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A New Incipient Fault Diagnosis Method Combining Improved RLS and LMD Algorithm for Rolling Bearings With Strong Background Noise

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ABSTRACT Aiming at the difficulty of extracting information for incipient fault symptoms from rolling bearings with strong background noise, an improved incipient fault detection method based on modified recursive least squares (RLS) adaptive equalization, and a local mean decomposition (LMD) algorithm is proposed. First, an efficient RLS de-noising model is established by introducing a momentum factor together with a forgotten factor to de-noise the incipient fault signal of the bearings. Then, the LMD algorithm is used to decompose the pre-processed signal to obtain an effective PF component, and complete the envelope demodulation to extract information from the incipient fault. Based on the above algorithm, an improved RLS and LMD identifying algorithm for incipient faults can thus be achieved. Finally, some actual fault signals of a large unit rolling bearing are used to simulate and verify the accuracy and efficiency of the proposed algorithm. The experimental comparison indicated that our algorithm can not only improve the de-noising effect, but also correctly extract the features of the incipient fault and identify them with good engineering operability and expansibility.

INDEX TERMS Bearing mechanical signal, improved RLS, local decomposition algorithm, incipient fault diagnosis, noise elimination.

I. INTRODUCTION

As one of the key components in mechanical equipment, rolling bearings have been paid increasing attention by industry and academia for safety monitoring. However, when an exception, such as pitting or crack failure, occurs while bearings are running, low amplitude bearing vibration acceleration signals are always provided owing to the concealment of unknown disturbances and noises. In terms of this phenomenon, the fault features of the bearing vibration acceleration signals are no longer obvious, leading to great difficulty in monitoring bearing safety in the running state. Therefore, aiming at the ambiguity of fault features for incipient fault bearings, how to devise adaptive methods to extract fault features in order to ensure accurate fault diagnosis and safety monitoring has drawn much attention from scholars at home and abroad [1]–[3].

In fact, fault features in the early stage are extremely inconspicuous, as the incipient faults possess the characteristics of concealment and randomness, making incipient faults difficult to diagnose. To solve the aforementioned problem, [4] proposed a multi-level incipient fault diagnosis method based on the PCA projection framework. This method achieved good fault diagnoses results but limited the noise to a Gaussian distribution by the PCA assumption, which is not extendable for industrial systems in reality. To eliminate the defect mentioned above, the reference [5] used frequency domain ICA technology to realize the separation of the multi-dimensional vibration signals in the gearbox and combined the Morlet wavelet filter to obtain fault features for the incipient faults. Although this method removed the defects of the PCA, it simply ignored the temporal correlations of the fault data. Reference [6] treated the features of the fault signal extracted by discrete wavelet transform as the input of the neural network and improved the incipient fault diagnosis effect of the gearbox. Unfortunately, the method in [6] overlooks the frequency distribution of fault signals within the time domain and thus is not conducive to delving deeper into the incipient fault feature information. Reference [7] designed a new continuous decision function for the SVM classifier, which can not only identify the type of faults but also monitor the severity of the fault. Incipient fault detection technology based on SVM for solving small sample, nonlinear and high dimensional fault pattern recognition shows many advantages, but there is still a defect in that the fault diagnosis accuracy depends largely on having representative and complete fault samples. Although SVM has good learning ability, it diagnoses the fault only from the classification points and does not profoundly excavate the structural information of the data. Owing to these defects, existing bearing incipient fault diagnosis algorithms lack adaptability and cannot meet the actual needs of the site security environment.

To solve these defects mentioned above, the empirical mode decomposition (EMD) algorithm has been proposed by some scholars [8], where the incipient bearing fault vibration signals are decomposed into the sum of multiple components (MF) and residuals, and the time frequency distribution of the signals is identified by the envelope spectrum analysis of the components. Therefore, the EMD algorithm has greater advantages and a high signal-to-noise ratio for addressing nonlinear and non-stationary signal sequences. Because of these advantages, the EMD algorithm makes up for the shortcomings of existing incipient fault diagnosis algorithms, such as a lack of adaptability, and is widely used in incipient fault diagnosis of mechanical equipment. However, the EMD algorithm still has its shortcomings, such as mode confusion, end effects, under envelope, and low decomposition accuracy. To solve these problems, some scholars have constructed a new adaptive local mean decomposition (LMD) algorithm based on local signal scale parameters [9]–[11]. Thankfully, the algorithm can adaptively decompose the signal into a finite number of product function (PF) components and each PF component is a single component AM-FM function that is composed of an envelope signal and pure FM function. It is noteworthy that the envelope signal represents the instantaneous amplitude information of the PF components, and frequency components of PF components can thus be obtained by the derivation of pure FM function directly.

The LMD algorithm can primarily make up for the shortcomings of EMD and effectively address nonlinear and non-stationary signals, so it is widely used in the field of incipient fault diagnosis. However, in practice, the bearing fault signals are often obscured by background noise, which seriously affects the accuracy of the LMD decomposition. This is because the LMD algorithm decomposes signals according to the characteristic scale determined by the extreme points of discrete signals. More precisely, due to the characteristics of this algorithm, even low noise will impose a strong negative impact on the decomposition and create obstacles and difficulties to its implementation for incipient fault diagnoses [12]–[17]. To weaken the effect of the strong background noise in the bearing vibration signals and extract the feature information of the vibration signals precisely, many de-noising algorithms have been proposed in recent years, and good results have been achieved. Among existing de-nosing algorithms, recursive least squares (RLS) algorithm is widely used because of its fast convergence and good de-noising effect. Unfortunately, the traditional RLS de-noising method cannot guarantee the convergence speed and stability simultaneously. In the past decades, some scholars have proposed improvement as following. Reference [18] has proposed an improved RLS algorithm which combined the advantages of RLS algorithm and square root Kalman algorithm with variable forgetting factor. In addition, Reference [19] has proposed an improved RLS algorithm which combined the advantages of RLS algorithm and LMS algorithm to obtain a better stability when the convergence is fast enough. Unfortunately, the tracking performance of the fixed forgetting factor RLS algorithm didn't satisfy the real demand in certain degree. So, an improved RLS algorithm was proposed by combining the advantages of variable forgetting factor RLS algorithm and disturbance RLS algorithm to improve the tracking performance in [20]. In fact, the improved algorithm may also overcome the imbalance between tracking speed and parameter maladjustment. Next, a further discussion was implemented for the dynamic selection of forgetting factor dynamic selection in RLS algorithm [21]. By recovering the system noise in the error signal of the algorithm, we dynamically calculated the value of forgetting factor to solve the problem that traditional RLS algorithm is difficult to take account of both steady-state accuracy and parameter tracking ability. Although the improvements mentioned above have solved the imbalance between convergence and stability, the de-nosing effect is still affected by noise because these algorithms merely refer to the current time error. So, a new improved algorithm needs to be proposed to solve the problems discussed above.

Based on the facts mentioned above, the layout of this paper is organized as follows: First, the RLS algorithm is improved by introducing a momentum term and variable forgetting factor, and the improved RLS de-noising model is constructed to improve the signal-to-noise ratio of the incipient fault signals and weaken the interference of strong background noise. Second, the bearing vibration signals de-noised in the first step are subsequently decomposed to PF component signals by means of the LMD algorithm. In addition, an envelope signal demodulation model is established based on the Hilbert transformation to obtain the features of envelope spectrum signals. After the previous steps, an improved model for incipient bearing fault diagnosis with strong background noise was achieved. Finally, a simulation comparison of bearing fault vibration signals is constructed to verify the effectiveness of the proposed algorithm.

II. IMPROVED RLS DE-NOISING MODEL AND ALGORITHM FOR BEARING VIBRATION SIGNALS WITH STRONG BACKGROUND NOISE

A bearing vibration signal is a typical non-stationary process signal, and it is the direct information source of the actual engineering problems for bearing equipment, including running state, fault monitoring, fault modes, and so on. However, the vibration signals obtained in practical engineering inevitably contain strong background noise, which makes the fault signal submerged, and thus, the fault features are not obvious. In this context, taking an effective de-noising algorithm to address the incipient fault feature signal is of great theoretical and practical significance for incipient fault identification and diagnosis.

However, we should note that the vibration signal de-noising model must achieve both convergence and stability. Therefore, the basic theory of the recursive least squares (RLS) algorithm will be introduced later. On this basis, an improved RLS de-noising model and algorithm was proposed by introducing the momentum factor and variable forgetting factor to ensure the convergence and stability of the de-noising algorithm.

A. BASIC THEORY OF THE RLS ALGORITHM

To improve the convergence, an error measure function $J(n)$ and a weighting factor λ (also called a forgetting factor) have been introduced in the RLS algorithm, where n represents the variable range of the data. Seeking the minimum sum of the exponentially weighted squared error is the basic principle of the RLS algorithm. The expression is described as follows:

$$J(n) = \sum_{i=0}^{n} \lambda^{n-i} |e(i)|^2 \tag{1}$$

Where $e(n)$ is the error signal and the range of λ is $0 < \lambda < 1$. To improve the sensitivity of the adaptive equalizer to input data, a new method λ^{n-i} has been introduced to distinguish new and old data and assign corresponding weights.

The error signal $e(n)$ in formula (1) is calculated as follows:

$$e(n) = d(n) - W(n)^T X(n) = X^T(n)W(n) \tag{2}$$

Where the desired signal is expressed as $d(n)$; the equalized signal is represented as $y(n)$ and $y(n) = W^T(n)X(n)$; the weight coefficient $W(n)$ and input signal $X(n)$ are expressed as follows:

$$X(n) = [x(n), x(n-1), \ldots, x(n-M-1)]^T \tag{3}$$

$$W(n) = [w_0(n), w_0(n), \ldots, w_{M-1}(n)] \tag{4}$$

Where M is the number of tap coefficients of the adaptive equalizer.

The inverse matrix is defined as follows:

$$P_{MM}(n) = \frac{1}{\lambda}[P_{MM}(n-1) - K(n)X^T(n)P_{MM}(n-1)] \tag{5}$$

Where $K(n)$ is known as the gain vector and is expressed as follows:

$$K(n) = \frac{P_{MM}(n-1)X(n)}{\lambda + X^T(n)P_{MM}(n-1)X(n)} \tag{6}$$

The weight coefficient is updated according to the following formula:

$$W(n) = W(n-1) + K(n)e(n) \tag{7}$$

In conclusion, the steps for designing the RLS algorithm are presented as follows:

Step 1: Set $W(n) = [w_0(n)\, w_1(n), \cdots, w_{M-1}(n)] = 0$ and the inverse matrix P_{MM} as an $M*M$ unit matrix to complete the parameter initialization;

Step 2: When $n = n + 1$, the parameters are updated as follows:

$$\begin{aligned} e(n) &= d(n) - W^T X(n) \\ K(n) &= \frac{P_{MM}(n-1)X(n)}{\lambda + X^T(n)P_{MM}(n-1)X(n)} \\ P_{MM}(n) &= \frac{1}{\lambda}[P_{MM}(n-1) - K(n)X^T(n)P_{MM}(n-1)] \\ W(n) &= W(n-1) + K(n)e(n) \end{aligned}$$

Unfortunately, although the algorithm can address noise mixed with vibration signals, to de-noise the vibration signal under strong background noise, the convergence is slow and stability is poor. Therefore, it is difficult to meet the demand for incipient fault diagnosis with strong background noise and it is a nontrivial problem to design an improved algorithm based on the existing RLS algorithm to meet the actual needs.

B. AN IMPROVED RLS ALGORITHM WITH VARIABLE FORGETTING FACTOR

In fact, the vibration signals of bearings are affected by many factors, such as the testing environment, testing methods and so on. As is well known, the characteristic signals amplitude of incipient fault is low. Furthermore, the incipient fault vibration signals contain strong background noise, so .the characteristic signals amplitude of incipient fault is so low that easily to be covered by background noise. In brief, strong background noises have brought great obstacles for diagnosis of incipient fault. To solve this problem, in this paper, an improved variable forgetting factor adaptive equalization algorithm is proposed for de-noising incipient fault signals with strong background noise, and the momentum is used to ensure the convergence and stability of the algorithm.

The traditional improved RLS algorithm based on variable forgetting factor is expressed as follows:

$$\lambda(n) = \frac{b(m+1)}{(m + e^{|ae(n)|})} + c \tag{8}$$

Where the range of b and c is 0-1, a and m are constants.

However, there are still many defects in this improved algorithm mentioned above. In formula (8), the updating of the forgetting factor is only related to the current time error $e(n)$, which results in serious noise interference. To solve this problem, $e(n)e(n-1)$ is introduced to adjust the step size, so that the step size is only related to the input signal; thus, the influence of noise on the signal is reduced. The new improved forgetting factor model is shown as follows:

$$\lambda(n) = \frac{b(m+1)}{(m + e^{\left|a\sqrt{e(n)e(n-1)}\right|})} + c \tag{9}$$

Furthermore, in order to improve the overall performance of the algorithm and accelerate the convergence, the momentum term is introduced to improve updating of the weight coefficient, which is expressed as follows:

$$W(n) = W(n-1) + K(n)e(n) + \rho(n) \tag{10}$$

Where $\rho(n)$ is known as the momentum term, which is expressed as follows:

$$\rho(n) = r \times (W(n) - W(n-1)) \tag{11}$$

Herein, r is called as momentum coefficient, and it is a constant.

In conclusion, the improved RLS algorithm can not only decrease the noise sensitivity but also improve the convergence performance. It is precisely because of the improvement mentioned above that the improved algorithm has the advantages of fast convergence rate and small stabilization error. Therefore, we can make use of the improved algorithm to de-noise bearing vibration signals with strong background noise, and finally realize the diagnosis and recognition of incipient faults [22]–[25].

III. A MODEL AND ALGORITHM FOR BEARING INCIPIENT FAULT DIAGNOSIS BASED ON AN IMPROVED RLS ALGORITHM AND LMD ALGORITHM

A. LOCAL MEAN DECOMPOSITION ALGORITHM (LMD)

The de-noised vibration signal $y(t)$, which is equalized by the improved RLS algorithm, is decomposed subsequently by the LMD algorithm. The pure FM signal and the envelope signal are isolated from the original signal by the LMD algorithm and by multiplying the two phases to obtain a PF component that is an instantaneous frequency with physical meaning. The step mentioned above will be repeated until all the PF components are separated from the original signal. For arbitrary $y(t)$, the basic decomposition steps are designed as follows:

Step 1: Determine all of the local extreme points N of the original signal $y(t)$ and compute the mean values of the two extremes N_i and N_{i+1}, i.e.,

$$l_i = \frac{N_i + N_{i+1}}{2} \tag{12}$$

Based on above result, the average values of all pairs of adjacent extreme points l_i are connected by a straight line, and the moving average method is used for smooth processing. Then, the local mean function $l_{pi}(t)$ is finally obtained.

Step 2: Compute envelope estimation value a_i by using local extreme point N_i.

$$a_i = \frac{|N_i - N_{i+1}|}{2} \tag{13}$$

Again, by using the moving average method, the envelope estimation value is smoothed to obtain the envelope estimation function $a_{pi}(t)$.

Step 3: The local mean function $l_{pi}(t)$ is then separated from the original signal $y(t)$, shown as below:

$$h_{pi}(t) = y(t) - l_{pi}(t) \tag{14}$$

Step 4: The demodulation of the envelope estimation function $a_{pi}(t)$ is obtained by the following formula:

$$s_{pi}(t) = h_{pi}(t)/a_{pi}(t) \tag{15}$$

Step 5: The envelope signals are obtained by multiplying all the envelope estimation functions generated in the iterative process and the formula is expressed as follows:

$$a_p(t) = a_{p1}(t)a_{p2}(t)\ldots a_{pL}(t) = \prod_{q=1}^{L} a_{pq}(t) \tag{16}$$

Step 6: The pth PF component of the original signal can be obtained by multiplying the envelope signal $a_p(t)$ with the pure frequency modulation signal $s_{pi}(t)$ and is expressed by following formula:

$$PF_p(t) = a_p(t) * s_{pi}(t) \tag{17}$$

Obviously, the PF components contain the highest frequency component of the original signal, which is the amplitude modulation and FM signal of the single component, where the instantaneous frequency can be obtained by the following formula:

$$f(t) = \frac{1}{2\pi}\frac{d[\arccos(s_{pi}(t))]}{dt} \tag{18}$$

Step 7: Similarly, the original signal is decomposed into many PF components and can be expressed as follows:

$$y(t) = \sum_{p=1}^{k} PF_p(t) + u_k(t) \tag{19}$$

Obviously, the original signal can be decomposed into many PF components by the LMD algorithm, and then the incipient fault diagnosis can be carried out.

B. A NOVEL MODEL AND ALGORITHM FOR INCIPIENT FAULT DIAGNOSIS OF BEARINGS

Based on the above analysis, combining the improved RLS noise elimination model with the LMD algorithm, the design of the incipient fault diagnosis algorithm for rolling bearings with strong background noise can be expressed in detail as below:

Step 1: The de-noised incipient fault vibration signal $x(t)$ of the rolling bearing is obtained using the improved RLS de-noising model. Thus, the equalized signal $y(t)$ is obtained;

a) Training stage: the optimal weight coefficient W can be obtained by using (2) - (7) to train the weight coefficients of the adaptive equalizer;

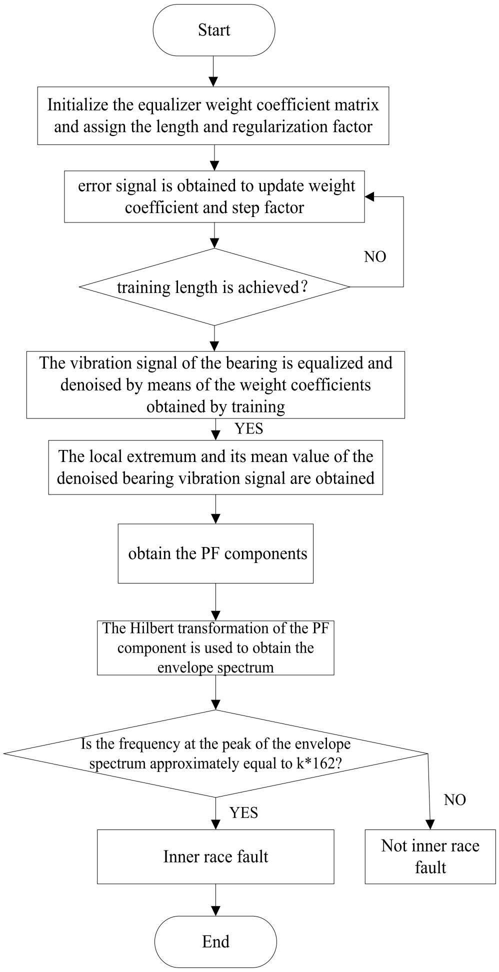


FIGURE 1. Fault diagnostic flowchart.

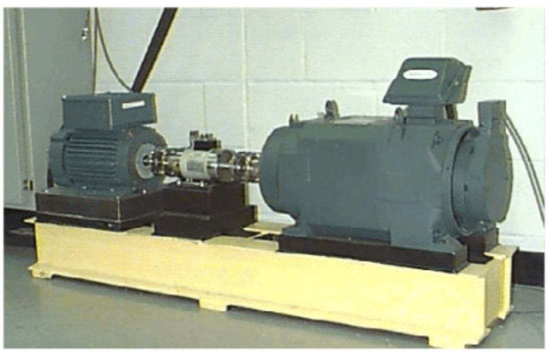


FIGURE 2. Bearing vibration data acquisition device.

b) Equalization stage: the optimum weight coefficient W obtained by the training stage is used to carry out equalization and noise elimination for bearing vibration signals.

Step 2: The de-noised signals are decomposed by LMD, and a series of PF components and their instantaneous amplitudes (i.e., envelope signals) are obtained.

a) All the extreme points N of the equalized and de-noised signal are obtained by using (12), and then the local mean value $l_{pi}(t)$ is calculated; the local mean value is separated from the original signal to obtain $h_{pi}(t)$ by using (14);

FIGURE 3. Bearing vibration inner race fault.

b) In terms of (13) - (16), the envelope value a_i is obtained and the envelope mean value $a_{pi}(t)$ is obtained by smoothing the envelope value. The envelope signal $a_p(t)$ is obtained by multiplying all the envelope mean values, and the pure frequency modulation signal $s_{pi}(t)$ is obtained by demodulating the envelope mean values;

c) The pure frequency signal and the envelope signal are multiplied, and the component can be obtained by using (17);

d) Repeat steps 1-2 until the signal can no longer be decomposed, and the final decomposed result is expressed as (18).

Step 3: The envelope signal is demodulated by using the Hilbert transformation, and then the envelope spectrum is obtained according to the analysis of the frequency spectrum. Based on this, the fault diagnosis can be carried out based on the peak frequency displayed in the envelope spectrum. If the peak frequency of the envelope spectrum is approximaely K times the characteristic frequency, the inner circle fault can be diagnosed; if not, it is not an inner circle fault.

The fault diagnostic flow chart is shown as Figure 1.

IV. PERFORMANCE ANALYSES

To verify the effectiveness and reasonableness of the designed algorithm, the standard data of the bearing database from American Case Western Reserve University is adopted as the experimental object [26]. In this database, the fault diameter of bearing inner race fault including $r = 0.1778$ mm, $r = 0.3556$ mm, $r = 0.5334$ mm, $r = 1.016$ mm. According to the related knowledge, the smaller the fault diameter is, the smaller the corresponding characteristic amplitude is, so it can be considered to be an incipient fault. Therefore, the drive end bearing inner race fault data named "105_IR007_0.mat" is regarded as the incipient fault data source, which contains a total of 121,256 data, where the sampling frequency of the data is $f = 12$ K and the bearing rotation speed $v = 1797$ rpm, whereas the fault diameter and the characteristic frequency of the inner fault are $r = 0.1778$ mm and 162.1852 Hz, respectively. The characteristic frequency is obtained as following formula.

$$\begin{aligned} f &= (D \times RPM)/60 \\ &= 5.4152 \times 1797/60 \\ &= 162.1852 \end{aligned} \tag{20}$$

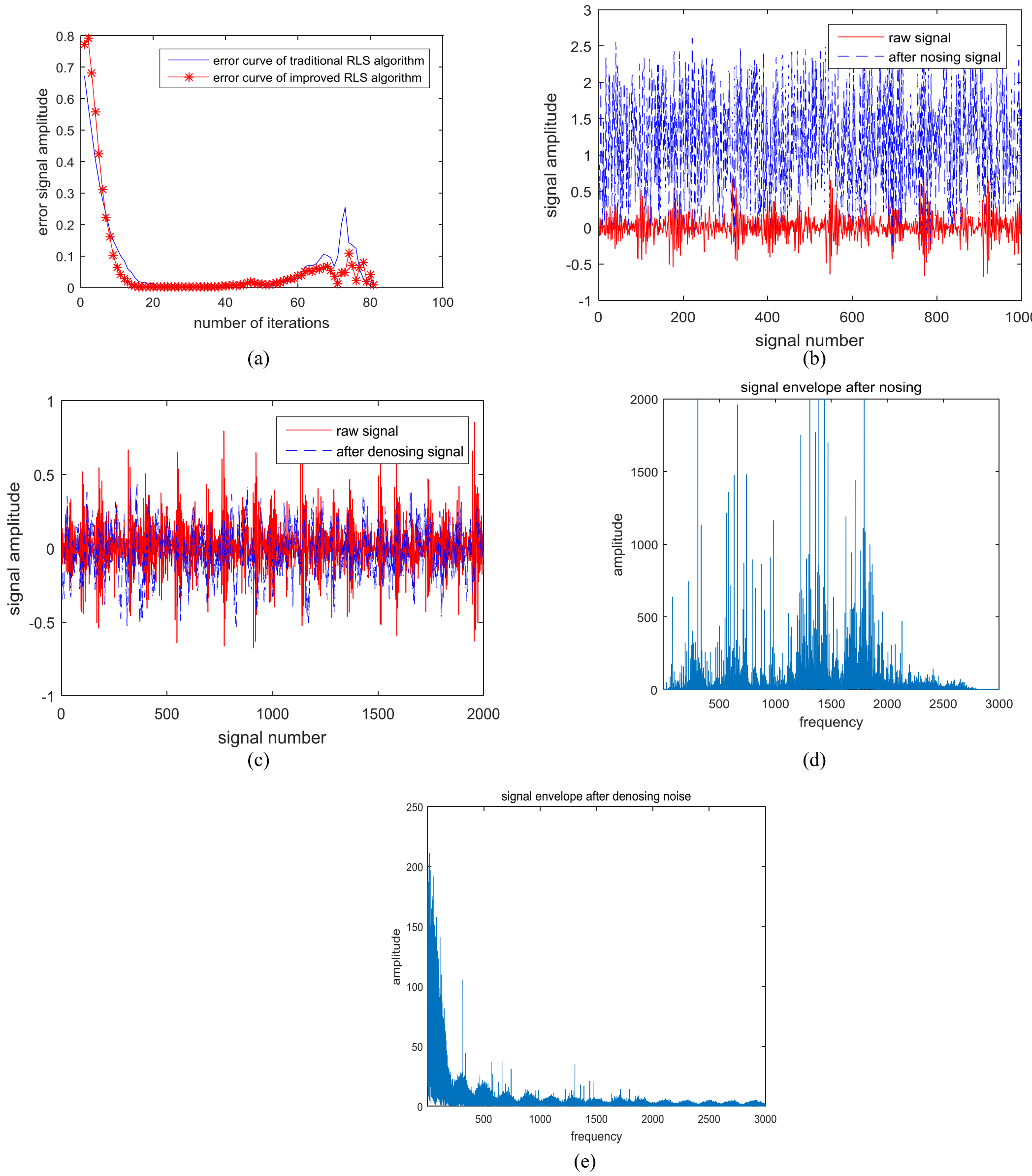


FIGURE 4. **(a) Adaptive equalization algorithm error curve. (b) Superimposed noise signal. (c) Signal after noise reduction. (d) Superimposed noise signal spectrum. (e) Signal spectrum after noise reduction.**

Bearing vibration data acquisition device and bearing inner race fault shown as Figure 2 and Figure 3.

First, noise is added into the original signal to simulate the incipient fault signal with strong background noise, which is provided with inconspicuous fault features. Second, in order to highlight the fault feature, the improved RLS algorithm is used in adaptive equalization de-noising. Finally, the equalized signal is decomposed by the LMD algorithm, and the fault diagnosis results are obtained according to the analysis of the envelope spectrum.

A. IMPROVED BEARING INCIPIENT FAULT SIGNAL RLS NOISE CANCELLATION ALGORITHM VALIDATION

To test the effectiveness of the improved algorithm, the traditional adaptive equalization algorithm is carried out in the simulation. In the traditional RLS algorithm, the length of the training data is 100, the regular factor is 0.001, and the forgetting factor is 0.89. In the improved RLS algorithm, $b = 0.2$, $c = 0.8$, $m = 140$, $r = 2$, and $a = 40$. The simulation results are shown as Figure 4.

Figure 4(a) illustrates both the error curves of the traditional and improved RLS algorithms. It is obvious that the convergence of the traditional RLS algorithm is slower than the improved RLS algorithm, and the stability of the improved RLS algorithm is not affected. Figure 4(b) indicates the incipient fault vibration signal with strong background noise, whereas Figure 4(c) shows the equalized results of Figure 4(b). Comparing Figure 4(b) and 4(c), we can find that the signal before equalizing was almost drowned by noise, so the equalized signal almost overlaps the original signal.

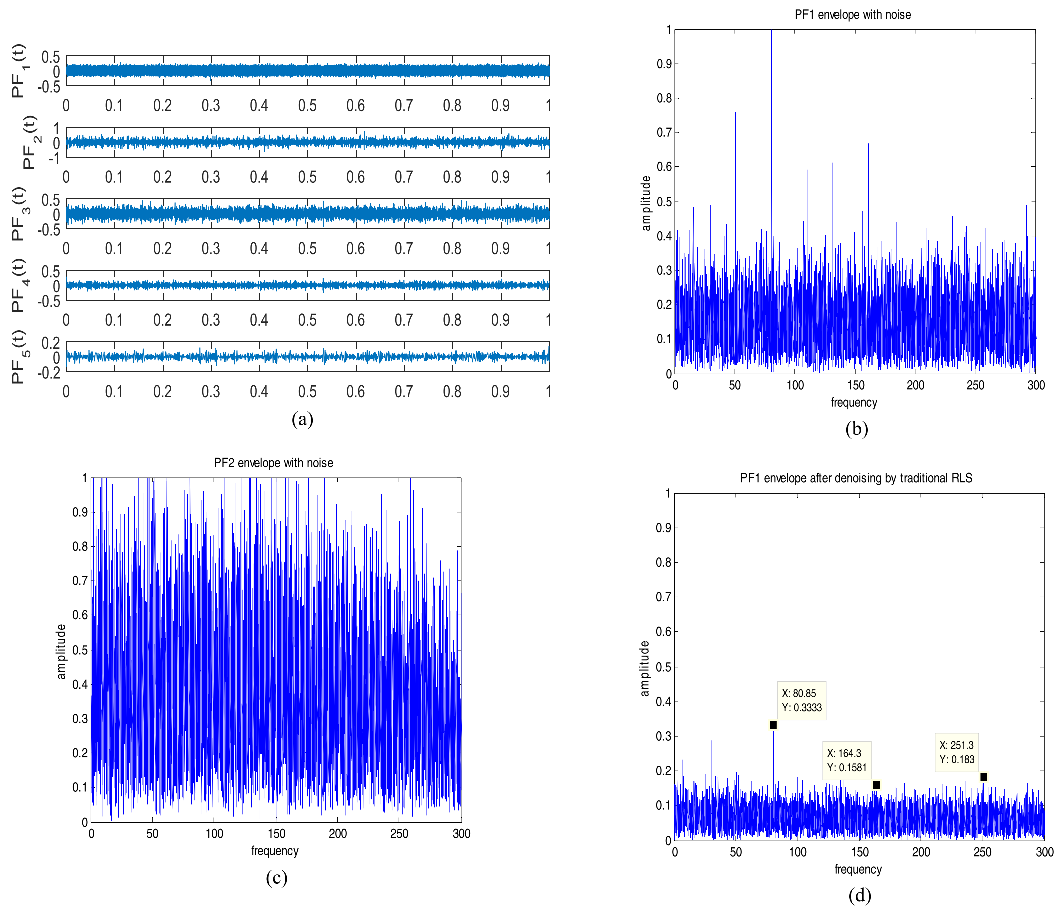


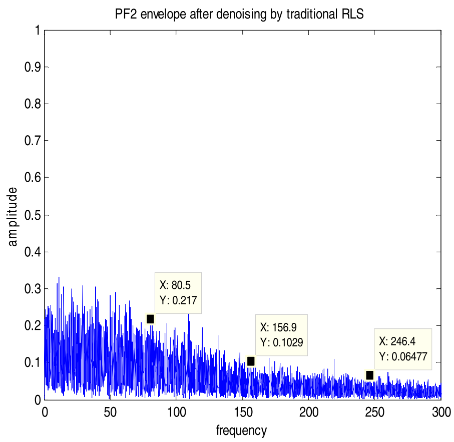
FIGURE 5. (a) LMD decomposition signal. (b) PF1 envelope spectrum with noise. (c) PF2 envelope spectrum with noise. (d) PF1 envelope spectrum of signal de-noised by traditional RLS. (e) PF2 envelope spectrum of signal de-noised by traditional RLS. (f) PF1 envelope spectrum of signal de-noised by improved RLS. (g) PF2 envelope spectrum of signal de-noised by improved RLS.

A conclusion can be obtained from the comparison, namely, the de-noising effect is preferable. Figure 4(d) and 4(e) show the frequency spectrums of signals with strong background noise and the equalized signal, respectively. Compared to the noisy signal spectrum, the impact signal (the noise signal is shown as a shock signal) in the equalized incipient fault vibration signal spectrum greatly decreased. As we know, the fault feature signal is almost shown as an impact signal, so strong background noise brings great challenges to the incipient fault diagnosis and affects the accuracy. Therefore, de-noising is an essential step in incipient fault diagnosis. After de-noising by the improved RLS algorithm, we find that the peaks of the frequency spectrum greatly decreased. More importantly, equalizing noisy signals can eliminate the interference brought by strong background noise to highlight the fault feature and greatly improve the signal to noise ratio of the incipient fault signal, which is conducive to further fault diagnosis.

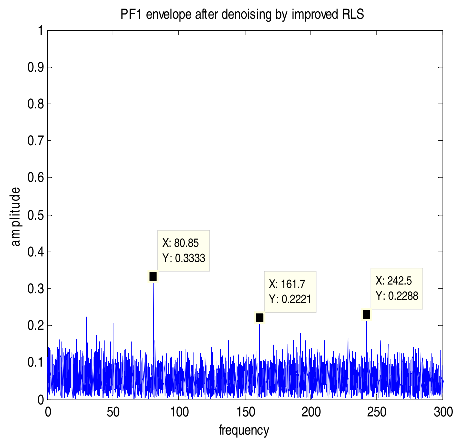
B. INCIPIENT FAULT DIAGNOSIS VERIFICATION BASED ON THE RLS AND LMD BEARING ALGORITHM

The LMD algorithm is an effective method for addressing nonlinear signals. Using the LMD algorithm to decompose the vibration signal, and then using the Hilbert transformation to obtain the envelope spectrum, can show the fault characteristic frequency effectively for bearing incipient fault diagnosis. The simulation results are shown as Figure 5.

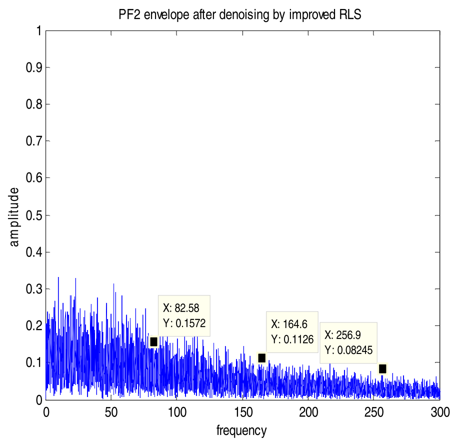
Figure 5(a) shows the results of LMD decomposition. According to correlation analysis, envelope demodulation of the first two PF components, PF1 and PF2, will be obtained by the corresponding algorithm and applied to the diagnosis, and then envelope spectrum analysis will be carried out. Figures 5(b) and 5(c) show the envelope spectrum of a signal with strong background noise. Figures 5(d) and 5(e) show the envelope spectrum obtained by LMD decomposition after the signal is de-noised by the traditional RLS algorithm. Figures 5(f) and 5(g) show the envelope spectrum obtained by the LMD decomposition after the signal is de-noised by the improved RLS algorithm. Comparing Figures 5(b), 5(d), and 5(f), we can find that the fault characteristic frequency of the envelope spectrum obtained by the traditional RLS de-noising algorithm combined with the LMD algorithm is more obvious than that only obtained by the LMD algorithm. But, we can discover that the traditional RLS algorithm has eliminated useful information while eliminating noise. Again, the fault



(e)



(f)



(g)

FIGURE 5. ***(Continued.)*** **(a) LMD decomposition signal. (b) PF1 envelope spectrum with noise. (c) PF2 envelope spectrum with noise. (d) PF1 envelope spectrum of signal de-noised by traditional RLS. (e) PF2 envelope spectrum of signal de-noised by traditional RLS. (f) PF1 envelope spectrum of signal de-noised by improved RLS. (g) PF2 envelope spectrum of signal de-noised by improved RLS.**

characteristic frequency of the envelope spectrum obtained by the improved de-noising RLS algorithm combining with the LMD algorithm is more obvious than the traditional de-noising RLS algorithm combining with the LMD algorithm. More importantly, the improved de-noising algorithm has kept the useful information to the maximum while eliminating noise. From Figure (f), we can clearly see that there are obvious peak values of at $f_0 = 80.85$Hz in the envelope spectrum of the PF1 component, and in 2 and 3, the doubling rate also has an obvious peak. Equally, from Figure 5(g) there are several peak values at the fault characteristic frequency, but it is not obvious. In conclusion, the characteristic frequency has shown in the figure accords with the frequency of bearing inner ring incipient faults, which is equal to 162.1852HZ, so the simulation results can accurately react to the 12K drive end bearing inner race faults.

V. CONCLUSION

As we know, there are great difficulties in diagnosing bearing incipient faults since the fault features of the bearing fault signal with strong background noise are weaker. To solve this problem, an improved bearing fault diagnosis algorithm is proposed based on the combination of improved RLS and LMD. First, an improved RLS algorithm with a variable forgetting factor is proposed, and the incipient fault signal of the bearing with strong background noise is used to verify the validity of the improved algorithm. The simulation results illustrate that the improved RLS algorithm has faster convergence speed with little influence on stability, and the effect of reducing background noise is obvious. Second, the LMD algorithm is used to decompose the signal that is equalized by means of the improved RLS algorithm. The envelope of the decomposed signal is demodulated by the Hilbert transformation to obtain the envelope spectrum. The experimental results show that the LMD algorithm can adaptively be used to decompose the de-noised incipient fault vibration signals of bearings, and the frequency components of the fault features can be accurately and effectively separated. Through the comparison and analysis of bearing incipient fault diagnosis results, it was noticed that in the traditional fault diagnosis model, there still are interferential impact components, resulting in ambiguity of features of the bearing incipient fault to some extent, and it is not conducive to the diagnosis of incipient faults. A cooperative incipient fault model based on RLS and LMD is constructed in this paper, and the diagnosis results obtained by the incipient fault model can clearly react to characteristic frequency peaks and absolutely ensure the efficiency and accuracy of bearing incipient fault diagnosis under strong background noise. But in this bearing incipient fault diagnosis model, the characteristic frequency in the envelope spectrum of the PF2 component is not obvious. This improvement will be done in the next step.

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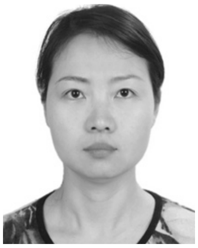

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