Nonlinear Time-Varying Weak Signal Enhancement Method Based on Particle Filter

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Abstract. Traditional weak signal enhancement methods have low signal-to-noise ratio, which affects the accuracy of weak signal recognition. Therefore, this paper proposes a nonlinear time-varying weak signal enhancement method based on particle filter. Collect nonlinear time-varying weak signals, extract nonlinear time-varying diffusion coefficients using particle filter, simulate the real distributed sampling process, build an adaptive neural network model, use subtractive clustering algorithm to determine the selection and number of hidden layer neuron centers, and improve the weak signal enhancement mode. The experimental results show that the signal-to-noise ratio of this method is up to 37.303 db, which shows that the nonlinear time-varying weak signal enhancement method designed by combining particle filter algorithm is more effective.

Keywords: Particle filter · Nonlinear time-varying · Weak signal · Signal enhancement · Signal-to-noise ratio · Background noise

1 Introduction

As an important part of the channel, the main purpose is to transmit the signal sent by the sending device to the receiving device. Coherent detection technology utilizes two opposite characteristics of coherent signal and incoherent noise, and will remove the noise part that is different from the signal phase. However, the channel gives the signal both the chance to successfully reach its destination and the risk that it will be riddled with all kinds of noise or interference. In the narrowband detection technology, based on the known signal frequency as a fixed value, a narrowband filter that limits the system bandwidth is designed to filter out the noise outside the bandwidth, so as to achieve the effect of suppressing noise and enhancing weak signals. Usually, noise is random and comes in a variety of forms. A common problem with signals passing through any communication channel is the presence of additive noise. Generally, additive noise is caused by the internal components of the communication system, such as resistors and solid-state devices. This noise is also known as thermal noise. Coherent and narrowband detection techniques are commonly used to process weak periodic signals in the frequency domain. When the weak signal is a pulse wave and the spectrum is a very wide segment, the coherent and narrowband detection technology for

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weak signal enhancement will fail [1, 2]. Other sources of noise and interference are caused by outside the system, such as harsh transmission environments. Under normal circumstances, the communication system has a certain anti-noise performance, but if the noise intensity is too large, it will interfere with normal communication, resulting in the inability to effectively and completely transmit and receive information. Since the randomness of noise is manifested in the positive, negative and magnitude of the amplitude, the noise interference can be eliminated to a certain extent by sampling the noisy signal multiple times point by point and averaging, thereby realizing the extraction and detection of weak signals. There are two ways to understand the "weakness" of a signal: one is that the amplitude or intensity of the target signal is too weak relative to the noise background, that is, the signal-to-noise ratio (SNR) is low. The other is that the amplitude of the signal itself is small. When the measured signal is irrelevant to noise, it can adaptively adjust the filter to the optimal state through successive iterations, so as to improve the extraction and detection performance of weak signals under low signal-to-noise ratio. Adaptive noise cancellation technology is suitable for the cancellation of both broadband and narrowband types of noise. Therefore, it has been widely used in signal detection, radar, sonar, array processing, oceanography and other fields. In a communication system, the signal-to-noise ratio is an important indicator to measure the reliability of communication quality. Since there is always noise in the actual received or measured signal, in the actual signal, the expected power of the useful signal component and the objectively existing noise power The ratio is always a finite value, which is the signal-to-noise ratio. The higher the signal-to-noise ratio, the stronger the anti-noise ability of the signal during the transmission process, and the higher the "fidelity".

Relevant scholars have studied this. For example, reference [3] proposes a method to enhance the characteristics of weak current signals of power distribution devices based on vector control, constructs a resonance model of weak current signals of power distribution devices through nonlinear coupling, obtains the characteristics of weak current signals of power distribution devices according to wavelet transform, realizes signal reconstruction using reversible transformation, and completes the enhancement of weak current signal characteristics through vector control. This method can reduce the line distance, but the signal-to-noise ratio is low.

In view of the above problems, this paper designs a nonlinear time-varying weak signal enhancement method based on particle filter.

2 Nonlinear Time-Varying Weak Signal Enhancement Method Based on Particle Filter

2.1 Analysis of Weak Signal Detection Technology

Weak signal detection technology is not only a subject but also a comprehensive technical means. With the deepening of research, it is gradually applied in many fields, including biomedicine, astronomy, seismology, mechanical fault detection, etc. Weak signal detection is a multi-disciplinary comprehensive application of detection methods. By using different methods to study and analyze the statistical characteristics of signals and noise, and use a variety of signal processing methods to analyze and process the input signal, the weak signal can be changed from strong noise to strong noise. In order to meet the requirements of high-precision detection technology required by modern scientific research and technical applications. Weak signal detection is to use the correlation principle to calculate the autocorrelation and cross-correlation of the signal containing noise, so as to extract the useful signal submerged in the noise [4]. When there is only noise and the signal to be measured, the noise is not correlated before and after the time axis and is also not correlated with the signal to be measured, and the signal to be measured has periodicity. After the autocorrelation calculation, the frequency value can be retained to filter out the noise. The characteristics of weak signal detection are as follows: the signal-to-noise ratio of the detected weak signal is relatively low. On the one hand, the measured characteristic signal itself is very weak, and on the other hand, it is disturbed by strong noise. If the failure of mechanical equipment is in the early stage, various characteristic signals caused by the failure are often mixed with the signals of other characteristic sources in a special way, which causes the characteristic signals to become relatively weak. When the two periodic signals have the same fundamental frequency, the useful signal in the extracted noise can be processed by cross-correlation. During cross-correlation, the fundamental frequency can be retained and the common harmonics can be left to remove the noise uncorrelated with the signal.

2.2 Detecting Weak Signals

The ratio of the power of the system output signal to the average power of the noise under the same frequency background noise is the output signal-to-noise ratio of the stochastic resonance system. The signal-to-noise ratio can be expressed by formula (1):

$$G \approx \frac{\pi}{2} \sum \left| \frac{\alpha - 1}{E} \right|^2 \tag{1}$$

In formula (1), α represents the average transition frequency, and E represents the number of times the potential barrier is flipped. It can be seen from the above formula that there is a nonlinear relationship between the output signal-to-noise ratio and the noise intensity, that is, it increases and then decreases with the increase of the noise intensity. When the noise intensity is close to 0, the signal-to-noise ratio should be 0. When the noise disappears, the output signal-to-noise ratio of the system should be infinite, which shows that the assumptions of the adiabatic approximation theory have certain limitations. If the device is running, the signal is also mixed with strong noise interference. The detection of signals has rapidity and real-time requirements. In engineering practice, it is necessary to collect and analyze signals, and the length of data or the duration of the acquisition process is limited, such as the collection of weak signals in the fields of pipeline leakage, communication facilities, earthquake detection, industrial measurement, and real-time monitoring of mechanical systems., the length of the collected data is short, so there are certain requirements for the rapidity and real-time detection. The relevant detection principle is simple, easy to implement, and has high detection efficiency, and can be widely used in actual engineering signal detection. Although this method has the above advantages, most of the noises are assumed to be uncorrelated in the detection, and the noise with small time interval in the actual detection may be correlated. Phenomenon. The characteristics of adaptive filtering are very prominent: in order to adjust the filter to the best filtering state, the parameters of the system can be adaptively adjusted according to some optimal criterion. The input and output power spectrum amplification factor is defined as follows:

$$H = \frac{\left|\frac{\alpha-1}{E}\right|^2}{\phi} \times \frac{1}{\alpha} \tag{2}$$

In formula (2), ϕ represents the response function. This can be achieved even without prior statistical knowledge of the signal and noise, and even when the statistical properties of the input signal change, the filter can satisfy the adaptive "learning process" by adjusting its own parameters. When the statistical characteristics of the input signal change, the process that the filter can adjust its own parameters to the optimal value is called the "tracking process", which reflects the ability of the system to learn and track. By constantly "screening" the signal, the different frequency components in the signal containing noise are decomposed into different modes, and several modes and residuals are formed. The EMD time-frequency analysis method is superior to the classical method in processing capability and effect in many application fields.

2.3 Extraction of Nonlinear Time-Varying Diffusion Coefficients by Particle Filter

Particle filter algorithm is the application of Monte Carlo method in Bayesian estimation. The algorithm uses the random state set of system state variables to obtain statistical indicators such as expected value and variance corresponding to the dynamic process. It is an algorithm based on statistical principles. The elements in these sets of random states are called "particles". Particle filtering can be used for systems described by any state space. Its core lies in constructing a posterior probability density function. The constructed posterior probability density function needs to reflect the real probability distribution. The constructed posterior probability function is sampled to simulate the real probability distribution. Distribution sampling process. The working process of nonlinear time-varying diffusion coefficient extraction is extremely complex, including the selection of the number of network layers, the selection of the number of nodes in each layer, and the determination of the connection mode between the transfer function of each node and the nodes. The PF algorithm based on the SMC structure recursively estimates the nonlinear system by continuously generating a series of particles with weights (weights). The weight of the particle is used to measure the conformity of the particle to the measured value after the transformation of the measurement equation. After the model structure of the extracted system is determined, the parameters in the model results must be extracted. In general, the extraction process is that the particle filter can learn and adjust the parameters to minimize the objective function. Among them, the particle filter parameter extraction is the most commonly used. The objective function of is the mean-squared error function. When the system input signal and noise exist, the bistable can be described by its Langevin equation. The specific expression formula is:

$$\varepsilon = \frac{\phi + \lambda + \eta}{2} \tag{3}$$

In formula (3), ϕ represents the periodic driving force, λ represents the potential barrier height, and η represents the system parameter. Then the algorithm calculates the required posterior distribution through this series of particles and their weights. Considering that the recursive estimation is convenient for computer processing, the nonlinear time-varying diffusion coefficient obtained by sampling must have a sequential relationship. Since Bayesian importance sampling requires the data of the state of the particle at all times when estimating the state, when the latest observation data comes, the weight value of the entire state sequence needs to be recalculated. In each recursive calculation step of the algorithm, more and more particles will deviate from the estimated true value, and their weights tend to 0. In order to avoid this situation, the algorithm needs to constantly eliminate particles with small weights, keep particles with large weights and multiply them to ensure a sufficient number of particles. With the increase of time, the amount of computation tends to be complex, so sequential importance sampling is introduced to solve it. When the latest observation data comes, it is only necessary to add the particles sampled at this moment to the existing particle set. On the basis of formula (3), the average mutual information of input and output is obtained, and the specific expression formula is:

$$D = \sum \frac{d(\varpi - 1)^2}{\|R\|} \tag{4}$$

In formula (4), d represents the information entropy of the output, ϖ represents the conditional entropy, and R represents the conditional probability. Online extraction is completed in the actual operation process of the extraction system, so this extraction process has the characteristics of real-time. The offline extraction can complete the relevant learning and training in advance before the particle filter works on the extracted system. The "array enhancement effect" formed by the combination of multiple parallel nonlinear units is found in weak signal processing devices. The parallel formation of a stochastic resonance array network for the same nonlinear stochastic resonance subsystem can amplify the output response of the system. Extended to array stochastic resonance theory. However, because the input and output training sets of its network are difficult to cover all possible working ranges of the system, and it is difficult to adapt to the parameter changes of the system during the working process, in order to overcome the shortcomings of these two extraction methods, two methods can be used. Extraction methods are used in combination. In an uncoupled parallel array network composed of arbitrary static nonlinear sub-modules, the SNR gain expression for weak periodic signals under strong background white Gaussian noise is derived, and it is demonstrated that the SNR gain is very important for a given stochastic resonance sub-module type. And the noise intensity increases monotonically with the increase of the number of arrays. Firstly, discrete extraction is performed, the weight matrix of particle filter is obtained through discrete training, and then online extraction is performed, and the obtained weight matrix is used as its initial weight through online learning, which is conducive to speeding up the learning process of online extraction. Due to the self-learning and self-adaptive characteristics of particle filter itself, when the characteristics of the extracted system change to different degrees, particle filter can adaptively track the extraction system by continuously adjusting the network connection weights or thresholds. Trend. It is worth noting that when the noise intensity in the array network is optimal, the system SNR gain cannot be further enhanced. Since the optimal array performance in reality is difficult to achieve, people can often generate more superior system response by increasing the number of array elements and adding array noise to the parallel array network composed of sub-optimal nonlinear submodules. The series-parallel model is realized by time-delay particle filter, and the parallel model is realized by internal time-delay feedback particle filter and output feedback network. Since the structure of the series-parallel model uses the input and output signals of the extracted system as the extraction information, and its network training can ensure the convergence and stability of the extracted model, the series-parallel model structure is used in particle filter extraction. Widely used. With a sufficiently large number of array elements and different types of noise, the input-output signal-to-noise ratio gain of the threshold nonlinear array proved to be able to be greater than 1.

2.4 Building an Adaptive Neural Network Model

The feedback particle filter is used for the identification and control of nonlinear time-varying systems, which can fully reflect the time-varying characteristics of nonlinear systems. Therefore, the research on the identification and control of nonlinear time-varying systems based on feedback particle filtering not only has important theoretical innovation value, but also has great guiding significance for practical engineering applications. In practical applications, the dynamics of physical systems change continuously with running time. In order to better describe the time-varying characteristics of nonlinear time-varying systems, time-varying neural networks have become an important choice for system identification. Then, the conventional RBF network and the time-varying RBF network are respectively used for the multi-input multi-output nonlinear time-varying system identification. After the network structure, input and state dimensions are determined, the network weights are adjusted by an iterative learning algorithm with the help of the repeated operation process to conduct network training. Then, the effectiveness of the proposed enhancement algorithm is verified by real-time simulation of the specific nonlinear system. After the network structure is determined, weight adjustment becomes the key to time-varying network applications. After the network structure, input and state dimensions are determined, the subtraction clustering algorithm is used to realize the selection of the hidden layer neuron center and the determination of the number. Considering the approximation error, the weights of the conventional RBF network are adjusted according to the integral learning law with dead zone correction. Considering the coexistence of periodic signals and random excitations, the overdamped motion of Brownian particles in three potential asymmetry cases can be described as the following Langevin equation:

$$\frac{h(\mu)}{g} = -\sum \frac{1}{\sqrt{|\mu - g|^2}} \tag{5}$$

In formula (5), h represents the amplitude of the external periodic modulation signal, μ represents the frequency of the external periodic modulation signal, and g represents the additive white Gaussian noise. And, formula (5) satisfies the following conditions:

$$\begin{cases} \frac{\mu}{g} = \frac{h^2}{2} \\ \sigma \langle h + g \rangle = \sum 2\frac{\mu}{T} \end{cases} \tag{6}$$

In formula (6), T represents the intensity of additive Gaussian white noise. Finally, the particle filter based enhancement algorithm is applied to the modeling of temperature and humidity in the process of wood drying. The effectiveness of the proposed enhancement algorithm can be further verified by comparing the real value of temperature and humidity in the process of wood drying with the simulation results. For time-varying RBF networks, learning from the idea of iterative learning, a semi saturated iterative learning law with dead zone correction is used to complete the training of network weights. Then, the convergence performance of identification error in each case is analyzed by Lyapunov like method. The theoretical analysis shows that with the increase of the number of iterations, the system identification error gradually converges to the given boundary value (the boundary value depends on the dead band range). As a kind of dynamic system model, nonlinear time-varying system is widely used in practical engineering field. However, due to the nonlinear dynamic characteristics of nonlinear time-varying systems, people can not obtain the dynamic model of the system in most cases. Therefore, when using control theory to solve practical problems, establishing the dynamic model of the system is the key to the successful application of control theory in production practice, and the task of system enhancement is to establish the dynamic model of the system. Finally, the conventional RBF network and the proposed time-varying RBF network are used to simulate the nonlinear time-varying system, which further shows the effectiveness of the proposed identification algorithm. Nonlinear time-varying systems have complex nonlinear dynamic time-varying characteristics. How to realize the effective modeling and identification of such systems has been widely studied. With its own strong approximation ability and generalization ability, neural network can complete the training of network weight by measuring the input/output of the system without predicting the system model, so as to realize the effective enhancement of nonlinear system. Therefore, particle filter has been widely used in the enhancement and control of nonlinear system [5]. Dynamic neural network has become an important choice. As a typical structure of neural network, the structure of dynamic neural network is different from feedforward neural network. Dynamic neural network introduces feedback mechanism to train network weights with system input and output data obtained by on-line measurement. Dynamic neural network has been successfully used in nonlinear system identification. The essence of particle filter enhancement is to transform the system enhancement problem into the approximation problem of specific nonlinear function, and the function approximation problem is one of the most basic problems in the research of particle filter. Particle filter trains the network weights by collecting the system input/output data, and realizes the effective approximation of the system output by minimizing the system output error function, so as to complete the whole signal enhancement process.

2.5 Improved Weak Signal Enhancement Mode

For approaching any complex nonlinear function, through theoretical analysis and practical verification, it is concluded that when the network has about 10 middle layer components, after "sufficient" learning, it can meet the identification accuracy requirements in most cases. The core of weak signal enhancement is that the nonlinear stochastic resonance system driven by weak signal and noise can achieve the best synergy among the system input signal, noise and nonlinear stochastic resonance system by adjusting and optimizing the system parameters, so as to make the stochastic resonance system at the resonance point, so as to enhance the weak input signal of the system [6, 7]. At the same time, when the network has the simplest structure, it is also conducive to practical application and meet the high real-time requirements of online identification. Therefore, the simplification of network scale is very necessary. This theory avoids the defect of traditional stochastic resonance theory that excites stochastic resonance by adding noise, and the way of adjusting system parameters is easier to operate and realize. SPN is defined as a network with multiple sensor nodes. The weight attenuation method is a common pruning method and belongs to the regularization method. Its working mechanism can be explained from the perspective of a priori distribution, that is, the minimization of loss function is equivalent to the maximization of a posteriori probability of weight parameters, which confirms the simplest principle of network structure design: for the network that has reached a given training accuracy, the fewer effective parameters, the better the generalization ability, Thus, it provides a theoretical basis for the rationality of designing the minimum structure network. It should be noted that the signal-to-noise ratio mentioned here is different from the concept of signal-to-noise ratio in the field of communication. It is for single frequency signals, that is, the signal is in the form of single peak impact in the frequency domain. Therefore, its definition formula is:

$$Y = \lim \int_{n=1}^{m+\Delta k} \sum \frac{km}{V(n)} \tag{7}$$

In formula (7), k represents the power spectral density, m represents the noise intensity near the signal frequency, n represents the cross-correlation coefficient, and V represents the signal amplitude at a specific target frequency. The input of each node is a common input information source of the network and their independent noise, and all these node outputs are fused to the sink Center for processing to obtain the compressed network output, which does not reduce (or slightly reduce) the amount of system mutual trust while compressing the data. Due to the unique properties of sink pool network, SPN shows the output response of redundancy compression. From the relationship between network structure and generalization ability, it can be seen that after simplifying the structure, the generalization ability of the network will be improved, which is also the direct reason why the regularization method can improve the generalization ability. Therefore, this part uses the particle filter algorithm to achieve the goal of reducing the structural complexity of the network. The algorithm introduces the regularization term representing the structural complexity into the objective function of identifying the network. The concept of SPN is applicable to system simulation in biological neural coding, Nano Electronics, distributed sensor networks, digital beamforming arrays, image processing, multiple access communication networks and social networks [8, 9]. Array stochastic resonance system is composed of nonlinear stochastic resonance subsystems of parallel array. Each subsystem is driven by a common input signal and independent and identically distributed noise. The output processed by the subsystem is merged at the fusion center and calculated, and then the output response of array stochastic resonance system is obtained. In order to avoid over fitting, a multidimensional Taylor network with the smallest structure should be designed, that is, if the fitting effect on learning samples is the same, the generalization ability in the average sense with the simplest structure is the best. The signal-to-noise ratio of the input and output signals of the array stochastic resonance system increases first and then decreases with the increase of the array noise intensity. The non-zero noise intensity corresponding to the peak signal-to-noise ratio is the optimal noise intensity of the stochastic resonance system [10]. In particle filter, the shortest description length is used to represent the complexity of machine learning, that is, given the learning data, the optimal model should have the shortest total description length. The lock-in amplifier can detect the amplitude and phase of the signal submerged in the noise. The weak signal enhancement method is composed of four parts, as shown in Fig. 1:

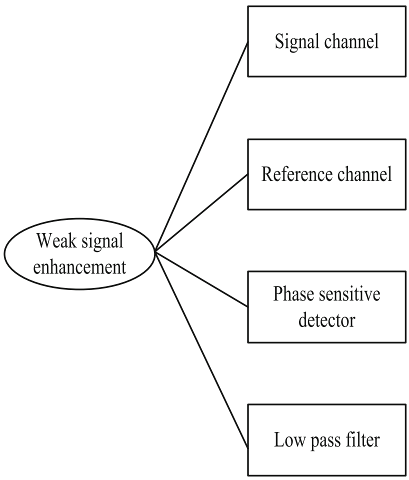

Fig. 1. Weak signal enhancement mode

It can be seen from Fig. 1 that the weak signal enhancement methods include: signal channel, reference channel, phase sensitive detector and low-pass filter. The main idea is to use the phase characteristics of the signal to select the signal with the same frequency and phase as the measured signal as the reference signal, According to the coherence characteristics of the phase sensitive detector, only the signals with the same frequency and phase as the reference signal respond during detection, while other frequency and phase signals are suppressed, so as to achieve the purpose of extracting useful signals. When the number of arrays is large enough, the output signal-to-noise ratio of the stochastic resonance system can be greater than the input signal-to-noise ratio of the system in a certain range of noise intensity range, that is, the signal-to-noise ratio gain of the parallel array stochastic resonance system can be greater than 1. Using this phenomenon can further improve the extraction and detection performance of weak signals in the field of signal processing. The total description length is the sum of description length (data model) and description length (model). The former is the residual of the model, and the latter is used to measure the complexity of the model. Therefore, the shortest description length is an integrated measure to comprehensively evaluate the residual error and model complexity. Its goal is to find an identification network that meets the target accuracy and has the best generalization ability.

3 Experimental Test

3.1 Experimental Preparation

According to the needs of experimental test, ad734 chip of ad company is selected in the circuit design. This chip is a high-precision and high-speed four quadrant analog multiplier divider. This chip is stable and reliable, has high precision when used as multiplier, and is basically insensitive to power supply. The theoretical model includes the inclined linear in-phase axis in the upper left corner and the sine cosine in-phase axis in the lower right part. It can be seen that there is an unconformity between them. The data volume size of the theoretical model is 160×160, its time sampling interval is 1.5 Ms. According to the design requirements of weak signal enhancement method, the multiplier in the circuit should have the characteristics of high signal-to-noise ratio, low drift and small calculation error. The performance of stochastic resonance circuit is tested in Proteus. The input is a sinusoidal signal with amplitude of 0.8 V and frequency of 0.5 Hz, and the noise intensity is 1.5. In the above experimental environment, carry out the experimental test.

3.2 Experimental Result

In order to verify the effectiveness of the nonlinear time-varying weak signal enhancement method, it is tested experimentally. The nonlinear time-varying weak signal enhancement method based on wavelet transform and the nonlinear time-varying weak signal enhancement method based on oma-srm are selected for experimental comparison with the nonlinear time-varying weak signal enhancement method in this paper. Test the signal enhancement effects of the three methods under different carrier frequencies. The larger the value, the better the signal enhancement effect is proved. The experimental results are shown in Tables 1, 2, 3, 4 and 5:

It can be seen from Table 1 that when the carrier frequency is 2500 Hz and the number of experiments is 9, the signal-to-noise ratio of the wavelet transform method is 4.319 dB, the signal-to-noise ratio of the vector control enhancement method is 3.687 dB, and the signal-to-noise ratio of the method in this paper is 6.848 db; The average SNR of the nonlinear time-varying weak signal enhancement method in this paper and the other two nonlinear time-varying weak signal enhancement methods are 7.071 db, 3.769 db and 4.044 db respectively.

It can be seen from Table 2 that when the carrier frequency is 2000 Hz and the number of experiments is 6, the signal-to-noise ratio of the wavelet transform method

Table 1. Carrier frequency 2500 Hz signal-to-noise ratio (DB)

Number of experiments	Nonlinear time-varying weak signal enhancement method based on Wavelet Transform	Vector control enhancement method	Nonlinear time-varying weak signal enhancement method in this paper
1	3.154	4.215	6.649
2	3.448	4.331	7.121
3	3.025	4.587	6.874
4	4.112	3.615	7.205
5	3.697	3.697	7.116
6	4.055	4.005	6.874
7	3.871	3.474	7.252
8	4.216	4.259	7.316
9	4.319	3.687	6.848
10	3.788	4.571	7.451

Table 2. Carrier frequency 2000 Hz signal-to-noise ratio (DB)

Number of experiments	Nonlinear time-varying weak signal enhancement method based on wavelet transform	Vector control enhancement method	Nonlinear time-varying weak signal enhancement method in this paper
1	8.346	8.647	10.202
2	7.994	7.992	11.313
3	8.312	8.313	12.474
4	8.259	7.698	10.948
5	7.314	8.215	12.037
6	8.269	7.994	12.457
7	7.102	8.352	11.362
8	8.315	7.649	11.584
9	7.821	8.152	12.065
10	7.404	7.664	11.488

is 8.269 db, the signal-to-noise ratio of the vector control enhancement method is 7.994 db, and the signal-to-noise ratio of the method in this paper is 12.457 db; The average SNR of the nonlinear time-varying weak signal enhancement method in this paper and

the other two nonlinear time-varying weak signal enhancement methods are 11.593 db, 7.914 db and 8.068 db respectively.

Table 3. Carrier frequency 1500 Hz signal-to-noise ratio (DB)

Number of experiments	Nonlinear time-varying weak signal enhancement method based on wavelet transform	Vector control enhancement method	Nonlinear time-varying weak signal enhancement method in this paper
1	15.649	12.647	19.648
2	13.487	13.008	17.316
3	14.602	15.316	18.487
4	15.717	14.718	18.261
5	13.622	14.949	19.364
6	14.945	13.602	20.157
7	13.687	14.718	18.479
8	15.649	15.602	19.592
9	13.050	16.947	20.087
10	13.487	15.499	19.874

It can be seen from Table 3 that when the carrier frequency is 1500 Hz and the number of experiments is 10, the signal-to-noise ratio of the wavelet transform method is 13.487 db, the signal-to-noise ratio of the vector control enhancement method is 15.499 db, and the signal-to-noise ratio of the method in this paper is 15.499 db; The average SNR of the nonlinear time-varying weak signal enhancement method in this paper and the other two nonlinear time-varying weak signal enhancement methods are 19.127 db, 14.390 db and 14.701 db respectively.

It can be seen from Table 4 that when the carrier frequency is 1000 Hz and the number of experiments is 5, the signal-to-noise ratio of the wavelet transform method is 17.699 db, the signal-to-noise ratio of the vector control enhancement method is 19.648 db, and the signal-to-noise ratio of the method in this paper is 27.055 db; The average SNR of the nonlinear time-varying weak signal enhancement method in this paper and the other two nonlinear time-varying weak signal enhancement methods are 26.715 db, 17.992 db and 18.313 db respectively.

It can be seen from Table 5 that when the carrier frequency is 500 Hz and the number of experiments is 8, the signal-to-noise ratio of the wavelet transform method is 28.316 db, the signal-to-noise ratio of the vector control enhancement method is 23.515 db, and the signal-to-noise ratio of the method in this paper is 33.610 db; The average SNR of the nonlinear time-varying weak signal enhancement method in this paper and the other two nonlinear time-varying weak signal enhancement methods are 32.712 db, 25.514 db and 25.249 db respectively.

Table 4. Carrier frequency 1000Hz signal-to-noise ratio (db)

Number of experiments	Nonlinear time-varying weak signal enhancement method based on wavelet transform	Vector control enhancement method	Nonlinear time-varying weak signal enhancement method in this paper
1	17.366	18.516	25.613
2	18.205	20.061	26.104
3	17.649	18.364	25.818
4	18.215	19.154	26.377
5	17.699	19.648	27.055
6	18.612	18.466	26.145
7	18.347	17.055	28.319
8	18.105	18.031	27.144
9	17.697	19.611	28.069
10	18.021	14.219	26.071

Table 5. Carrier frequency 500Hz signal-to-noise ratio (DB)

Number of experiments	Nonlinear time-varying weak signal enhancement method based on wavelet transform	Vector control enhancement method	Nonlinear time-varying weak signal enhancement method in this paper
1	22.316	23.619	31.205
2	25.169	25.177	29.648
3	24.718	26.384	32.007
4	25.337	27.224	31.482
5	26.914	29.6161	32.907
6	26.822	23.487	33.642
7	25.677	23.441	32.544
8	28.316	23.515	33.610
9	24.018	24.919	34.464
10	25.848	25.106	35.614

It can be seen from Table 6 that when the carrier frequency is 250 Hz and the number of experiments is 10, the signal-to-noise ratio of the wavelet transform method is 28.316 db, the signal-to-noise ratio of the vector control enhancement method is 29.115 db, and

Table 6. Carrier frequency 250 Hz signal-to-noise ratio (DB)

Number of experiments	Nonlinear time-varying weak signal enhancement method based on wavelet transform	Vector control enhancement method	Nonlinear time-varying weak signal enhancement method in this paper
1	26.348	31.201	37.458
2	27.158	29.847	36.225
3	31.205	30.474	38.201
4	30.177	29.645	37.966
5	29.848	30.277	36.288
6	30.255	31.201	37.916
7	31.102	30.224	36.074
8	29.848	29.845	37.508
9	31.025	30.468	38.19
10	29.648	29.115	37.206

the signal-to-noise ratio of the method in this paper is 37.206 db; The average SNR of the nonlinear time-varying weak signal enhancement method in this paper and the other two nonlinear time-varying weak signal enhancement methods are 37.303 db, 29.661 db and 30.230 db respectively.

In order to further verify the signal enhancement effect of this method, wavelet transform method, vector control enhancement method and this method are used to verify the time-consuming signal enhancement. The results are shown in Fig. 2.

By analyzing Fig. 2, it can be seen that the signal enhancement efficiency is different under different methods. When the number of experiments is 20, the signal enhancement time of wavelet transform method is 36 s, the signal enhancement time of vector control method is 57 s, and the signal enhancement time of this method is 18 s; When the number of experiments is 60, the signal enhancement time of wavelet transform method is 60 s, the signal enhancement time of vector control method is 43 s, and the signal enhancement time of this method is 15 s; The method in this paper always has high efficiency of signal enhancement.

4 Concluding Remarks

In this paper, a nonlinear time-varying weak signal enhancement method based on particle filter is proposed. The particle filter is used to enhance the weak signal, extract the nonlinear time-varying diffusion coefficient, simulate the real distributed sampling process, build an adaptive neural network model, use the subtractive clustering algorithm to determine the selection and number of hidden layer neuron centers, and improve the weak signal enhancement mode. The experimental results show that the average signal-to-noise ratio of this method can reach 37.303 db at different carrier frequencies; In

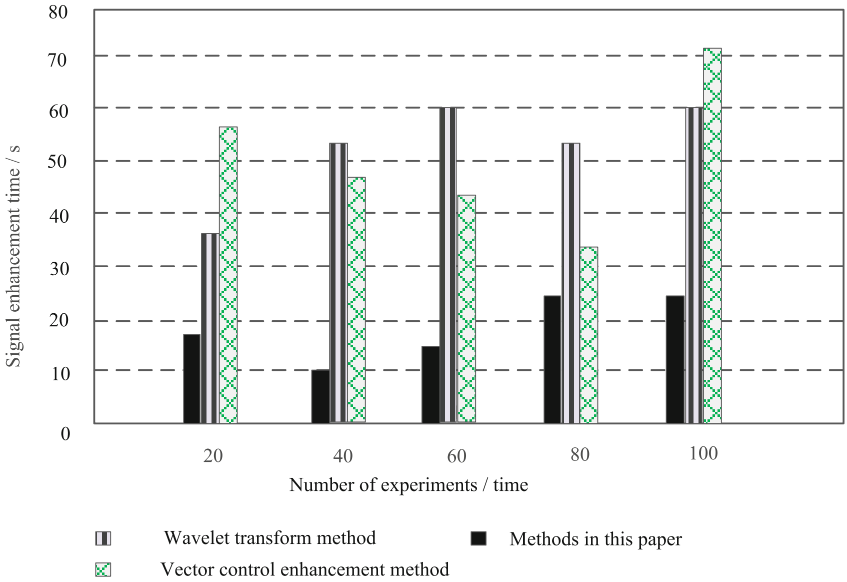

Fig. 2. Signal enhancement time

multiple iterations, the signal enhancement time of this method is no more than 25 s; This method always has high signal enhancement efficiency and improves the signal-to-noise ratio of weak signals. At the same time, it enriches the academic research on weak signal enhancement. In order to further improve the research of nonlinear time-varying weak periodic signals, we need to continue to improve the details in the future.

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