A Method for Pulse Signal Denoising Based on VMD Parameter Optimization and Grey Wolf Optimizer

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Abstract. Aiming at the difficulty of parameter determination when using variational modal decomposition algorithm (VMD) to decompose photoplethysmographic (PPG) pulse wave signals, a VMD parameter optimization method based on Grey Wolf Optimizer (GWO) is proposed. In this paper, the envelope entropy of the K eigenmode component (IMF) after VMD decomposition is used as the fitness function, and the grey wolf optimization algorithm (GWO) is used to find the K sum corresponding to the minimum envelope entropy of the eigenmode component α, to determine the optimal value of the VMD algorithm parameters, and then use the parameter optimized VMD algorithm to filter out the noise in the PPG signal. The experimental results show that after decomposing the PPG signal using the algorithm in this paper, the effective component and the noise component of the signal are well separated. After selecting the appropriate IMF component for reconstruction, the noise in the PPG signal is effectively filtered out.

1. Introduction

With the development of society and the advancement of technology, wearable human health testing equipment has gradually become popular in people’s lives. However, while wearable equipment brings convenience to the detection of physiological parameters, it also introduces the photoplethysmographic signal larger noise, the current methods to remove motion artifacts in PPG signals mainly include adaptive filtering, empirical mode decomposition and improved algorithms. Chen Chen et al. [1-3] used EMD to process PPG signals. Due to its theoretical flaws, the decomposition process is prone to problems such as modal aliasing and endpoint effects [4], and the denoising effect is not ideal. In addition, adaptive filtering methods are often used in PPG signal processing. Han et al. [5] used the synchronously measured acceleration signal as the reference signal of the adaptive filter to filter out motion artifacts. Compared with EMD, the time complexity was reduced, but the denoising effect was too dependent on the quality of the reference signal. When the quality is poor, the noise is usually not completely filtered out. Kang et al. [6-7] used VMD to process PPG signals, which overcomes the influence of modal aliasing and boundary effects, and the denoising effect is ideal. However, the quality of the signal processing by the VMD algorithm is mainly determined by the number of modes K and the value of the penalty factor α. At present, the selection methods of VMD parameters are mainly divided
into the center frequency observation method [8] and a variety of intelligent optimization algorithms. The central frequency observation method is to determine K and $\alpha$ based on subjective observations, and the results may have large errors; There are many intelligent optimization algorithms, such as Genetic Algorithm [9], Particle Swarm Optimization [10], Bat Algorithm [11], Grey Wolf Optimizer and so on. Although the Genetic Algorithm has good global search capabilities, it has many initial parameters, high algorithm complexity, too long optimization time, and the choice of parameters seriously affects the quality of the solution, but most of these parameters are currently selected by experience [12]; the Particle Swarm Optimization has fast search speed, few parameters that need to be adjusted, simple structure and easy to implement, but the algorithm lacks dynamic adjustment of speed as a whole, and is prone to fall into local optimality, resulting in slow algorithm convergence and low convergence accuracy, which cannot be solved Some combinatorial optimization problems [13]; the Bat Algorithm model is simple, the algorithm parameters are few, and the applicability is strong, but there are also problems with slow convergence in the later stage of algorithm evolution and easy to fall into local optimality [14]. Grey Wolf Optimizer (GWO) is a new swarm intelligence optimization algorithm proposed by Griffith University mirjalili [15] in 2014. The algorithm simulates the nature of predation behavior of grey wolves, and seeks the global optimal solution mainly through the process of tracking, encircling, chasing, and attacking prey. It is essentially a method of finding the best through statistics. The Grey Wolf Optimizer has few input parameters, high solving speed and accuracy, and its advantages of simplicity and efficiency show higher competitiveness than other algorithms. Therefore, this paper proposes a VMD parameter optimization method based on the Grey Wolf Optimizer, which obtains the optimal solution of the parameters by calculating the minimum envelope entropy of each IMF after VMD decomposition. Then, the parameter optimized VMD algorithm is used to remove the noise in the PPG signal.

2. Algorithm principle

2.1. VMD Algorithm

Variational modal decomposition [16] is an adaptive signal processing method proposed in 2014. Through iterative search for the optimal solution of the variational modal, each modal function and center frequency are constantly updated, and a number of bandwidths with a certain bandwidth are obtained. Modal function. VMD is an improvement of the EMD, and its advantage is that it can better avoid problems such as modal aliasing and end effects. The accuracy of the decomposition result of the VMD depends on the number of modes K and the value of the penalty factor A. If the value of K is too large, it will cause excessive signal decomposition, so that a component determined by the center frequency is scattered in different eigenmode components; while the value of K is too small, it will cause modal aliasing, that is, different centers. The frequency signal components are in the same eigenmode component after VMD decomposition, resulting in components with no practical significance. Both of these situations will lead to inaccurate decomposition results. The value of A will affect the frequency bandwidth of each mode obtained after the signal is decomposed by the VMD. If the value of A is inappropriate, the problem of modal aliasing also occurs. Therefore, selecting appropriate parameter values is very important for the accuracy of the PPG signal decomposition results.

2.2. Grey Wolf Optimization Algorithm

In the Grey Wolf Optimizer, the first three best wolves (the three optimal solutions of the algorithm) are considered to be $\alpha$, $\beta$, and $\delta$ wolves, and the remaining wolves are all $\omega$ wolves. Among them, $\alpha$ is the leader and decision-maker in the group, responsible for making decisions on predation, work and rest, and food and location distribution. Wolf $\beta$ is the military division of wolf $\alpha$, and is mainly responsible for assisting wolf $\alpha$ in making decisions and disseminating the decisions of wolf $\alpha$ to other members of the wolf pack. He is also a candidate for wolf $\alpha$. When the position of wolf $\alpha$ is vacant, he will become wolf $\alpha$; wolf $\delta$ will dominate the lower wolves according to the orders of wolf $\alpha$ and $\beta$, and is mainly responsible for detection, sentry, and predation in the group. Nursing and other tasks. The rest of the
wolves are called \( \omega \), which is mainly responsible for dealing with the balance of the relationship between the wolves. The GWO algorithm restores the entire predation process of grey wolves. Among them, \( \alpha \), \( \beta \), and \( \delta \) lead other wolves as the leader to continuously search for prey in the search space, and other wolves surround the three wolves \( \alpha \), \( \beta \), and \( \delta \) to continuously update their position with the prey to realize the tracking and encirclement prey.

3. VMD parameter optimization based on grey wolf optimization algorithm

3.1. Fitness function construction
Using the grey wolf optimization algorithm to search for the best parameter combination of \([K, \alpha]\) in the algorithm, it is first necessary to determine the fitness function for the iterative calculation of the optimization algorithm optimization process. In this paper, the envelope entropy \( E_p \) proposed in literature [10] is used as the fitness function of the Grey Wolf Optimizer.

In this article, the PPG signal is decomposed by VMD to obtain K IMFs. If the obtained IMF contains more noise components, the periodic characteristics related to the pulse signal are not obvious, and it can represent the noise component rather than the pulse signal component, then the envelope entropy is larger; On the contrary, the envelope entropy value is smaller. Therefore, this paper uses envelope entropy as the fitness function of GWO algorithm to optimize VMD, and transforms the process of optimizing VMD parameters into the process of using GWO algorithm to find the minimum envelope entropy value \( E_{\text{IMF}} \).

3.2. VMD parameter optimization process based on GWO algorithm

(1) Initialize the parameters of the GWO algorithm, and initialize the individual position and fitness value of the grey wolf. Set the initial number of grey wolf population individuals to 10, the maximum number of iterations to 10, the search range of K value to [2, 10], the step size of each K value update to 1, and the search range of \( \alpha \) to [500, 10000], the step size is set to 100;

(2) Using the K and \( \alpha \) corresponding to the current grey wolf individual position as the parameters of the VMD algorithm, decompose the PPG signal to obtain K IMFs. Then calculate the envelope entropy value \( E_p \) corresponding to each IMF, and get the fitness value of the current position at the current position, and keep the current optimal three individuals as the optimal solution before the next iteration of the GWO algorithm;

(3) Update the parameters and the location of the grey wolf individual;

(4) Judge whether the iteration reaches the end condition, if it is reached, output the optimal parameter combination \([K, \alpha]\) corresponding to \( \alpha \) wolf, otherwise return to step 2 to continue the iterative optimization.

4. Results and discussion

4.1. Data collection and preprocessing
In this paper, SFH7050 sensor, AFE4404 analog front end and Bluetooth transmission module are used to build PPG signal acquisition device, and the sampling frequency is set at 256Hz. We know that the normal pulse wave frequency of the human body is 0.7 ~ 3.5Hz. Therefore, the Butterworth band-pass filter is selected in this paper to preprocess the acquired PPG signals to obtain the signal components we are interested in. Among them, the passband frequency is set as 0.7 ~ 3.5Hz, the stopband cut off frequency is set as 0.5 ~ 5.0Hz, the maximum attenuation coefficient of the big band is 3 dB, and the minimum attenuation coefficient of the stopband is 18dB.
4.2. Analysis of parameter optimization results

Use the built signal acquisition equipment to collect PPG signals and optimize VMD parameters. The iterative process is shown in Figure 1. It can be seen from Figure 1 that when the algorithm evolves to the fourth generation, the minimum envelope entropy value of 2.1905 is found, and the corresponding \([K, \alpha] = [7, 3300]\), therefore, \(K = 7, \alpha = 3300\) is used as the input parameter of VMD to decompose the PPG signal, and the result is shown in Figure 2:

![GWO optimization process](image1)

![Decomposition result of GWO-VMD algorithm](image2)

It can be seen from Figure 2 that after the PPG signal is decomposed by the GWO-VMD algorithm, each mode represents a different center frequency, and the decomposition result is better. In order to verify the accuracy of the parameters obtained by the GWO algorithm, this paper uses a frequency comparison method. First, the signal before decomposition is Fourier transformed to obtain the frequency spectrum of the signal, and then through the spectral peak tracking algorithm, the frequency value corresponding to the peak in the frequency spectrum is found to compare with the center frequency value of the 7 modal components after VMD decomposition in Table 1.

| Corresponding frequency | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 | IMF7 |
|-------------------------|------|------|------|------|------|------|------|
| Center frequency        | 0.6125 | 0.8321 | 1.4048 | 2.0289 | 2.7461 | 3.2911 | 4.0116 |

It can be seen from Table 1 that the center frequency values of the 7 IMFs obtained after decomposition basically correspond to the main frequency values of the PPG signal before decomposition, which can better reflect the frequency characteristics of the original signal; in addition, as can be seen from Figure 2, there is no aliasing between the 7 modal components obtained after decomposition. Therefore, the \(K\) value and \(\alpha\) value sought by the GWO algorithm are similar to the manually determined parameter values, which proves the effectiveness of the GWO optimization algorithm for the parameter optimization results of the variational modal decomposition algorithm.

4.3. PPG signal denoising result analysis

After the PPG signal is decomposed into 7 IMFs with different center frequencies, the appropriate IMF components must be selected to reconstruct the PPG signal. In this paper, permutation entropy (PE) is selected as an index to judge whether IMF is a noise component. PE reflects the order of the signal. In this article, the larger the PE, the more chaotic the signal, and the closer it is to the noise component. The smaller the PE, the more orderly the signal and the closer it is to the effective component. The calculation of PE needs to determine the appropriate time delay \(\tau\) and embedding dimension \(m\). This paper selects \(\tau = 2\) and \(m = 3\) based on experience. The calculated permutation entropy values of the seven IMFs are: 0.1411, 0.2307, 0.2359, 0.2777, 0.3390, 0.3728, 0.4122.
This paper uses the final denoising effect to determine the optimal range of the permutation entropy threshold. In the experiment, 50 sets of PPG signals were collected for experiment. After 50 experiments, the IMF permutation entropy threshold range used to reconstruct the signal was distributed in (0.2320, 0.3450) times for 43 times. Therefore, when \( PE \leq 0.2320 \), the IMF is considered to be the low-frequency noise component; when 0.2320<\( PE <0.3450 \), it is the effective component of the PPG signal; when \( PE \geq 0.3450 \), it is the high-frequency noise component. Therefore, this paper selects appropriate components to reconstruct the PPG signal. In addition, the EMD algorithm and the adaptive filtering algorithm of normalized minimum mean square error are used to decompose and reconstruct the PPG signal to filter out the noise components in the signal. The result is shown in Figure 3.

As can be seen from the above figure, after using the EMD algorithm to process the PPG signal, the signal is distorted, which cannot reflect the periodic characteristics and peak characteristics of the PPG signal; after using the NLMS method to process the PPG signal, some of the noise of the signal is suppressed, but there is still some distortion. A lot of high-frequency noise is manifested as signal fluctuations superimposed on the PPG signal. After using the VMD algorithm to process the signal, the high-frequency noise and baseline drift are suppressed, and the denoised signal can better reflect the periodic characteristics of the pulse.

![Figure 3 Using different methods to process PPG signals](image)

In order to more accurately evaluate the denoising effect of the algorithm on the pulse signal, this paper introduces two numerical indicators: Signal-Noise Ratio and Mean-Square Error. From this, the SNR value and the mean square error value after using three different methods to remove the noise in the PPG signal are calculated as shown in Table 2.

| Method | SNR     | MSE      |
|--------|---------|----------|
| NLMS   | 2.2935  | 0.01277  |
| EMD    | 2.7593  | 0.00942  |
| VMD    | 4.4676  | 0.00515  |

From the SNR and MSE shown in Table 3, it can be seen that the PPG signal obtained after VMD denoising is about 2 dB higher than the SNR of the PPG signal denoised by EMD and NLMS, and the MSE is also reduced by one. The order of magnitude represents that the residual noise in the PPG signal is the least after the method is processed in this paper, which proves the effectiveness and superiority of the algorithm in removing motion artifacts.

5. Conclusion

This paper mainly proposes a VMD parameter optimization method based on the GWO algorithm to remove the motion noise in the PPG signal. Firstly, the minimum envelope entropy is selected as the fitness function of the GWO algorithm to find the best parameter combination of the VMD algorithm, and then the VMD algorithm after parameter optimization is used to remove the noise in the PPG signal. The advantage of the method in this paper is that it solves the problem of difficult parameter selection when using VMD to process PPG signals, and the rationality and accuracy of the parameter optimization
method are verified through experiments. In addition, two different denoising algorithms are compared, which proves the accuracy of VMD algorithm to deal with the noise in the pulse signal.

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References
[1] Chen C C, Niu C W, Zhu J M. A method for extracting respiratory waves from photoplethysmographic signals using empirical mode decomposition algorithm[J]. Research in Biomedical Engineering, 2019(2).
[2] Pang B, Liu M, Zhang X, et al. Advanced EMD method using variance characterization for PPG with motion artifact[C]// Biomedical Circuits & Systems Conference. IEEE, 2017.
[3] Madhav K V, Krishna E H, Reddy K A. Detection of sleep apnea from multiparameter monitor signals using empirical mode decomposition[C]//2017 International Conference on Computer, Communication and Signal Processing (ICCCSP). IEEE, 2017.
[4] Thompson, J.N. (1984) Insect Diversity and the Trophic Structure of Communities. In: Ecological Entomology. New York. pp. 165-178.
[5] Hao H, Wang H L, Wei Q. The Theory and Application of Empirical Mode Decomposition[J]. High Technology Letters, 2016, 26(01): 67-80.
[6] Han H, Kim J. Artifacts in wearable photoplethysmographs during daily life motions and their reduction with least mean square based active noise cancellation method[J]. Computers in Biology & Medicine, 2012, 42(4):387-393.
[7] Kang W, Li M, Che X, et al. Pulse Rate Estimation using PPG Affected with Motion Artifacts Based on VMD and Hilbert Transform[C]// 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO). IEEE, 2019.
[8] Yue Y J, Sun G, Cai Y P. Application of Variational Mode Decomposition in Bearing Fault Diagnosis[J]. Bearings, 2016(8): 50-54.
[9] Liu J M, Peng L, Liu J W. Genetic Algorithm VMD parameter optimization and wavelet threshold bearing vibration signal denoising analysis[J]. Mechanical Science and Technology, 2017(11): 61-66.
[10] Tang G J, Wang X L. Application of Parameter Optimization Variational Modal Decomposition Method in Early Fault Diagnosis of Rolling Bearings [J]. Journal of Xi'an Jiaotong University, 2015, 49(5): 73-81.
[11] Yang L. VMD time-frequency analysis method and its application in mechanical fault diagnosis [D]. Guilin University of Electronic Technology, 2018.
[12] Li Y, Yuan H Y, Yu J Q, et al. Overview of the application of Genetic Algorithms in optimization problems[J]. Shandong Industrial Technology, 2019(12): 242-243+180.
[13] Wu Q H, Zhang Y, Ma Z M. Overview of particle swarm optimization algorithms and their applications[J]. Microcomputer Information, 2010, 26(30): 34-35+10.
[14] Fan Lei, Wei Z N, Li H J, et al. Short-term wind speed interval prediction based on variational modal decomposition and Bat Algorithm-correlation vector machine[J]. Electric Power Automation Equipment, 2017, 37(01): 93-100.
[15] Mirjalili S, Mirjalili S M, Lewis A. Grey Wolf Optimizer[J]. Advances in Engineering Software, 2014,69(3):46-61.
[16] DRAGOMIRETSKIY K, ZOSSO D. Variational Mode Decomposition[J]. IEEE Transactions on Signal Processing, 2014, 62(3):531-544.