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Research Article

A Cooperative Denoising Algorithm with Interactive Dynamic Adjustment Function for Security of Stacker in Industrial Internet of Things

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In order to more effectively eliminate the disturbance of vibration signal to ensure the security monitoring of stacker be more accurate in Industrial Internet of Things (IIoT), a cooperative denoising algorithm with interactive dynamic adjustment function was constructed and proposed. First, some basic theories such as EMD, EEMD, LMS, and VSLMS were introduced in detail according the characteristics of stacker in IIoT. Meanwhile, the advantages and disadvantages of varieties of algorithms have been analyzed. Secondly, based on the traditional VSLMS-EEMD, an improved VSLMS-EEMD was proposed. Thirdly, to guarantee the denoising effect of security monitoring in IIoT, a cooperative denosing model and framework named as IDVSLMS-EEMD was designed and constructed based on the advantages of LMS, VSLMS, and improved VSLMS-EEMD. In addition, the assignment rules and models of the corresponding weight coefficients were also set up according to the features of the error signal of denoising process in IIoT. At the same time, we have designed a cooperative denoising algorithm with interactive dynamic adjustment function. And some evaluated indexes such as NSR and SDR were selected and introduced to evaluate the effectiveness of the different algorithms. Thirdly, some simulation examples and real experiment examples of stacker running signals under abnormal condition, which has been developed and applied in Power Grid of China, was used to verify and simulate the effectiveness of our presented algorithm. The experiment comparison results have shown that our algorithm can improve the denosing effect. Finally, some conclusions were discussed and the directions for future engineering application were also pointed out.

1. Introduction

With the development and evolution of society, the Industrial Internet of Things (IIoT) plays a significant role in guiding the process of intelligent manufacturing for global industry [1–3]. So, the IIoT has been embedded in various industry systems, especially in the ASRS system. As we all know, the main function of ASRS is to grab, move, and stack goods from one piece of equipment to another. Therefore, stacker is the most important element in ASRS. In practice scene of ASRS, one point of the stacker running which cannot reach the design requirement can be deemed as an accident. As an indispensable device of IIoT, this accident is related not only to the security of ASRS but also to the data acquisition and the data exchange of IIoT [4–6]. For example, because of the long-term wear and tear of the stacker track, the weld seam of the track is enlarged or pits appear which leads to the decrease of positioning accuracy, thus seriously affecting the data acquisition of the whole IIoT. So, how to use monitoring data to ensure the security of stacker is very important in IIoT [6–8]. Notice, in practice, as the primary data resource for security monitoring and maintenance of the systems, mechanical vibration signals are always influenced by any strong interferences of surrounding environment. However, the strong noise always conceals the abnormal characteristic information or forms false characteristics, which has greatly affected the further abnormal detection of stackers in IIoT [9–11]. Hereby, denosing the noise of vibration data for stacker under the abnormal condition is not only the primary premise to ensure the further effective detection of the abnormity, but also the necessary measure to ensure the security of the IIoT. Moreover, along with the continuous improvement of operation speed, to find the algorithm and model to denoise has become more and more urgent for vibration signals in IIoT.

At present, how to effectively eliminate and filter the disturbance noise from measured signals is the prerequisite for health monitoring of industrial systems [12]. So, domestic and foreign researchers have made a lot of progress from various aspects. For instance, some researchers have constructed some data denoising models by combining with the Kalman filter and machine learning to separate the noise and useful stationary signals by high pass, low pass, band pass, or band stop in several ways in [13, 14]. The simulation results showed that the proposed model and algorithm have better performance of separation for mixed signals with nonoverlapping power spectrum. Unfortunately, the data resources acquired in health monitoring for IIoT always contain lots of noise. This perhaps leads to appearance of spectrum aliasing. Obviously, the filter model and algorithm based on frequency domain are not suitable. So, it is necessary to construct the reasonable algorithm to improve the denoising effect for mixed signal with nonoverlapping spectrum.

To overcome the shortage, the multipoint mean smoothing denosing method was constructed and simulated to distinguish and separate useful signals from noise by the frequency difference in [15]. However, the presented algorithm may achieve the denoising effect for stationary signals. Nevertheless, most of the mechanical vibration signals, which are measured from real IIoT, are nonstationary. Because of this, some scholars have studied and established the denoising method by combining with canonical correlation analysis and empirical model decomposition (EMD) in [16]. In their experiments, this denoising model has improved the denoising accuracy based on multipoint mean smoothing denosing method to some extent, but there is the problem of end effect on EMD. Thus, there are still many defects when the above methods were used to implement noise-elimination in the university.

Furthermore, the wavelet theory was introduced to depict the characteristics according to the different amplitude of signals and noise in [17–20]. In that case, the simulation results showed that the presented algorithms and methods were effectively for the nonstationary signals to a certain extent. But, it is difficult to determine the threshold and set up a reasonable order of the filter in real practical project. In fact, to select the perfect threshold and set up the reasonable order is the key step of wavelet denoising model for health monitoring and safety maintenance of IIoT. Similarly, the denoising model based on EMD algorithm also has the defect of selection principle of the threshold and filter order [21]. In order to solve this problem, some scholars has discussed and analyzed some solutions in [22–25]. Although these solutions have achieved certain improvement, EMD has end effect. For improving the end effect of EMD, the Ensemble Empirical Mode Decomposition (EEMD) has been introduced to solve the shortage of denoising algorithm based on EMD in [26]. However, EEMD still faces the problem of threshold selection. Therefore, the adaptive equalizing algorithms without threshold selection have been widely used for industry signal denoising in [27, 28]. Their experiment had verified and indicated that the denoising performance may be achieved to a certain extent. But the denoising performance based adaptive equalizing algorithm is not stable for wide-band signals. So, the engineers need constantly to improve and update the denoising algorithms to ensure the effectiveness of health monitoring and safety maintenance in IIoT.

Based on this, many scholars and engineers have tried to construct and establish the improved model combined with EMMD and other methods such as LMS, Gath-Geva clustering, and so on in [29–31]. And then the wide-band signals may be transformed to the narrow band signal by these improved models. The denoising effect of these improved models may be guaranteed in processing data of IIoT. Regrettably, the convergence speed is very slow while the step size of LMS algorithm cannot be adaptive adjusted. Therefore, considering that the step factor may be adaptive adjusted, some scholars had presented an improved algorithm based on LMS. The new model is named as VSLMS. Based the thesis, Yu Xiao and his coauthors had constructed the new denoising algorithm by combining with VSLMS and EEMD to solve the accuracy of the denoising performance in [32]. But, in [32], the adjustment of the step factor for VSLMS is seriously affected by error signal at the present time. To remedy this problem, another VSLMS algorithm is introduced into combining with EEMD to construct an improved VSLMS-EEMD algorithm. Notice that the practical data acquired from IIoT will be influenced by the different factors such as the fault of sensors, the performance degradation of equipment, and so on. So, the noise in the practical engineering is particularly complex. For all points of the vibration signal, the above algorithm cannot achieve the best performance for all points. Aiming at each point of the vibration signal, different algorithms have different denoising performance. Thus, based on the fact that the improved VSLMS-EEMD algorithm is proposed, to find a cooperative mechanism to maximize the denoising performance at each point based on the above denosing algorithms is very important to process the nonstationary signal in IIoT.

Based on this thesis, a cooperative denoising algorithm and model with interactive dynamic adjustment function have been analyzed and discussed in further section. The layout of this paper is arranged as follows. In Section 2, we have introduced the basic theories and methods such as EMD, EEMD, LMS, and VSLMS. In Section 3, an interactive dynamic adjusted denoising algorithm has been designed and analyzed. Meanwhile, some evaluated indexes were selected and introduced to evaluate the effectiveness of the different algorithms. In Section 4, to verify the effectiveness of the proposed algorithm, some simulative examples were implemented to compare the denoising performance of LMS, VSLMS, VSLMS-EEMD, and presented algorithm. In addition, to enlarge the applications, the practical denoising project of stacker running signals, which have been developed and applied in Power Grid of China, was used to verify the effectiveness of our presented algorithm. Finally, some conclusions and the directions for future engineering application are discussed according to the real simulation results in health monitoring and safety maintenance of IIoT.

2. Introduction and Analysis of Basic Theory and Model in Health Monitoring of IIoT

In practical engineering of IIoT, as we all know, the measurement signals are always typical and nonstationary, and they are the direct information resource of actual sense for IIoT, including running state, fault modes, and so on. Thus, the measurement signals obtained in actual IIoT contain inevitably strong background noise, which makes the useful information submerged. Obviously, the information features of health monitoring are not obvious for IIoT. Thus, how to design and find an effective denoising algorithm with interactive dynamic adjustment function is key step to guarantee the performance of safety maintenance of IIoT. Meanwhile, the denoising model and algorithm must achieve both timeliness and stability in health monitoring of IIoT. Only then can the work be of great theoretical and practical significance for nonstationary signals of health monitoring in IIoT.

On this basis, some basic theoretical models will be introduced and discussed for designing the cooperative denoising algorithm with interactive dynamic adjustment function in the next section.

2.1. Empirical Mode Decomposition Algorithm (EMD). For simplicity of analysis in health monitoring of IIoT, the measurement signal $S(t)$ including the useful signal and noise may be simply described as follows:

$$S(t) = s(t) + v(t) \tag{1}$$

where $s(t)$ represents the useful vibration signal and $v(t)$ describes the disturbance noise.

According to the basic thesis, the detailed decomposition process of measurement mixed signals is shown as follows.

Step 1. Suppose that the symbol $S(t)$ represents the original signal of IIoT. If all local extremums can be found, the upper envelope $u(t)$ and the lower envelope $l(t)$ may be computed by using the cubic spine function. Meanwhile, the envelope line should contain all the data.

Step 2. Combined with $u(t)$ and $l(t)$, the mean value of the upper and lower envelope may be used to process the original envelope; i.e.

$$m_1 = \frac{u(t) + l(t)}{2} \tag{2}$$

To separate first component from original signal, we have introduced the computing formula as follows:

$$h_1(t) = S(t) - m_1(t) \tag{3}$$

If $h_1(t)$ meets IMF condition, it is the first component of $S(t)$. Otherwise, go on the next step.

Step 3. Let $h_1(t)$ be the new original signal and repeat Step 2 again until the IMF condition can be met. The corresponding computed formula is as follows:

$$h_{11}(t) = h_1\text{-}m_{11}, \ldots, h_{ik}(t) = h_{1(k-1)}\text{-}m_{1k} \tag{4}$$

where m_{1k} indicates the mean value of the upper and lower envelope of $h_{1(k-1)}$ and k is the number of iterations.

In that case, h_{1k} should meet the IMF conditions. Then, the first IMF component of original signal can be gotten; i.e., $c_1(t) = h_{1k}(t)$.

Meanwhile, the new signal may be separated from the original signal by the following formula:

$$r_1(t) = S(t) - c_1(t) \tag{5}$$

And go on to the next step.

Step 4. The filtering process in Step 2 is used to repeatedly execute for $r_1(t)$ until the IMF condition is met. In other words, the second IMF component and the similar new signal are denoted as c_2 and $r_2(t)$, respectively. Similarly, all IMF components and new original signals are represented as follows:

$$r_2(t) = r_1(t) - c_2(t), \ldots, r_n(t) = r_{n-1}(t-1) - c_n(t) \tag{6}$$

Step 5. It is rewriting the original signal $S(t)$ by the following mode:

$$S(t) = \sum_{i=1}^{N} c_i(t) + r_n(t) \tag{7}$$

where $r_n(t)$ is the remainder which presents the monotonous trend of $S(t)$. Obviously, the decomposition results IMF $s(c_1, \cdots, c_n)$ indicate the different IMF components which represent from high frequency to low frequency distribution of the original signal.

If we use the EMD to decompose the nonstationary signal in practice, there is one thing we have noticed: the EMD method has serious end effect and mode mixing of different time-scale IMF. Of course, the lacks caused by EMD signal decomposition will affect the denoising effect of the original signal in IIoT. So, how to improve the efficiency of noise reduction is very important in practice engineering. Next, we will introduce in depth the basic principles and related situations to establish an improvement algorithm.

2.2. Ensemble Empirical Mode Decomposition (EEMD). To overcome the influence of the end effect and mode mixing in health monitoring of IIoT, an improved denoising algorithm named as Ensemble Empirical Mode Decomposition (EEMD) has been proposed based on EMD for signal denoising. The decomposition steps of EEMD are shown as follows.

Step 1. It is adding a Gaussian random white noise $w(t)$ to original measurement signal of IIoT; i.e.,

$$S_1(t) = S(t) + w(t) \tag{8}$$

where $w(t) \sim N(\mu, \sigma^2)$.

Step 2. It is decomposing the new original signal $S_1(t)$ by using EMD algorithm. And then each IMF component $c_{ij}(t)$, $j = 1, 2, \ldots K$ may be obtained and acquired in time, where $c_{ij}(t)$ presents the jth IMF component when the ith white noise has been added into the original signal.

Step 3. It is repeating Steps 1–2 to decompose the renewal signal with different Gaussian white noise again. And we may obtain a set of new IMFs, which are quite different from the original ones.

Step 4. It is computing the average value of the IMFs obtained by decomposing the corresponding renewal signal with different Gaussian white noise; i.e.,

$$c_i(t) = \frac{1}{T}\sum_{i=1}^{T} c_{ij}(t) \tag{9}$$

where $c_i(t)$ is the ith IMF component.

So, the decomposition results IMF $s(c_1, \cdots, c_n)$ can be selected to represent the different IMF components from high frequency to low frequency distribution of the original signal.

In fact, the highest advantage of EEMD is that IMFs decomposed by the algorithm are independent and can prevent IMFs from mode mixing. In that case, it is vital to adaptively decompose the measurement signal of IIoT. But, as we all know, the effect of signal processing is always greatly influenced by choice of the decomposition threshold when EEMD is used to denoise for the measurement signal in IIoT.

Therefore, to further guarantee the effect and accuracy of selecting the decomposition threshold in processing the mixed signal, many engineers and researchers have tried to focus on finding out some helper methods to modify the defect of EMMD. Based on this, the typical LMS algorithm will be introduced to solve the problem of the decomposition threshold in further section.

2.3. Least Mean Square (LMS) Algorithm. In the security monitoring of IIoT, it is necessary to find an adaptive algorithm to reduce or inhibit the correlative noise. So, to get the more ideal signal, IMF $s(c_1, \cdots, c_n)$ or original signal should be used as the training specimen to further process. In that case, take the IMF $s(c_1, \cdots, c_n)$ as an example, so the initial input vector of training is described as follows:

$$\mathrm{IMF}s(n) = [c(n), c(n-1), \ldots, c(n-M-1)]^T \tag{10}$$

where M represents the number of tap coefficients.

For the sake of simplicity, the equalized signal of the training iteration is supposed as follows:

$$y(n) = \sum_{i=0}^{M-1} w_i(n)\, c(n-i) \tag{11}$$

where $w_i(n)$ is the weight coefficient of every component of IMFs.

For the convenience of calculation, the above formula may be simplified as follows:

$$Y(n) = W^T(n) \cdot \mathrm{IMFs}(n) \tag{12}$$

where $W(n)$ is the weight coefficient matrix; i.e.,

$$W(n) = \left[w_0(n), w_1(n), \cdots, w_{M-1}(n)\right]. \tag{13}$$

where $W(n)$ is calculated as follows:

$$W(n+1) = W(n) + 2\mu \cdot e(n) \cdot \mathrm{IMFs}(n) \tag{14}$$

where μ is the step factor and $e(n)$ is error signal which is modeled as follows:

$$e(n) = d(n) - y(n) = d(n) - W^T(n) \cdot \mathrm{IMFs}(n) \tag{15}$$

where $d(n)$ represents the actual value of each iteration training.

Although the algorithm may reduce the error accumulation effect in fine processing of nonstationary signal and improve the denoising accuracy, the convergence is slow. From a practical situation, one reason might be that the fixed step size cannot keep the insistency between the fast convergence speed and steady residual error [33–35]. Therefore, we need to find a method to modify the shortage according to the actual requirements.

2.4. LMS Algorithm with Variable Step Factor (VSLMS). As is well known, the denoising accuracy of nonstationary signal in IIoT is usually affected by varieties of factors, such as the testing environment, test methods, and so on. Furthermore, the training signals acquired by using LMS algorithm may still contain the strong noise because of the fixed step size. So, the amplitude of characteristic information cannot be evidently separated from the noise information. In brief, the residual noise has brought great obstacles for the denoising performance of nonstationary signal in IIoT. To overcome the problem, in this section, the variable step factor is inducted to the denoising control to balance the insistency between the fast convergence speed and steady residual error. The core of the thesis is that the step size can be dynamically adjusted according to the error signal of each training.

In formula (14), the updating of the fixed step size should to be related to the current time error $e(n)$, which results in the characteristic's confusion. So, the computing method is shown as follows.

$$\mu(n) = \left(\frac{1}{1 + \exp\left(-\alpha \left|e(n)\right|^m\right)} - 0.5\right) \tag{16}$$

where α is the control parameter. The value of parameter is taken according to various concrete statuses.

In practical health monitoring of IIoT, we find the abnormal phenomenon that the error signal has the cumulative effect with experimental time. Further, the phenomenon results in the serious overlapping interference of denoising signal. So, to overcome the shortage, the error values at the current time and the last time are inducted to the adjustment of the step size. In other words, the step size may be gotten by the following formula.

$$\mu(n) = \left(\frac{1}{1 + \exp\left(-\alpha \left|e(n) * e(n-1)\right|^m\right)} - 0.5\right) \tag{17}$$

Thus, the weight coefficients may be rewritten as follows:

$$W(n+1) = W(n) + 2\mu(n) \cdot e(n) \cdot \mathrm{IMFs}(n) \quad (18)$$

In conclusion, the improved LMS with variable step factor can not only decrease the noise sensitivity but also improve the convergence performance. This is because of the improvement mentioned above that the improved weight coefficients can filter the influence of the cumulative effect in the training. Therefore, we can make use of the improved algorithm to denoise the nonstationary health monitoring of IIoT.

Obviously, we can see from the above analysis that each method has advantages and disadvantages in denoising process of nonstationary signal. If we may establish an integrated strategy to exert the advantages of each method and minimize the influence to disadvantages, thus the denoising effect of nonstationary signal may be vastly improved in health monitoring of IIoT. Next, the work will be in detail depicted.

3. Design and Analysis of Cooperative Denoising Algorithm and Model with Interactive Dynamic Adjustment Function (IDVSLMS-EEMD)

3.1. Analysis and Establishment of Cooperative Denoising Model with Interactive Dynamic Adjustment Function. To guarantee the denoising performance of nonstationary signal in health monitoring of IIoT, we have tried to design some cell modules to realize the task of the integration and configurable controls. With this goal, we have designed the LMS denoising module, VSLMS denoising module and proposed the improved VSLMS-EEMD denoising module based on the traditional VSLMS-EEMD, respectively. The denoising module by using LMS or VSLMS is shown as Figure 1.

In addition, to overcome the shortage of the VSLMS-EEMD proposed in [24], the step updating algorithm is redesigned as (17) to construct an improved VSLMS-EEMD denoising algorithm. The framework of the improved VSLMS-EEMD is shown as Figure 2.

In fact, all these cell modules can be used to denoise of nonstationary signal in IIoT, and then each module can be used as a single denoising processor. However, the operations staff of health monitoring always want to highlight the advantages of these cell modules as large as possible. In order to maximize the denoising performance at each point, on the basis of the improved VSLMS-EEMD algorithm, a cooperative denosing algorithm with interactive dynamic adjustment function named as IDVSLMS-EEMD has been designed and constructed by using the stackable technology as Figure 3

Obviously, the framework can allow both those cell denoising modules (i.e., conventional and complementary) to exist in a framework that embarrasses neither. From an application perspective, the IDVSLMS-EEMD algorithm is a standardization of a set of denoising patterns based on a common set of denosing algorithm. So, one of the features of the IDVSLMS-EEMD model is able to move applications from one processor environment to another. From viewpoint of practical operation, the outputs of three denoising algorithms embedded in the IDVSLMS-EEMD framework are different, the differences can make up for each other's mutual limitations. Therefore, the engineers can achieve the most optimal elimination at every point of the vibration signal for IIoT.

For the sake of analysis, relevant definition and calculation of the proposed cooperative denoising model IDVSLMS-EEMD are set as follows.

Firstly, the ith output of the IDVSLMS-EEMD algorithm may be defined as the following formula:

$$\widehat{S}_F(i) = w_i(1) \times \widehat{S}_1(i) + w_i(2) \times \widehat{S}_2(i) + w_i(3) \times \widehat{S}_3(i) \quad (19)$$

where $\widehat{S}_1(i)$ is the ith output of the LMS denosing module, $\widehat{S}_2(i)$ is the ith output of the VSLMS denosing, $\widehat{S}_3(i)$ is ith output of the improved VSLMS-EEMD denosing module, and $w_i(m)$ $(m = 1, 2, 3)$ is the weight of output in every denoising processor.

From this model, the hub of the cooperative denoising framework is to determine the weights of denoising output at different time. In fact, if the denoising module is more suitable for nonstationary some point of signal in IIoT, the weight is bigger. Otherwise, the weight is smaller. But, for error signals, the opposite is true. So, it can be inferred that the error signal is inversely related to the weight coefficient, and the weight coefficient can be obtained by the error signal.

Define the error signal set at ith point as follows:

$$e(i) = [e_1(i), e_2(i), e_3(i)] \quad (20)$$

According to the errors, the dynamical assignment rule of the weights is shown as follows.

Rule 1. The larger the error of single denoising processor is, the smaller the weight is. That is, consider the following.

(1) If $e_m(i)$ $(m = 1, 2, 3)$ is maximum value in $e(i) = [e_1(i), e_2(i), e_3(i)]$, the weight $w_i(m)$ may be assigned by the following formula:

$$\omega_i(m) = \frac{\min(e_1(i) e_2(i) e_3(i))}{e_1(i) + e_2(i) + e_3(i)} \quad (21)$$

(2) If $e_m(i)$ $(m = 1, 2, 3)$ is minimum value in $e(i) = [e_1(i), e_2(i), e_3(i)]$, the weight $w_i(m)$ may be assigned by the following formula.

$$\omega_i(m) = \frac{\max(e_1(i) e_2(i) e_3(i))}{e_1(i) + e_2(i) + e_3(i)} \quad (22)$$

(3) If $e_m(i)$ $(m = 1, 2, 3)$ is intermediate value in in $e(i) = [e_1(i), e_2(i), e_3(i)]$, the weight $w_i(m)$ may be assigned by the following formula.

$$\omega_i(m) = \frac{e_m(i)}{e_1(i) + e_2(i) + e_3(i)} \quad (23)$$

Through the assignment rule, the weight of every denoising module may be determined on each point according

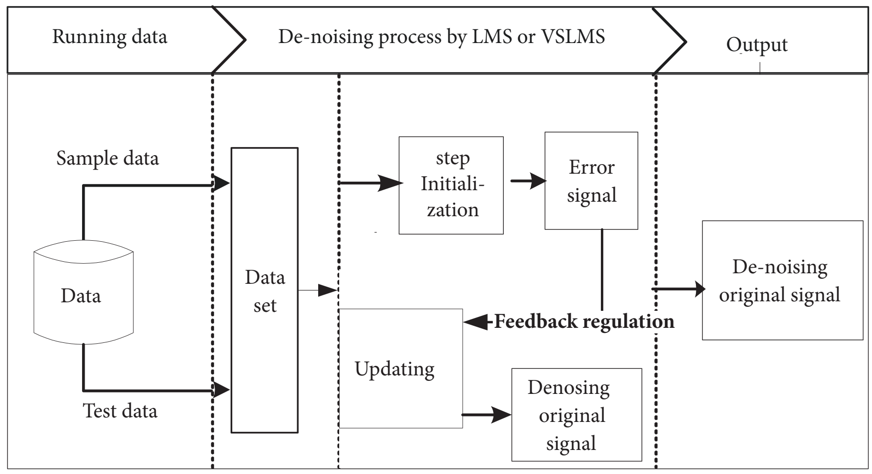


Figure 1: Denoising module of LMS or VSLMS.

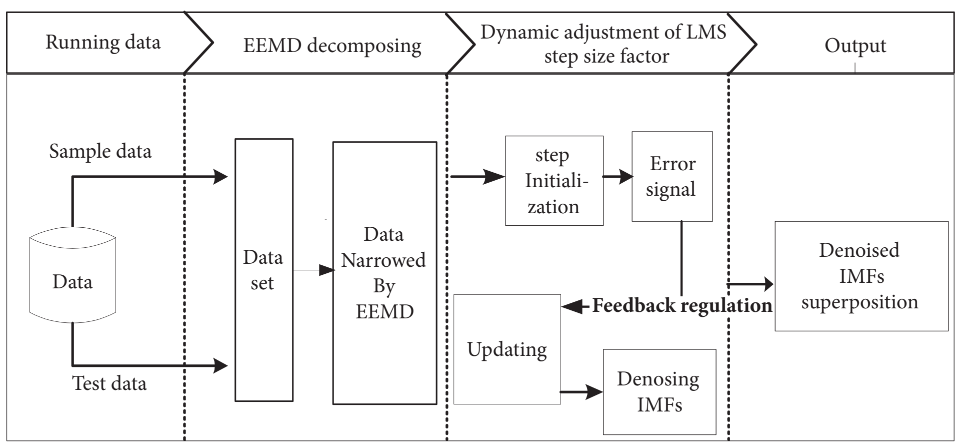


Figure 2: Improved VSLMS-EEMD denoising module.

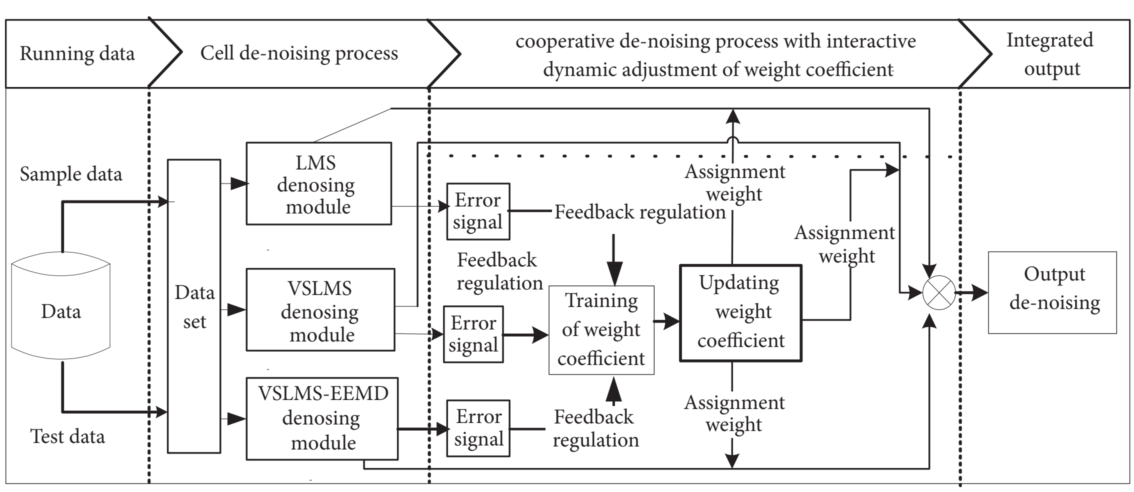


Figure 3: Integrated cooperative denoising framework of IDVSLMS-EEMD.

to the effect of denoising in IIoT. Obviously, the output of the single denoising module is ensured when the weight coefficient is dynamically adjusted in time. Of course, the denoising performance of the integrated system may be improved because each other makes use of mutual advantage and make up own shortage.

3.2. Evaluation Indexes of Integrated Cooperative Denoising Model. In the actual operation of integrated cooperative denoising framework, the success of achieving the performance goals depends on how well we develop the denoising strategy in health monitoring of IIoT. So, it is necessary to establish some scientific, systematic evaluation indexes of the cooperative denoising algorithm as feedback [36, 37].

To evaluate the effectiveness of presented model, we have constructed two indexes according to the actual situation of health monitoring in IIoT. These evaluating indexes and rules are set as follows.

(1) Absolute Value Error is

$$C = mean\left|\hat{S} - s\right| \tag{24}$$

where s is the original signal and $\hat{S}$ is the denoising output.

By formula (24), the evaluation rule is defined as follows.

Rule 2. The bigger the C is, the worse the denoising effect is and vice versa.

(2) Normalized Cross Correlation (NCC) is

$$NCC = \frac{\sum_{i=1}^{N} \hat{S}(n)\, s(n)}{\sqrt{\left(\sum_{i=1}^{N} \hat{S}^2(n)\right)\left(\sum_{i=1}^{N} s^2(n)\right)}} \tag{25}$$

where $\hat{S}(n)$ and $s(n)$ are the denosing output and the real value of the presented algorithm and n indicates the testing time. NCC represents the curve similarity between the denoising signal and the initial signal.

Similarity, the corresponding evaluation rule is designed as follows.

Rule 3. The larger the value of NCC is, the better the denoising effect is and vice versa.

So, the effect of the cooperative denoising model with interactive dynamic adjustment function may be evaluated by the above evaluation indexes.

3.3. Construction and Analysis of the Cooperative Denoising Algorithm with Interactive Dynamic Adjustment Function. Based on the above discussion, combining with the cooperative denoising framework, the cooperative denoising algorithm for nonstationary signal in IIoT may be designed in detail as below.

Step 1. It is initialization of system. Load the original signal of IIoT and determine the states of the algorithm switches to be off or on.

Step 2. Calculate the number of the switches that are on. If the number is equal to 3, step 3 is performed; otherwise Step 5 is performed.

Step 3. Obtain three denoised signals by using LMS, VSLMS, and VSLMS-EEMD denoising algorithms, respectively. The denoising process is divided into training stage and equaling stage.

(1) Training stage: for LMS denoising algorithm, the optimal weight coefficient W can be obtained by using (14)-(15); for VSLMS and VSLMS-EEMD denoising algorithm, the optimal weight coefficient W can be obtained by using (17)-(18).

(2) Equalizing stage: the optimum weight coefficient W obtained by the training stage is used to carry out equalization and noise elimination for original signals of IIoT by using (12) to obtain the denoised signals named $\hat{S}_1(i)$, $\hat{S}_2(i)$, and $\hat{S}_3(i)$, respectively.

Step 4. Obtain the dynamic adjustments of weight coefficients w.

(1) Obtain the error signal $e(i)$ shown as (20) by using (14).

(2) Obtain weight coefficients ω based on error signal obtained from a) by using Rule 1 that is shown as (21)-(23).

Step 5. Interactively denoising the IIoT signal by using (19).

Step 6. Repeat steps 1–5 until the number of processed signals is equal to length of the original signal.

Step 7. Evaluate denoising algorithms by using Rules 2 and 3 that are shown as (24)-(25) based on the denoised signals obtained from step 5.

The cooperative denoising flow chart is shown as Figure 4.

4. Simulation Examples

To verify the effectiveness and rationality of the presented algorithm, the simulation examples were first used to test the denoising ability to the network data packet of health monitoring in IIoT. In general, the simulation original signal $S(t)$ was described as follows.

$$S(t) = s(t) + v \tag{26}$$

where $s(t)$ represents the useful signal and $v(t)$ indicates the random noise.

In our simulation experiments, $s(t)$ and $v(t)$ were set up as below.

$$\begin{aligned} s(t) &= 0.13\cos(2\pi \times 20 \times t) + 0.08\sin(2\pi \times 10 \times t) \\ &\quad + 0.02\sin(2\pi \times 40 \times t) \\ v &= 0.18\,\mathrm{wgn}(L, 0) \end{aligned} \tag{27}$$

where L represents signal length.

In our simulation examples, L is set up as 2000. The comparison results between the original signal and compounded signal with noise are shown as Figure 5.

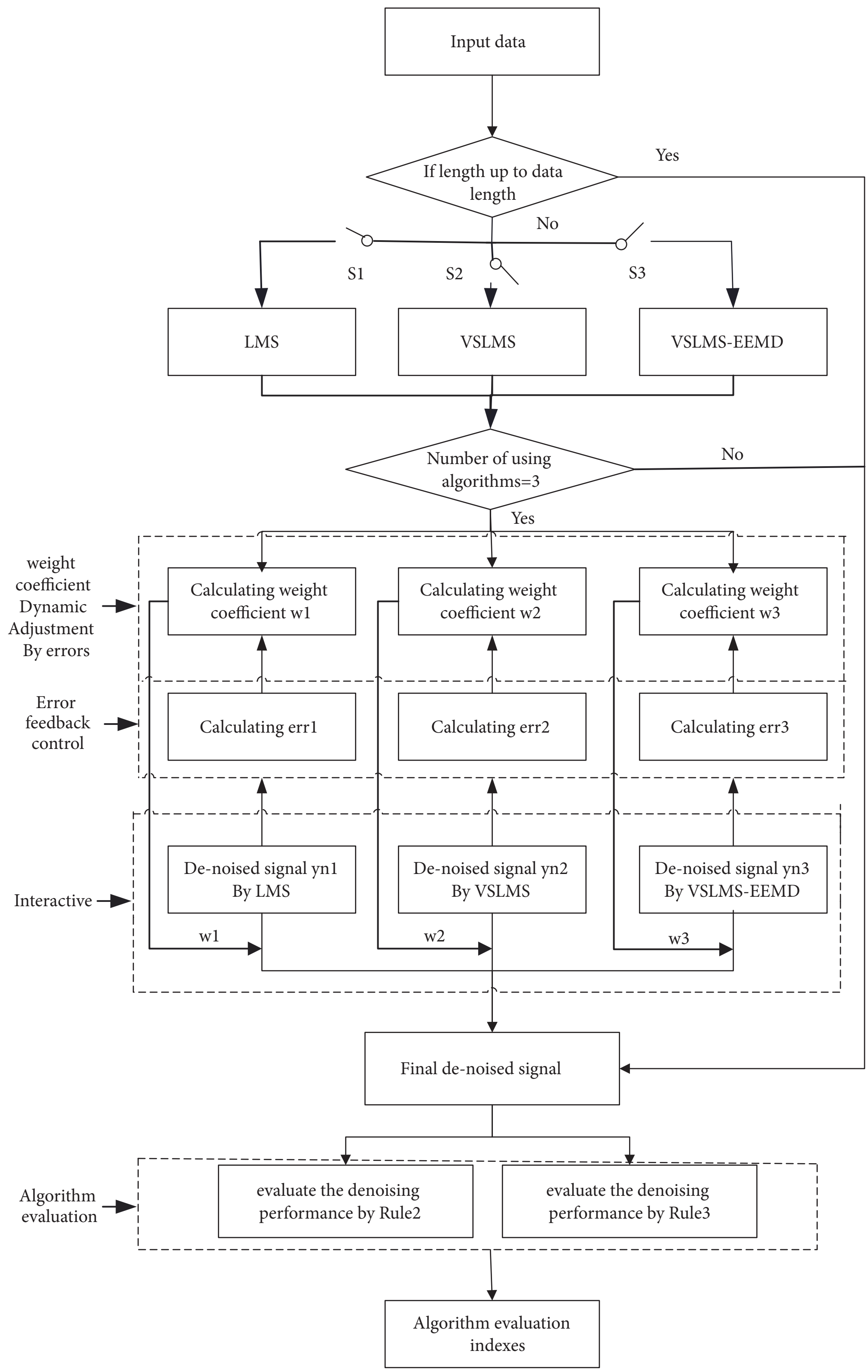


Figure 4: The cooperative denoising flowchart with interactive dynamic adjustment function.

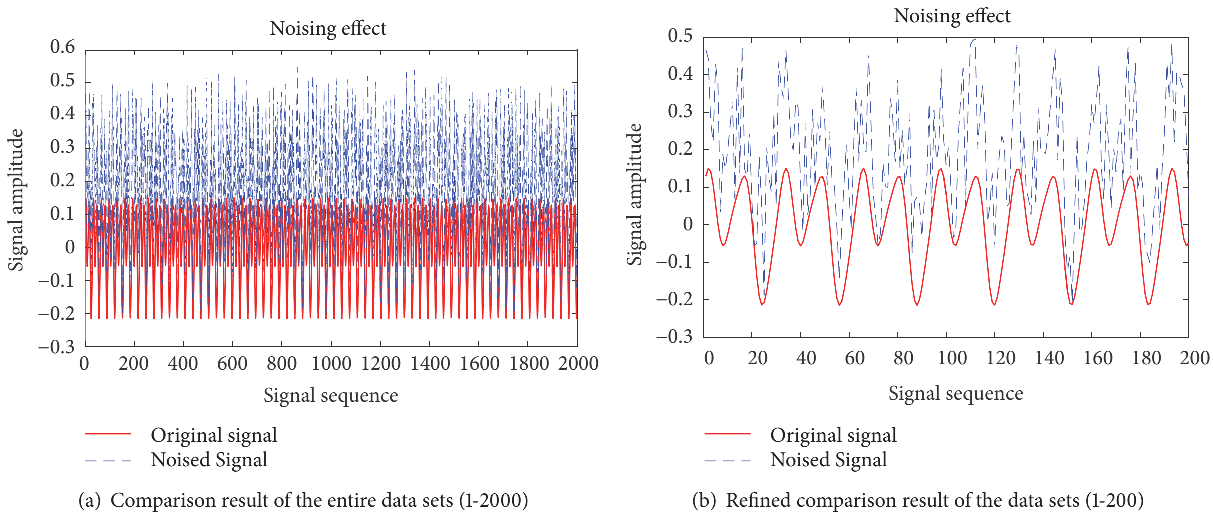


Figure 5: Comparison result between the original signal and noised signal.

Further, to prove the efficiency and superiority of the improved VSLMS-EEMD and the proposed IDVSLMS-EEMD algorithm, some comparative simulations were done, including LMS, VSLMS, and wavelet with soft threshold combined with EEMD (WTS-EEMD) denoising model in [38, 39]. The corresponding denoising results were shown as Figure 6.

Where, Figures 6(a), 6(c), 6(e), 6(g), and 6(i) illustrate the whole effectiveness of these denoising algorithms. In addition, Figures 6(b), 6(d), 6(f), 6(h), and 6(j) have shown more clear and specific effectiveness by selecting anterior 200 signals. In that case, the effectiveness of the presented algorithm may be better depicted.

To compare the effect of varieties of denoising algorithms, we have selected the Noise Suppression Ratio (NSR) and Signal Distortion Rate (SDR) to evaluate denoising effect, which are defined as follows:

$$\mathrm{NSR} = 1 - \frac{\left[\sum_{i=1}^{N}\left(\hat{S}(n) - s(n)\right)^2\right]^{1/2}}{\left[\sum_{i=1}^{N}\left(\hat{S}(n) - s(n)\right)^2\right]^{1/2}} \qquad (28)$$

$$\mathrm{SDR} = \frac{\left[\sum_{i=1}^{N}\left(\hat{S}(n) - s(n)\right)^2\right]^{1/2}}{\left[\sum_{i=1}^{N} s(n)^2\right]^{1/2}} \qquad (29)$$

where $\hat{S}(n)$ and $s(n)$ indicate the original signal with noise as well as the denoised signal.

Without loss of the generality, the following rule needs to be noticed.

Rule 4. The larger the NSR is, the smaller the SDR will be. Meanwhile, this also means that the elimination effect of noise is better.

Table 1: Denosing evaluations of LMS, VSLMS, WTS-EEMD, VSLMS-EEMD, and IDVSLMS-EEMD.

Method/parameter	NSR	SDR
LMS	0.7011	0.6266
VSLMS	0.8369	0.3419
WTS-EEMD	0.8603	0.5896
VSLMS-EEMD	0.8644	0.2842
IDVSLMS-EEMD	0.8674	0.2779

Based on the rule, the comparison results are shown in Table 1.

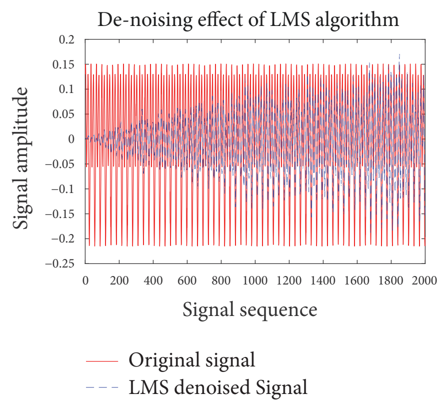
Combining with Figures 6(b), 6(d), 6(f), 6(h), and 6(j), we can know that the denoised curve of IDVSLMS-EEMD algorithm is the smoothest and is closest to original signal. The simulation results and the denoising method parameters in Table 1 illustrated that the denoising effect of LMS, VSLMS, WTS-EEMD, and VSLMS-EEMD is inferior to proposed IDVSLMS-EEMD. Moreover, the improved cooperative denosing algorithm may be provided with the maximum NSR and the minimum SDR. Thus, the denoising effect of the improved algorithm is the best.

In addition, to illustrate the influence of noise, the comparison result of SNR between noised signal and denoised signal is also shown in Table 2.

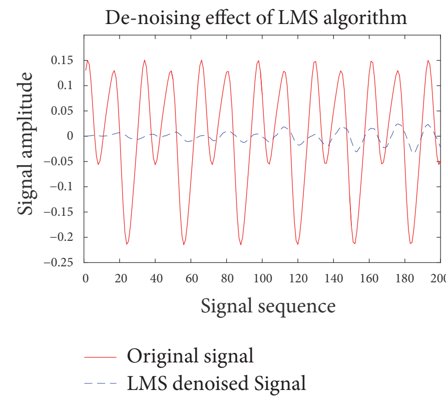
As seen in Table 2, the effect of the cooperative denosing algorithm is very good. So, after the function testing, this integrated framework may be applied to actual project.

5. Real Experiment Examples

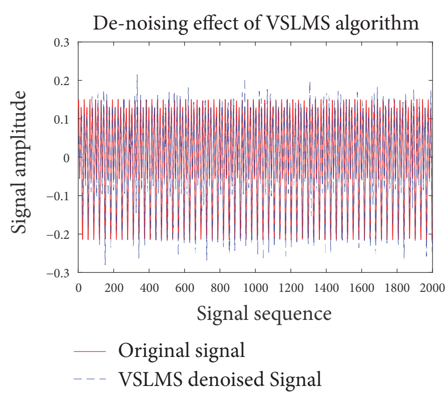
Denosing is the essential premise for further security analysis of stacker in IIoT. To further verify the performance of the proposed algorithm, the real-time simulation signal of stacker under abnormal condition in ASRS, which has been developed and applied in Power Grid of China, was selected to test the denoising performance of the presented algorithm.



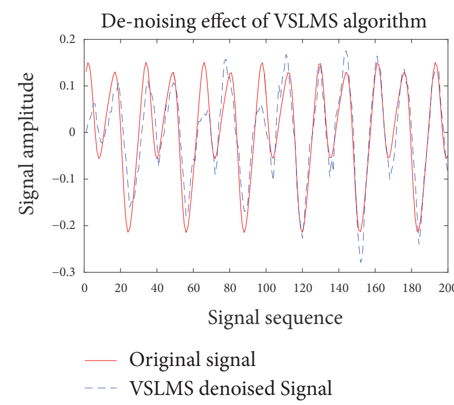
(a) LMS denoised results (1-2000)



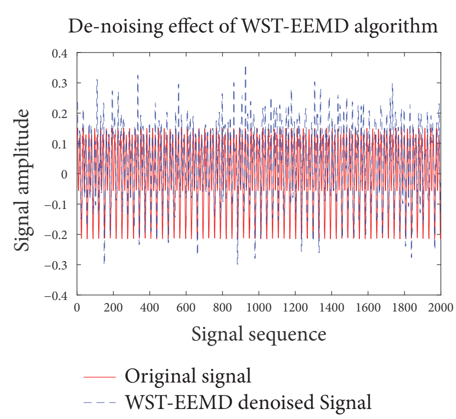
(b) LMS denoised results (1-200)



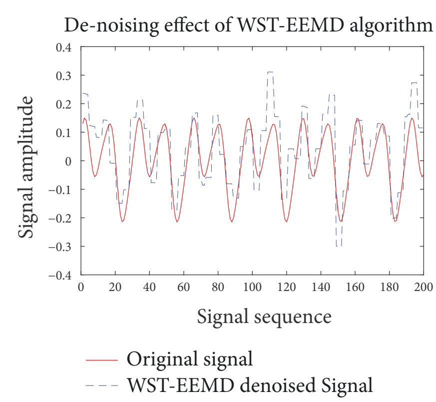
(c) VSLMS denoised results (1-2000)



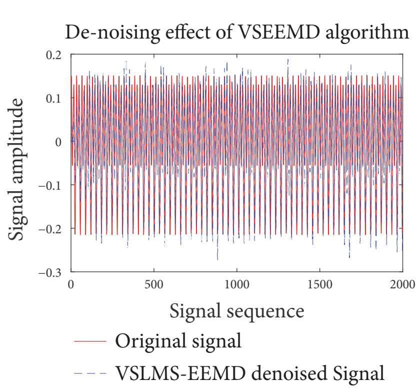
(d) VSLMS denoised results (1-200)



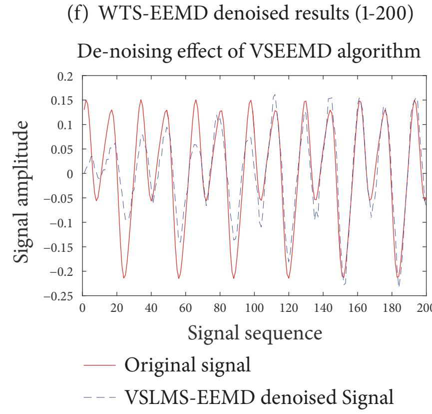
(e) WTS-EEMD denoised results (1-2000)



(f) WTS-EEMD denoised results (1-200)

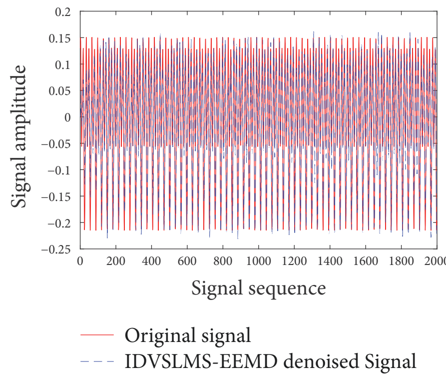


(g) VSLMS-EEMD denoised results (1-2000)

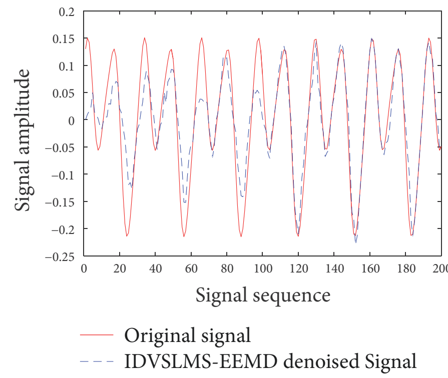


(h) VSLMS-EEMD denoised results (1-200)

Figure 6: Continued.



(i) IDVSLMS-EEMD denoised results (1-2000)



(j) IDVSLMS-EEMD denoised results (1-200)

Figure 6: Denosing simulation results of simulation signal by varieties of denoising algorithms (1-2000).

Figure 7: Simulate rigs of ASRS.

Table 2: SNR of the noised and denoised simulated signal.

Signal/parameter	SNR
Noised signal	-1.1238
Denoised signal	10.1160

The test rig of the prototype systems in IIoT is shown as Figure 7.

The simulation rig of ASRS is constructed and developed according to the real requirements of Power Grid in China. Their main function is to grab, move, and stack goods from one piece of equipment to another. As the crucial equipment of ASRS, the security and the positioning accuracy of stacker will directly affect the data acquisition and the data exchange of the whole IIoT system. In addition, the stacker is driven by motor, so the running state of stacker is directly reflected by the driving vibration signal. In real engineering, the test rig of stacker signal is shown as Figure 8.

In real application, the sampling time is from a.m. 9:03:51 to p.m. 15:04. The column of starting and stopping range is from 0 to 23. The size of the detecting signal is 2000. Then, the comparison results between the original signal and compounded signal with noise measured were simulated by the stacker's running. The results were shown as Figure 9.

Table 3: Simulation results of Rule 1.

Signal/parameter	C
Original signal	0
Noisy signal	0.1424
LMS	0.0823
VSLMS	0.0820
WST-EEMD	0.0810
VSLMS-EEMD	0.0726
IDVSLMS-EEMD	0.0589

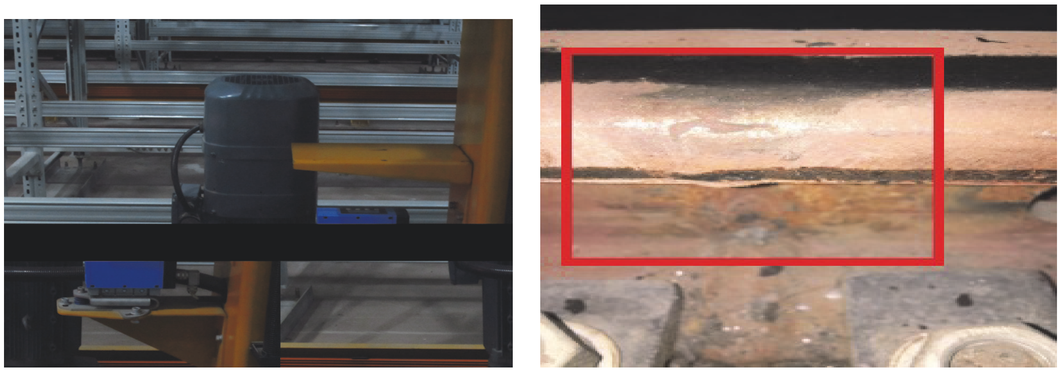
Secondly, to further prove the efficiency and superiority of the improved VSLMS-EEMD and the proposed IDVSLMS-EEMD algorithm, some comparative experiments were done. The results of stacker's running signal were simulated by the above relevant denoising algorithms, respectively. The denoising results were shown in Figure 10.

To see more clearly the performance of denoising algorithm, we had selected the anterior 200 signals to refine the display degree of the denoising effect. The results are illustrated as Figure 11.

Figures 11(a)–11(e) highlight the refined display degree and more clearly reveal the difference between the original signal and denoising signal when the nonstationary signal was denoised using different algorithms. As can be seen from the refined illustration in Figure 11, the presented algorithm with interactive dynamic adjustment function approaches accurately high quality.

Moreover, to quantitatively illustrate and assess the difference of denoising effect, we have used the evaluation indexes to compute the evaluated results. These values are listed in Tables 3 and 4.

As measured in Table 3, the denoising absolute error value is minimal when the proposed algorithm with interactive dynamic adjustment function was used to denoise for the running signals of Stacker. Meanwhile, Table 4 shows that NCC of the proposed algorithm is maximum. By the evaluation of Rules 2-3, we know that the proposed algorithm



(a) Driven motor

(b) Depression of lower track

Figure 8: Test rig of stacker' signal.

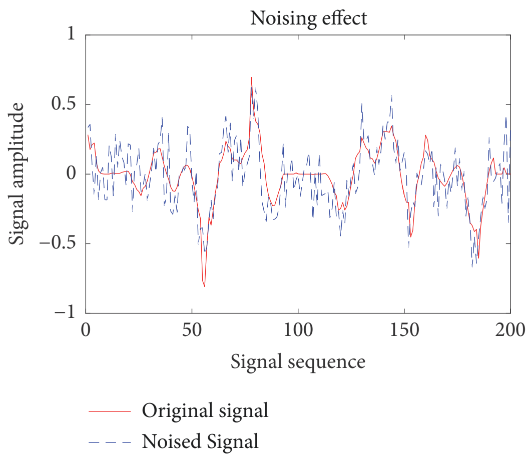


Figure 9: Comparison result between the original signal and noised signal of the stacker running.

Table 4: Simulation results of Rule 2.

Method/parameter	NCC
LMS	0.7500
VSLMS	0.7978
WST-EEMD	0.8005
VSLMS-EEMD	0.8429
IDVSLMS-EEMD	0.8658

with interactive dynamic adjustment function may achieve the desired performance in real systems.

The overall idea here is the same as what we have discussed in the previous simulation examples; the SNR between noised signal and denoised signal was also computed to illustrate the influence of noise for security analysis of stacker in IIoT. The numerical results are shown in Table 5.

Obviously, the SNR is strengthened because the proposed algorithm may obtain and integrate more abundant information compared to traditional methods for security of stacker in real health monitoring of IIoT. That means that the effect of the cooperative denosing algorithm is very good.

Table 5: SNR of the noised and denoised signal for stacker.

Signal/parameter	SNR
Noised signal	-0.7437
Denoised signal	14.6039

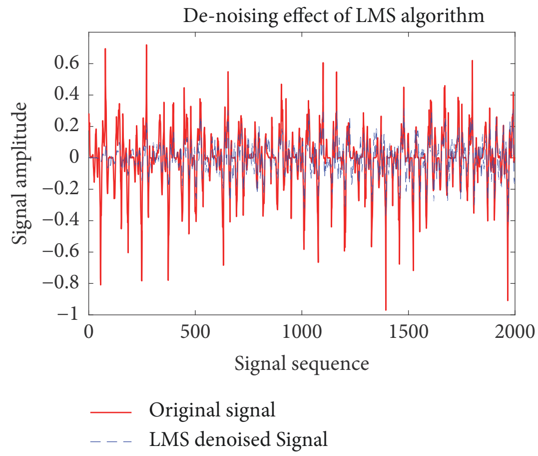
The analysis results on the actual examples show that the proposed denoising algorithm may improve the accuracy of denosing to provide higher reliability for security monitoring of stacker in IIoT. That means that our algorithm may be applied to monitoring the security of the devices in the real IIoT.

6. Conclusions

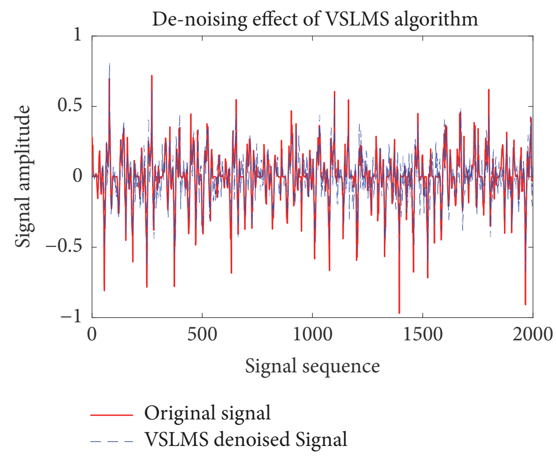
In this paper the cooperative denoising algorithm with interactive dynamic adjustment function was depicted and analyzed based on LMS, VSLMS, and VSLMS–EEMD via the integrated optimization strategies. Meanwhile, some basic theories and corresponding evaluated indexes were also selected and established. The simulation examples and actual examples show the validity and rationality of the proposed algorithm in monitoring the security of real IIoT devices. The main conclusions of our work are listed as follows:

(1) In IIoT system, the original signal is seriously interfered by the surroundings resulting in low SNR. Because of this phenomenon, it is difficult to obtain accurate and reliable features from the confused signals, which has seriously hindered the security analysis, health detection, and the maintenance of IIoT system. Therefore, it is necessary to denoise the nonstationary signal of IIoT.

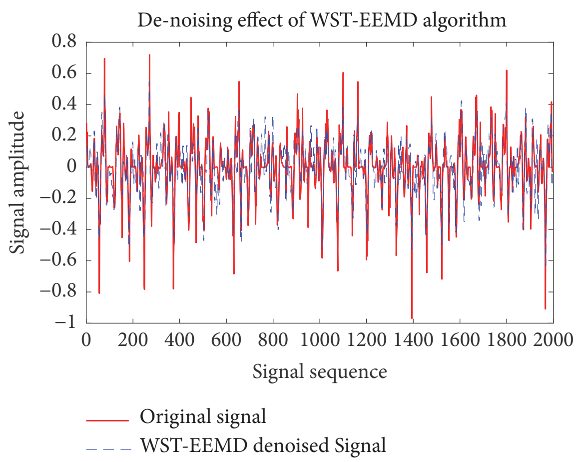
(2) The shortcomings of traditional EMD algorithm and traditional LMS algorithm with fixed step are considered. To maximize the advantages of LMS, VSLMS, and EEMD, the VSLMS-EEMD denoising algorithm has been constructed. On this basis, a cooperative denoising algorithm with interactive dynamic adjustment function is proposed to further improve the denoising accuracy of VSLMS-EEMD. Meanwhile, the evaluated indexes and rules were designed according to the features of the information for IIoT devices.



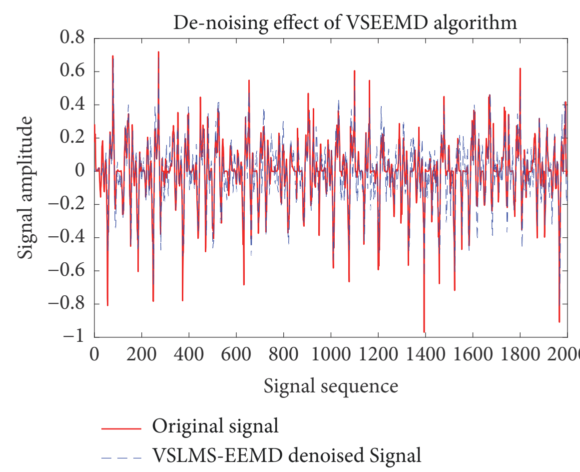
(a) LMS denoised results of stacker's signal



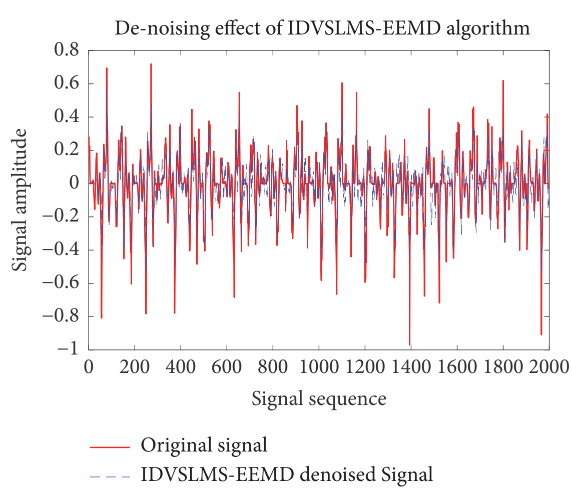
(b) VSLMS denoised result of stacker's signal



(c) WST-EEMD denoised results of stacker's signal



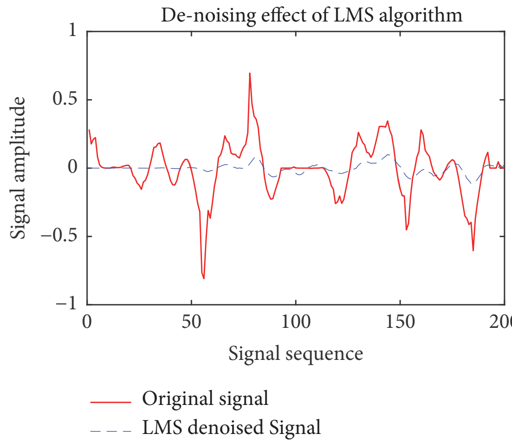
(d) VSLMS-EEMD denoised results of stacker's signal



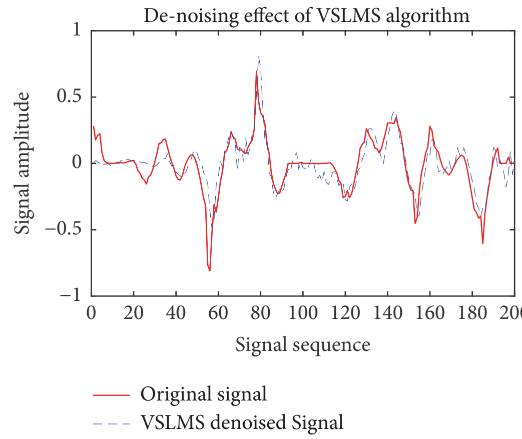
(e) IDVSLMS-EEMD denoised results of stacker's running signal

FIGURE 10: Denosing simulation results of stacker's running signal by using varieties of denoising algorithms (1-2000).

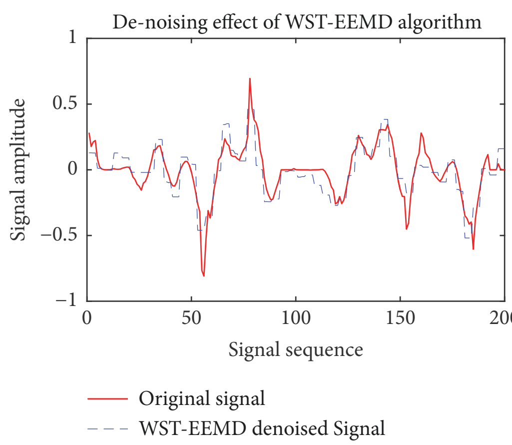
(3) Simulation examples and real data examples were used to implement and verify the efficiency of the proposed algorithm. Moreover, the comparison results were computed via the denoising evaluating indictors (i.e., model and rule). The simulation results show that the new algorithm has a better synchronous precision and security. Compared with the traditional method, the presented method can greatly reduce the noise ratio of security monitoring of IIoT devices.



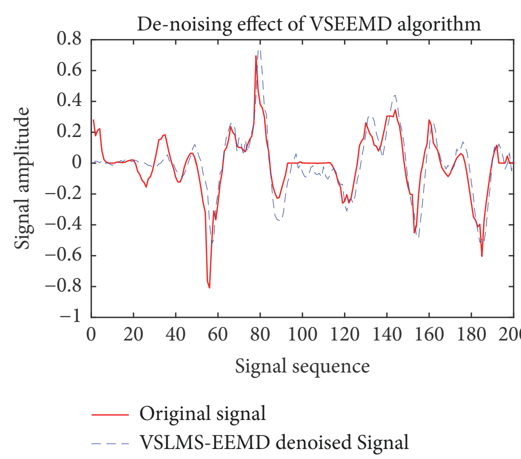
(a) LMS refined denoised effect of stacker's signal



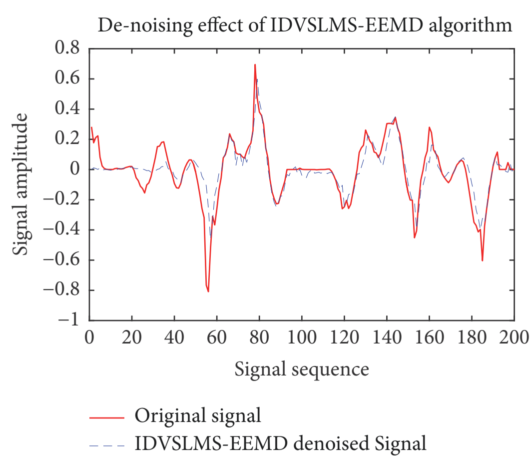
(b) VSLMS refined denoised effect of stacker's signal



(c) WTS-EEMD refined denoised effect of stacker's signal



(d) VSLMS-EEMD refined denoised effect of stacker's signal



(e) IDVSLMS-EEMD refined denoised effect of stacker's signal

FIGURE 11: Denosing refined simulation chart of stacker's running signal by varieties of denoising algorithms (1-200).

Unfortunately, this cooperative denoising algorithm is only for one or three kinds of denoising algorithms, and no specific design is made for the cooperation of the two algorithms; the weight coefficients ω is calculated by error signal, so its calculation can be further optimized. Due to the limited space, this work will be given in another paper.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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