondly, a prediction model based on Elman neural network is adopted to forecast the health state of superheterodyne receiver system. The time sequence analysis method is utilized with the Elman network model to make an effective *M-N* step prediction.

Besides, sufficient experiments are conducted based on a simulated superheterodyne receiver model with typical faults injection. The feasibility and effectiveness of our proposed model matching the receiver system are verified.

The paper is organized as follows: in Section 2, the structure of a typical superheterodyne receiver is introduced. Section 3 elaborates the entire scheme of performance assessment and prediction for the superheterodyne receiver including data preprocessing, feature extracting, assessment, and prediction. In Section 4, the results of simulation experiments are provided and discussed, followed by our open challenges and conclusions in Sections 5 and 6, respectively.

2. System Model

Figure 1(a) shows the block diagram of a typical superheterodyne receiver which consists of antenna, Additive White Gaussian Noise (AWGN) channel, local oscillator, mixer, filters, amplifiers, and demodulator. In Figure 1(b), we can find that the system input $U(t)$ and the system output $Y(t)$ are used as inputs of the system state observer. The residual error is then obtained by calculating the difference value between the actual system output amplitude $Y(t)$ and the estimated output amplitude $\widehat{Y}(t)$ given by the observer. Based on the calculated error, performance assessment and prediction can be carried out.

The faults of superheterodyne receiver have a great influence on the reliability and robustness of the system operation. According to statistical maintenance data, main faults of superheterodyne receivers include amplifier faults, local oscillator faults, and filter faults. In our study, intermediate frequency (IF) amplifier faults and local oscillator faults are selected to simulate the system degradation states, which are marked with red points in Figure 1(a). They represent the gradual degradation fault and the abrupt degradation fault, respectively. If an IF amplifier fault occurs, the gain of the transmitted IF signal will change with it. As a result, the amplitude of the system output signal will change accordingly. As for a local oscillator fault, it will cause frequency deviation and affect the output of the mixer. The IF signal containing the original modulation (transmitted information) will change significantly when the local oscillator degrades severely. Besides, the mixer products will also cause the change of the output signal when there is a local oscillator fault.

In the receiver system, the radio signal is firstly collected by the suitable antenna and then processed and transmitted to the mixer with random noise interference, which is an equivalent of a range of uncertainties. A local oscillator provides the mixing frequency, which is variable for tuning the receiver to different stations. The frequency mixer does the

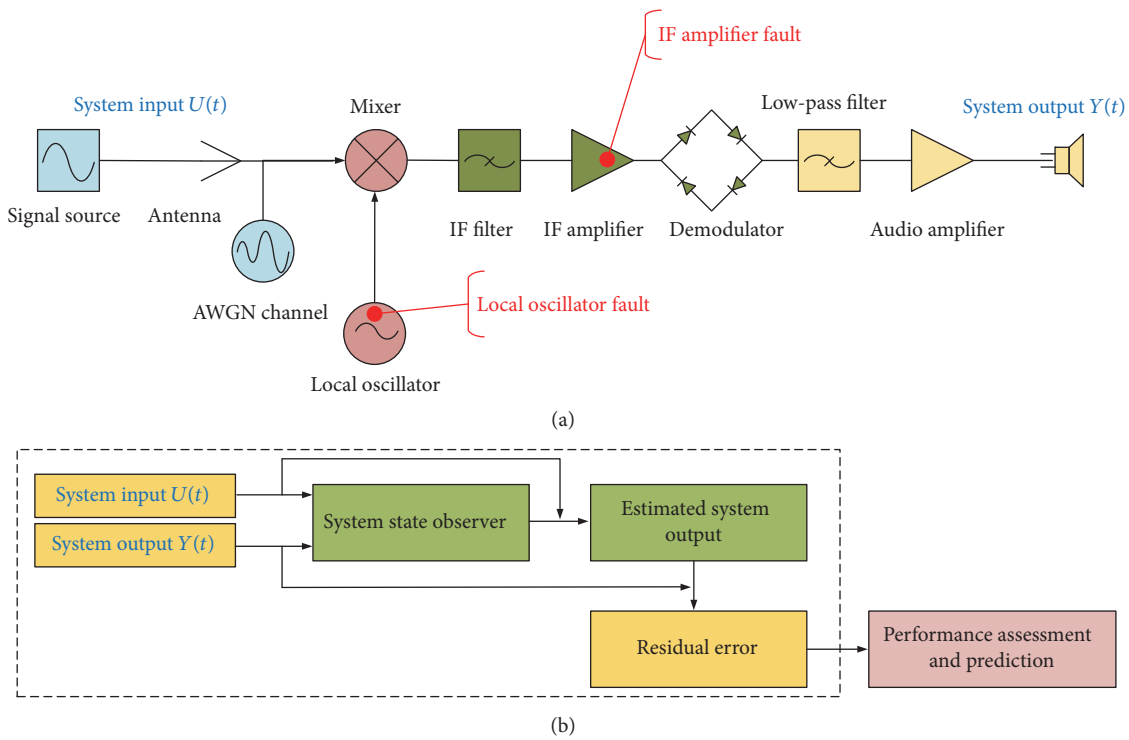


Figure 1: The block diagram of a superheterodyne receiver system model.

actual heterodyning which changes the incoming frequency signal to a fixed IF radio frequency. The IF bandpass filter and the amplifier supply most of the narrowband filtering and the gain for the signal. The demodulator extracts the audio or other modulation from the IF radio frequency, and then the extracted signal is amplified by the audio amplifier. The simulation model is established in MATLAB/Simulink environment, based on the principle of the superheterodyne receiver. The details of the simulation model are as follows:

(i) The signal source has a wave carrier with a frequency of 1000 kHz. The modulated baseband signal can be changed as required. And the signal module is packaged into a subsystem.

(ii) The parameter of the attenuator module is 0.1, simulating the attenuation caused by the transmission distance from the transmitter to the receiver.

(iii) In order to simulate the interference of electromagnetic environment, the AWGN channel is employed to add random white noise with a mean of 0 and a variance of 0.01 into the input radio signal, before the signal is transmitted to the receiver.

(iv) The local oscillator (LO) is designed to generate local oscillator signal, which is used to mix with the input signal by changing the LO frequency. And the frequency is set to 465 kHz lower than the input radio frequency based on

$$f_{\mathrm{IF}} = f_{\mathrm{RF}} - f_{\mathrm{LO}}. \tag{1}$$

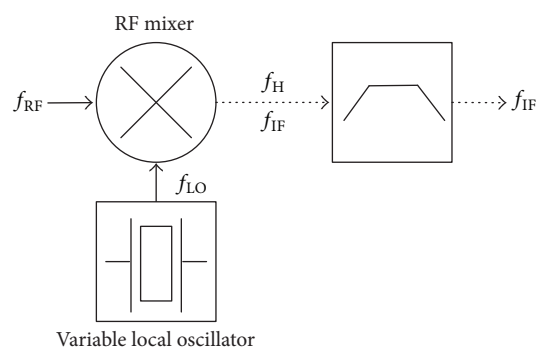


Figure 2: Mixer of superheterodyne receiver.

(v) The mixer, shown in Figure 2, is established to perform channel selection and frequency translation in a single step. By mixing the input radio signal (RF) with the LO signal, the mixer outputs a fixed intermediate frequency (465 kHz).

(vi) The IF signal obtained from the mixer is then fed into the IF filter, a bandpass filter centered at 465 kHz with a bandwidth of 12 kHz.

(vii) The IF amplifier can change the frequency levels in circuits that are too selective, difficult to tune. The gain for signal output is 20. Another IF filter is modeled to further eliminate the band noise with the same parameters of the former filter.

(viii) The envelope detector is then designed to demodulate the signal from the filter and provide an output which

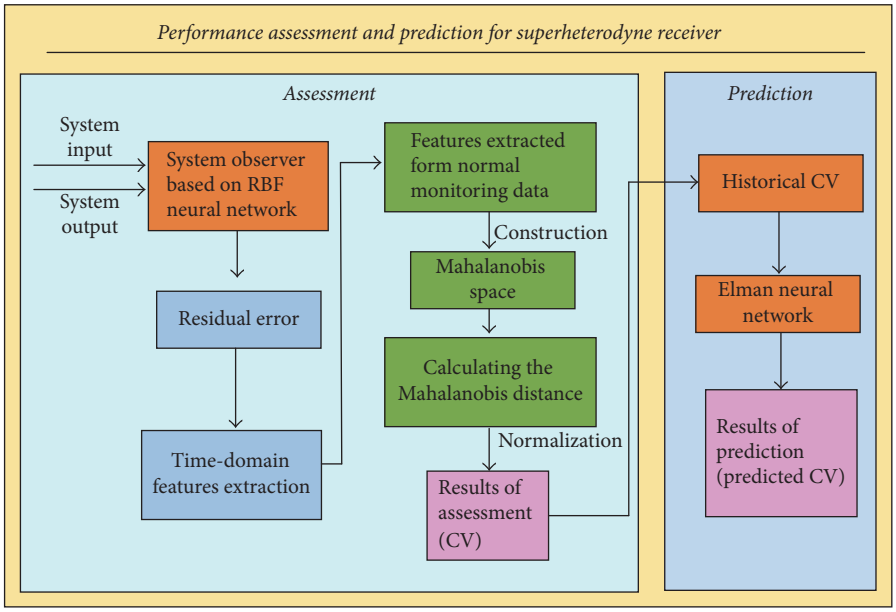


Figure 3: Performance assessment and prediction for a superheterodyne receiver.

is the envelope of the input IF signal. The upper and lower limits are set to inf and 0, respectively.

(ix) The low-pass filter finally processes the signal obtained from the detector and send it to the audio amplifier. The passband edge frequency of the low-pass filter is 6 kHz.

3. Methodology

This paper provides performance assessment and prediction for superheterodyne receivers, and the schematic diagram is shown in Figure 3.

The system health monitoring can be divided into two processes, that is, the assessment process and the prediction process. Both the performance assessment and prediction are based on the residual error of fault observer established upon a radial basis function (RBF) neural network.

Performance assessment hinges on the Mahalanobis space constructed by the features extracted from the residual error under normal operation condition. Then the similarity for features of monitoring data under different faults is calculated using the Mahalanobis distance in the Mahalanobis space. Finally, assessment for superheterodyne receiver is accomplished by normalizing the distance. The result of performance assessment is quantitatively indicated by a confidence value (CV). CV ranges from 0 to 1, indicating unacceptable and normal performance, and it usually decreases over time [15]. As for performance prediction, an Elman neural network trained using historical data is employed to predict the performance of the system so that timely maintenance can be conducted before severe faults occur [16]. The time sequence analysis method makes the performance prediction update constantly, which is significant for preventative maintenance.

The assessment process and the prediction process are two respective steps. The prediction process needs to be carried out based on the result of the performance assessment. Both of them are updated over time with the time-invariant receiver system input and output.

3.1. Residual Error Generation Based on RBF Neural Network. A superheterodyne receiver is a nonlinear system in which the values of the parameters of the inner parts are inconvenient to obtain; hence the state observer is established with the system input and output signals. In the proposed performance assessment method, the previous-moment output amplitude in the normal state and time is utilized as input for the RBF neural network, whereas the output signal amplitude is used as target values for network training. After training, the created observer can generate the expected values of normal output signals. In this way, the residual error of the test data is obtained by calculating the difference values between the actual output signals and the estimated output signals. The residual error contains a large amount of state information of the system, which can be used to extract features for performance assessment of the system.

Suppose that the superheterodyne receiver system can be described as

$$\begin{aligned} X(t) &= g(t, X, U, Y, f), \\ Y(t) &= h(t, X, U, Y, f), \end{aligned} \tag{2}$$

where $X(t)$, $Y(t)$, $U(t)$, and $f(t)$ indicate the state vector, output vector, input vector, and failure vector of the superheterodyne receiver system, respectively. In (2), g and h are nonlinear functions.

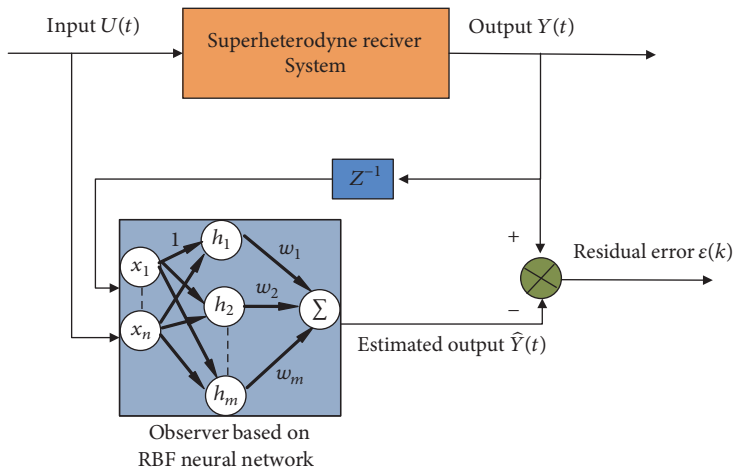


Figure 4: Observer based on RBF neural network.

The system state observer can be defined as

$$\widehat{X}(t) = g\left(t, \widehat{X}, U, Y, \widehat{f}\right),$$
$$\widehat{Y}(t) = h\left(t, \widehat{X}, U, Y, \widehat{f}\right). \tag{3}$$

Then the state error is defined as

$$e(t) = X(t) - \widehat{X}(t). \tag{4}$$

If $\lim_{x\to\infty} e(t) = 0$ when $f(t) = 0$ or $f(t) \neq 0$, (3) is defined as the system state observer of (2).

Since it is difficult to deduce the mathematic transfer function of the receiver system, RBF neural network is applied as the system observer considering its nonlinear fitting capability. As shown in Figure 4, the RBF neural network is a three-layer neural network, and the function of the network is

$$y = f_i(x) = \sum_{K=1}^{N} \omega_{iK} \varphi_K \left(\|x - C_k\|^2\right). \tag{5}$$

Here, a Gaussian function is employed as the radial basis function:

$$\varphi_K(x) = \exp\left(-\frac{\|x - C_K\|^2}{2\sigma_K^2}\right). \tag{6}$$

In (5) and (6), N is the number of neurons in the hidden layer, ω_{iK} is the weight of neuron K in the linear output neuron, C_K is the center vector for neuron K, and φ_K is the radial basis function for neuron K.

In this study, the training parameters for the system observer are as follows: training error goal is $1e-5$, function spread is set as 1, and maximum neuron number is 100.

The residual error is calculated as follows:

$$\varepsilon(k) = Y(t) - \widehat{Y}(t). \tag{7}$$

When the superheterodyne receiver system works normally, the system operation station is similar to the normal state; thus the residual error is close to zero. The residual error in this situation is $\varepsilon_0(k)$, which can be considered as a baseline residual error. When there are failures occurring in the system, the residual error becomes greater accordingly.

3.2. Feature Extraction with Time-Domain Analysis. The residual error can reflect the running state of the superheterodyne receiver system. Hence, time-domain analysis is applied to extract features from the residual error datasets. Here, the time-domain analysis refers to signal amplitude processing. The time-domain parameters of the signal include the mean value, the maximum value, the minimum value, and the root mean square value (RMS). In this study, we choose the RMS value, the mean value, and the peak value.

If $x_s(t)$ is a set of sampling data $x_1, x_2, \ldots, x_N$, three chosen time-domain parameters are calculated as follows:

The RMS value:

$$\alpha = x_{\text{rms}} = \sqrt{\frac{1}{T}\int_0^T x^2 dt}. \tag{8}$$

The mean value:

$$\beta = \overline{X} = \frac{1}{N}\sum_{i=1}^{N} x_i. \tag{9}$$

The peak value:

$$\gamma = C_f = \frac{X_{\max}}{X_{\text{rms}}}. \tag{10}$$

Then the feature vectors of superheterodyne receivers can be expressed as $C = [\alpha, \beta, \gamma]$.

3.3. Assessment with Mahalanobis Distance Measurement. The Mahalanobis distance is a measure of the distance between a point P and a distribution D. The distance is zero if P is at the mean of D and grows as P moves away from the mean. When calculating the distance between the unknown

point and the sample space, the intrinsic relationship between the sample points is taken into consideration. As a statistical distance, the calculation of the Mahalanobis distance is relatively simple and fast. In order to achieve the purpose of rapid assessment, Mahalanobis distance measurement is proposed for the performance assessment of superheterodyne receivers.

If the feature vectors of the residual error are extracted, the Mahalanobis distances can be calculated as follows:

(1) Calculate the mean value of each feature vector:

$$\overline{x}_i = \frac{\sum_{j=1}^{n} x_{ij}}{n}. \tag{11}$$

(2) Calculate the standard mutation of each feature vector:

$$s_i = \sqrt{\frac{\sum_{j=1}^{n} \left(X_{ij} - \overline{x}_i\right)^2}{n-1}}. \tag{12}$$

(3) Orthogonalize each feature vector and obtain its orthogonal matrix and transpose matrix:

$$Z_{ij} = \frac{\left(X_{ij} - \overline{x}_i\right)}{s_i}. \tag{13}$$

(4) Calculate the correlation matrix of the orthogonal data:

$$c_{ij} = \frac{\sum_{m=1}^{n} \left(Z_{im} Z_{jm}\right)}{n-1}. \tag{14}$$

(5) Then, the Mahalanobis distances are calculated using

$$\mathrm{MD}_j = Z_{ij}^T \mathrm{C}^{-1} Z_{ij}. \tag{15}$$

The residual error obtained under normal condition of the superheterodyne receiver is used to extract the feature vectors, which can be denoted as $C_1(\alpha_{0\_1}, \beta_{0\_1}, \gamma_{0\_1})$, $C_2(\alpha_{0\_2}, \beta_{0\_2}, \gamma_{0\_2}), \ldots,$ $C_n(\alpha_{0\_n}, \beta_{0\_n}, \gamma_{0\_n})$, where $\{C_1, C_2, \ldots, C_n\}$ is used to construct the base vector of the Mahalanobis space.

When the superheterodyne system operates in the condition of performance degradation, the feature vectors extracted from the residual error can be represented by $X_1(\alpha_1, \beta_1, \gamma_1), X_2(\alpha_2, \beta_2, \gamma_2), \ldots, X_n(\alpha_n, \beta_n, \gamma_n)$. Based on the above-mentioned Mahalanobis space, each feature vector's distance can be calculated as $d_1, d_2, \ldots, d_n$.

Finally, the calculated Mahalanobis distances are normalized to CVs as follows:

$$\mathrm{CV}_i = 1 - \frac{\arctan\left(d_i + a\right) - \arctan\left(a\right)}{\pi/2 - \arctan\left(a\right)}. \tag{16}$$

In (16), d_i is the Mahalanobis distance; a is the normalized parameter. By adjusting a, the sensitivity of CVs for different fault patterns can be changed.

According to the definition of the Mahalanobis distance, the feature vector obtained in the case of better performance has the nearer distance from the Markov space, and thus the CVs are higher accordingly [17].

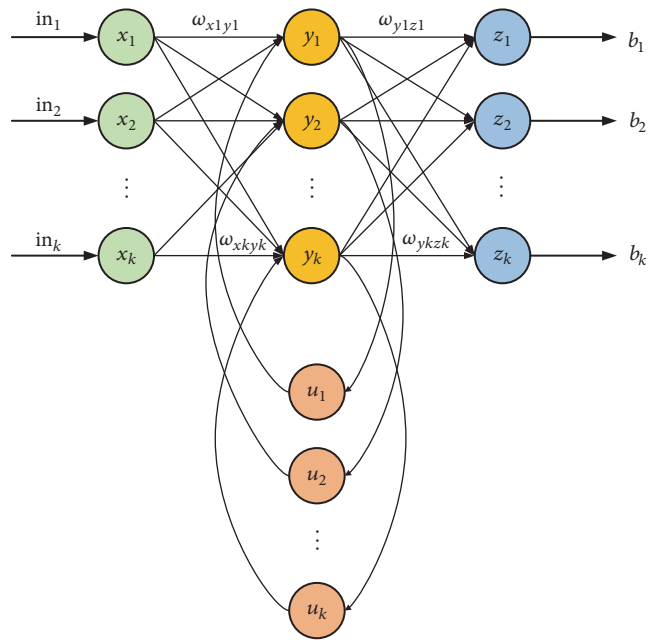


Figure 5: Structure of Elman neural network.

3.4. Prediction Based on Elman Neural Network. The Elman neural network, as shown in Figure 5, is a typical dynamic neural network, which consists of four layers: input layer x, hidden layer y, acceptor layer u, and output layer z. The connections between layers x, y, and z are similar to those of the feed-forward network. The acceptor layer is used for maintaining a copy of the previous time step values of hidden layer; thus it can be regarded as a one-step time delay operator.

The characteristic of the Elman neutral network is that it can maintain a sort of state since the output of hidden layer connects with its input by acceptor layer. This kind of self-connection makes the network sensitive to its historical state values, which increases the ability of dynamic information processing [18]. With these characteristics, Elman neural network can be employed to perform the sequence prediction of CV generated by the Mahalanobis distance.

Mathematical model of the Elman neural network can be defined as follows:

$$\begin{aligned} x(k) &= f\left(w_{I1} x_c(k) + w_{I2} \mu(k-1)\right), \\ x_c(k) &= \alpha x_c(k-1) + x(k-1), \\ y(k) &= g\left(w_{I3} x_c(k)\right), \end{aligned} \tag{17}$$

where w_{I1}, w_{I2}, and w_{I3} are the weight matrices of acceptor layer-output layer, input layer-hidden layer, and hidden layer-output layer, respectively. $x(k)$ and $x_c(k)$ indicate the outputs of acceptor layer and hidden layer, and $y(k)$ is the output of output layer. The transform function is set as sigmoid function and the gain factor is denoted as $\alpha \in [0, 1]$.

As shown in Figure 6, the manner of performance prediction process is called M-step prediction, which uses the last N $(N \geq 1)$ values to predict the future M $(M \geq 1)$ values.

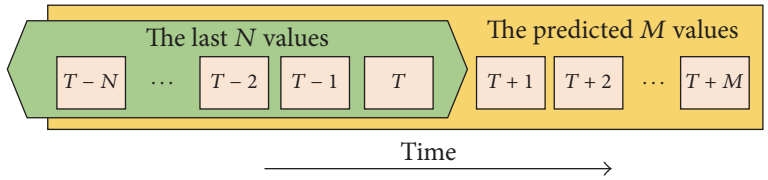


Figure 6: Manner of the prediction process.

Table 1: Inputs and outputs of performance prediction.

N inputs	M outputs
$X_1, X_2, \ldots, X_N$	$X_{N+1}, X_{N+2}, \ldots, X_{N+M}$
$X_2, X_3, \ldots, X_{N+1}$	$X_{N+2}, X_{N+3}, \ldots, X_{N+1+M}$
$\cdots$	$\cdots$
$X_k, X_{k+1}, \ldots, X_{N+k}$	$X_{N+k+1}, X_{N+k+2}, \ldots, X_{N+k+M}$

The predicted CV can be used to train the Elman neural network together with the historical CV, which makes the network more accurate and adapt to the dynamic monitoring information. The process is like a sliding window; that is, $N+M$ adjacent samples are used to utilize the prediction, with N samples mapped to M values, as is shown in Table 1. This kind of prediction process can give timely warnings when the receiver system operates abnormally and improve the ability of preventative maintenance.

4. Case Study

4.1. Simulation Parameters and Fault Injection. In our study, several typical faults are injected into the simulation model to demonstrate effectiveness of the proposed method. In this simulation experiment, the input signal is a sine signal. The amplitude of system input is 1; the frequency of system input is 100 Hz. In the simulation, the sampling rate is 120 kHz, while the simulation duration is set 0.05 s. Thus 6000 data points of input and 6000 data points of output are collected in each case.

According to statistical maintenance data, main faults of superheterodyne receivers include amplifier faults, local oscillator faults, and filter faults. In this study, IF amplifier fault and local oscillator fault were introduced into the simulation model by changing some specific parameters of the fault components, and they represented the gradual degradation fault and the abrupt degradation fault. The details are listed in Table 2. All the faults were introduced into the simulation model from $t = 0.01$ s.

4.2. Obtaining the Residual Error. The RBF neural network was firstly trained using the normal dataset, including the input/output data under normal working condition. Then it was applied to get the estimated output under these faults by inputting each fault dataset into the RBF neural network observer. By comparing the estimated output and the actual output, 6000 discrete residual errors were calculated in each case as shown in Figures 7 and 8.

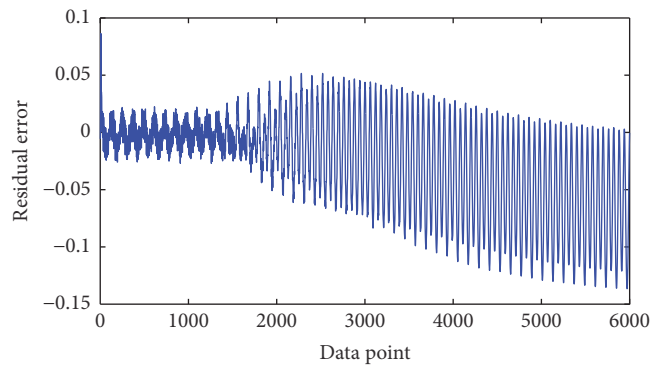


Figure 7: Residual error of amplifier fault state.

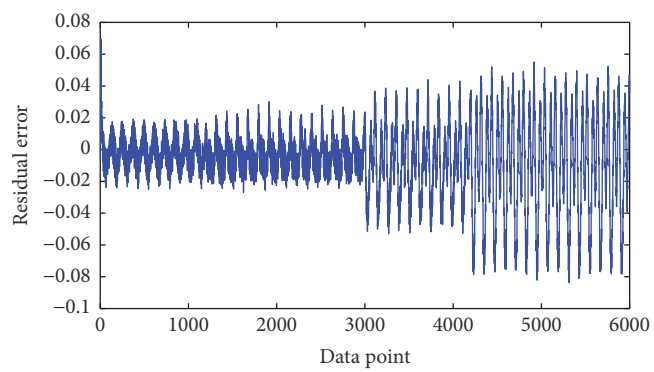


Figure 8: Residual error of oscillator fault state.

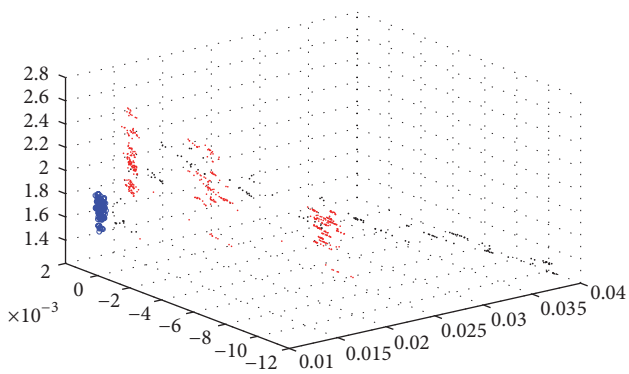
4.3. Performance Assessment and Result Analysis. To assess the performance of the superheterodyne receiver system, one feature vector including 3 features was extracted from each 120 samples of the residual error. And the starting point of feature extraction slided every 10 points, which could be listed as $1, 11, 21, \ldots, 5881$. Eventually 589 feature vectors were extracted from 6000 residual error samples in each case as shown in Figure 9.

The three-dimensional feature vectors of normal state could construct the Mahalanobis space. Then the Mahalanobis distances of the two fault states were calculated and normalized to CVs. To demonstrate the proposed approach presented in the study, three tests were conducted and the results of the Mahalanobis distances and CVs were shown in Figures 10 and 11.

In test 1, the superheterodyne receiver worked normally; thus the residual error kept a regular range and the values of

Table 2: Fault injection details.

Test number	Fault mode	Changed parameters for fault injection	Parameter (normal)	Parameter (fault)
1	Normal	—	—	—
2	Amplifier fault	Gain	20	gain $= 20\exp(-100 * (t - 0.01))$
3	Local oscillator fault	LO frequency (kHz)	465	frequency $= \begin{cases} 462\,\text{kHz}, & 0.01 \le t < 0.025 \\ 461\,\text{kHz}, & 0.025 \le t < 0.035 \\ 460\,\text{kHz}, & 0.035 \le t \end{cases}$



Blue rings: normal state
Black points: amplifier gradual fault state
Red points: local oscillator abrupt fault state

Figure 9: Feature vectors of superheterodyne receivers.

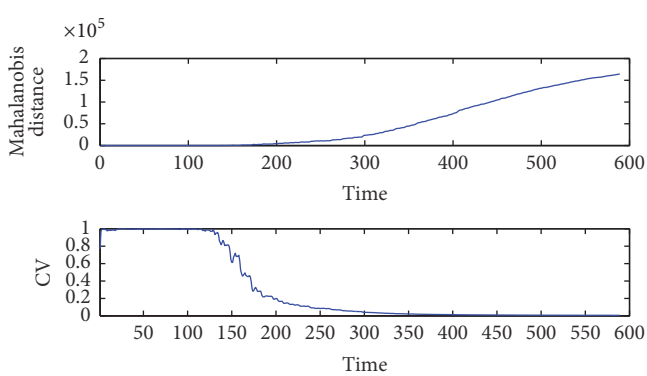


Figure 10: Performance assessment of amplifier fault state.

Mahalanobis distance were close to zero, while its CVs were close to 1.

In test 2, an IF amplifier gradual fault was injected into the system at $t = 0.01$ s. Then, it was observed that the residual error began to increase gradually from $t = 0.01$ s in Figure 6. The values of Mahalanobis distance increased with the injected IF amplifier fault, while the CVs decreased synchronously as shown in Figure 8. We can find that there was a considerable difference in the magnitude between the normal and fault states. The CVs fell from around 1 to around 0 gradually with the performance degradation of the system.

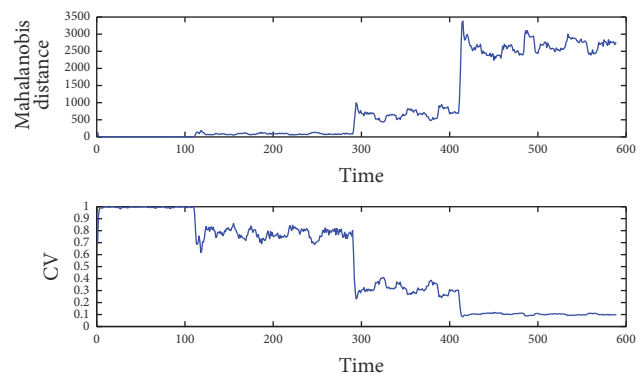


Figure 11: Performance assessment of oscillator fault state.

In test 3, a local oscillator fault was introduced into the superheterodyne system, and then, as shown in Figure 7, the residual error began to have a larger wave range than before at $t = 0.01$ s, 0.025 s, 0.035 s. Accordingly, the values of Mahalanobis distance appeared to have a stepped increase. And the CVs declined continuously along with the variation of LO frequency, which explained that the performance of the system degraded in different degrees when they worked abnormally as shown in Figure 9.

According to the simulation results, the performance assessment for the superheterodyne system under noise was effective with injected faults of different degrees. The CVs obtained by this approach can quantitate the performance degradation of the system.

4.4. Performance Prediction and Result Analysis. Performance assessment results of the IF amplifier gradual fault were used to validate the performance prediction. In order to know the performance degradation trend of the superheterodyne receiver after performance assessment, the Elman neural network was employed to predict the performance.

Let variable T be the current time; an Elman neural network was firstly trained to predict the CVs of next 10 values from $T = 135$. Considering precision and synchronization of the prediction, the width of the slide window was set to 30, and the prediction length was set to 10 steps. That means the future 10 CVs were predicted by the last 20 values, which kept the CV calculation and prediction synchronous. The prediction wound supports the system maintenance with useful predictive information.

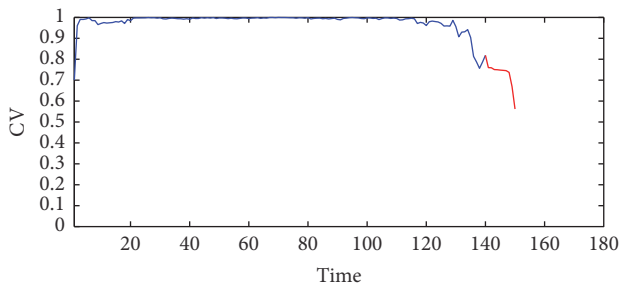


Figure 12: Performance prediction under amplifier gradual fault at $T = 140$.

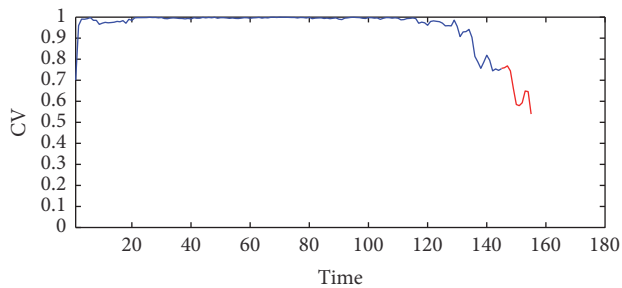


Figure 13: Performance prediction under amplifier gradual fault at $T = 145$.

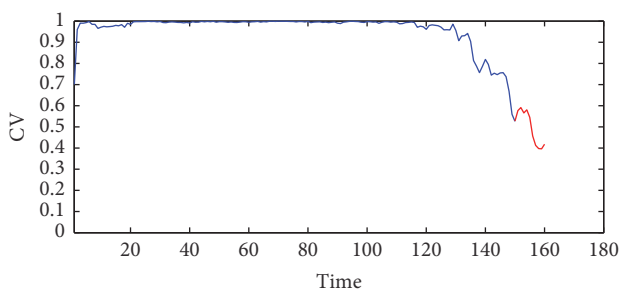


Figure 14: Performance prediction under amplifier gradual fault at $T = 150$.

The prediction results were shown in Figures 11–15. The blue lines were the historical CVs, while the red lines were the predicted CVs. Four graphics at different time ($T = 140$, $T = 145$, $T = 150$, and $T = 155$) had illustrated the feasibility of the time sequence prediction by using Elman neural network, based on the performance assessment results.

5. Future Work and Open Challenges

The advantage of the proposed method lies in the efficient synergy between RBF neural network observer and Mahalanobis distance measurement, which can make good use of the extracted feature vectors. On the other hand, there are some disadvantages in the study. The CVs, though useful in describing the performance of superheterodyne receivers quantitatively, need to be carefully investigated in their physical meaning.

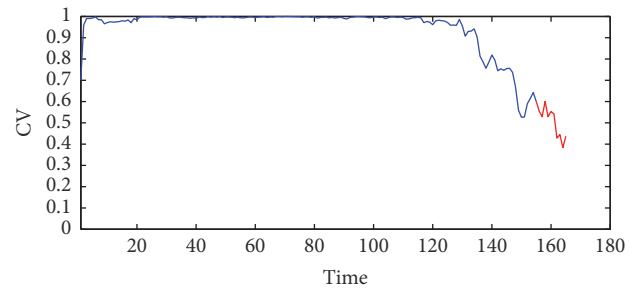


Figure 15: Performance prediction under amplifier gradual fault at $T = 155$.

Furthermore, there are several important open challenges as follows, which need to be further considered:

(i) The variables in the assembly process, which have an impact on the system performance, can be taken into account to fulfill a more integrated assessment [19, 20].

(ii) The reliability and robustness of the system model should be analyzed properly, based on the main sources of uncertainty and disturbance affecting the considered system [21].

(iii) The effectiveness of the proposed algorithms should be validated and improved by data sampled from the actual superheterodyne receivers.

6. Conclusions

This work presents a method for performance assessment and prediction of superheterodyne receivers based on Mahalanobis distance measurement and time sequence analysis. The residual error is obtained by using a RBF observer and utilized to calculate Mahalanobis distance to measure the distance indicating the performance state of the superheterodyne receiver. Finally, an Elman neural network is used to predict the degradation trend of the superheterodyne receiver, which is critical to preventative maintenance. The simulation results showed that the proposed method can effectively assess and predict the performance of superheterodyne receivers.

Conflicts of Interest

The authors declare that there are not any potential conflicts of interest in the research.

Acknowledgments

This study was supported by the State Key Laboratory of Complex Electromagnetic Environment Effects on Electronics and Information System, China, and the Fundamental Research Funds for the Central Universities (Grant no. YWF-17-BJ-J-42), as well as the National Natural Science Foundation of China (Grant nos. 51575021 and 51605014).

References

[1] C. Stagner, A. Conrad, C. Osterwise, D. G. Beetner, and S. Grant, "A practical superheterodyne-receiver detector using stimulated emissions," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 4, pp. 1461–1468, 2011.

[2] D. Middleton, "Canonical non-Gaussian noise models: their implications for measurement and for prediction of receiver performance," *IEEE Transactions on Electromagnetic Compatibility*, vol. 21, no. 3, pp. 209–219, 1979.

[3] Z. Wu, Z. Yang, H. Sun, Z. Yin, and A. Nallanathan, "Hybrid radar emitter recognition based on rough k-means classifier and SVM," *Eurasip Journal on Advances in Signal Processing*, vol. 2012, no. 1, article 198, 2012.

[4] B. Samanta, K. R. Al-Balushi, and S. A. Al-Araimi, "Bearing fault detection using artificial neural networks and genetic algorithm," *Eurasip Journal on Applied Signal Processing*, vol. 2004, no. 3, pp. 366–377, 2004.

[5] J. Wang, C. Jiang, Z. Han, Y. Ren, and L. Hanzo, "Network association strategies for an energy harvesting aided super-wifi network relying on measured solar activity," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 12, pp. 3785–3797, 2016.

[6] D. Zhai, L. An, J. Dong, and Q. Zhang, "Observer-based fault detection and accommodation for nonlinear time-delay systems with a prescribed performance mechanism," *Applied Mathematical Modelling. Simulation and Computation for Engineering and Environmental Systems*, vol. 40, no. 19-20, pp. 8377–8390, 2016.

[7] H. Yuan, C. Lu, J. Ma, and Z.-H. Chen, "Neural network-based fault detection method for aileron actuator," *Applied Mathematical Modelling*, vol. 39, no. 19, pp. 5803–5815, 2015.

[8] C. Lu, N. Ma, and Z. Wang, "Fault detection for hydraulic pump based on chaotic parallel RBF network," *Eurasip Journal on Advances in Signal Processing*, vol. 2011, article 49, 2011.

[9] S. Shi, L. Zhang, and W. Liang, "Condition monitoring and fault diagnosis of rolling element bearings based on wavelet energy entropy and SOM," in *Proceedings of the 2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering (ICQR2MSE'12)*, pp. 651–655, Chengdu, China, June 2012.

[10] A. Soylemezoglu, S. Jagannathan, and C. Saygin, "Mahalanobis taguchi system (MTS) as a prognostics tool for rolling element bearing failures," *Journal of Manufacturing Science and Engineering, Transactions of the ASME*, vol. 132, no. 5, Article ID 051014, 2010.

[11] D. Djurdjanovic, J. Lee, and J. Ni, "Watchdog agent - An infotronics-based prognostics approach for product performance degradation assessment and prediction," *Advanced Engineering Informatics*, vol. 17, no. 3-4, pp. 109–125, 2003.

[12] X. Zhao, C. Hou, and Q. Wang, "A new SVM-based modeling method of cabin path loss prediction," *International Journal of Antennas and Propagation*, vol. 2013, Article ID 279070, 7 pages, 2013.

[13] G. P. Zhang, B. E. Patuwo, and M. Y. Hu, "A simulation study of artificial neural networks for nonlinear time-series forecasting," *Computers & Operations Research*, vol. 28, no. 4, pp. 381–396, 2001.

[14] C. C. Chan, E. W. C. Lo, and S. Weixiang, "Available capacity computation model based on artificial neural network for lead-acid batteries in electric vehicles," *Journal of Power Sources*, vol. 87, no. 1, pp. 201–204, 2000.

[15] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, and D. Siegel, "Prognostics and health management design for rotary machinery systems—reviews, methodology and applications," *Mechanical Systems and Signal Processing*, vol. 42, no. 1-2, pp. 314–334, 2014.

[16] L. Liao and J. Lee, "Design of a reconfigurable prognostics platform for machine tools," *Expert Systems with Applications*, vol. 37, no. 1, pp. 240–252, 2010.

[17] J. Lee, "Machine performance monitoring and proactive maintenance in computer-integrated manufacturing: Review and perspective," *International Journal of Computer Integrated Manufacturing*, vol. 8, no. 5, pp. 370–380, 1995.

[18] P. Li, Y. Li, Q. Xiong, Y. Chai, and Y. Zhang, "Application of a hybrid quantized Elman neural network in short-term load forecasting," *International Journal of Electrical Power & Energy Systems*, vol. 55, pp. 749–759, 2014.

[19] J. Ni, W. C. Tang, and Y. Xing, "Assembly process optimization for reducing the dimensional error of antenna assembly with abundant rivets," *Journal of Intelligent Manufacturing*, pp. 1–14, 2015.

[20] J. Ni, W. Tang, and Y. Xing, "A simple algebra for fault tree analysis of static and dynamic systems," *IEEE Transactions on Reliability*, vol. 62, no. 4, pp. 846–861, 2013.

[21] S. Ding, *Model-Based Fault Diagnosis Techniques: Design Schemes, Algorithms, and Tools*, Springer Science & Business Media, 2008.