Proceedings Paper:

Zhao, X, Liu, D, Ma, L et al. (3 more authors) (2020) EEG Signals De-Noising with Wavelet by Optimizing Threshold Based on Fruit Fly Optimization. In: ICNCC 2020: 2020 The 9th International Conference on Networks, Communication and Computing. ICNCC 2020: 2020 The 9th International Conference on Networks, Communication and Computing, 18-20 Dec 2020, Tokyo, Japan. ACM . ISBN 978-1-4503-8856-6

https://doi.org/10.1145/3447654.3447665

EEG Signals De-Noising with Wavelet by Optimizing Threshold Based on Fruit Fly Optimization

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ABSTRACT

EEG signal de-noising is the preprocessing part of brain-computer interface (BCI), which provides a relatively pure source for controlling external devices with EEG signals. In this paper, a new combination of threshold and threshold function based on wavelet threshold (WT) de-nosing method with undetermined coefficients is proposed. Using fruit fly optimization algorithm (FOA), these coefficients are determined by the combined fitness function of signal-to-noise ratio (SNR), mean square error (MSE) and smooth factor (S), and the noise in the signal is adaptively removed. Experimental results show that under different noise addition conditions, the wavelet threshold and threshold function determined by FOA are better than the combination of fixed threshold and traditional hard and soft thresholds, and other improved methods. The experiment is carried out using MATLAB simulation software. According to the wavelet basis function and the number of decomposition levels, two experimental conditions are designed to generate simulated EEG signals and add noise respectively, and then obtain reconstructed signals. The highest SNR of our method can reaches 18.0297 dB. In Condition 1, the overall average SNR of our method is increased by 27.98%, 38.29%, 31.96% 18.36% and 6.29%, respectively, compared with the above comparison methods. In Condition 2, the overall average SNR of our method is 23.67%, 31.13%, 35.33%, 12.53% and 7.45% respectively higher than the above same methods. In addition, FOA can help reconstruct a smoother signal. In Condition 1, the lowest S of our method drops to 0.1735, and the overall average S is 7.86% and 5.80% lower than particle swarm optimization algorithm (PSO) and artificial fish swarm algorithm (AFSA) respectively. The method proposed in this paper can better preprocess the EEG signal, so as to achieve a more accurate BCI.

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CCS CONCEPTS

• **Theory of computation**; • **Design and analysis of algorithms**; • **Mathematical optimization**;

KEYWORDS

Brain-computer interface (BCI), Preprocessing, Threshold and threshold function, Fruit fly optimization algorithm (FOA)

1 INTRODUCTION

Brain-computer interface (BCI) is a new active therapy to help the stroke patients, which builds a bridge between machine and human physical needs through their brain signal [1]. A complete BCI system is composed of four important parts: signal acquisition, signal processing, equipment control and feedback. Since EEG signal is a very weak and unstable random signal, which is easy to be disturbed by noise [2], and the collected scalp potential changes are generated by a large amount of neuron activity, a series of subsequent processing of the collected EEG signal is required. Signal processing is further divided into three parts: preprocessing [3], feature extraction and classification [4]. The main task of preprocessing is to identify and filter the noises of the original EEG signals to obtain relatively pure EEG signals. The noises of EEG signal mainly come from the interference of environment and physiological signal [5, 6]. The presence of these interference can affect the classification results, thus affecting the correct control of external devices.

In recent years, researchers have proposed a variety of EEG signal de-noising algorithms, mainly based on the following four categories: one is the mean artifact regression analysis method. Assuming that there is a certain conduction coefficient among scalp electrodes and electrical electrodes, the correlation between them is used to estimate the conduction coefficient and eye electrical signals are subtracted from the scalp, so the relatively pure EEG signal can be obtained finally [7]; The second is the blind source separation algorithm, which is to separate mixed signals when the characteristics of source signals and transmission system are unknown

[8].The third is the wavelet transform method. Through wavelet decomposition of the mixed signal, the noise component is removed and then reconstructed [9]. The last method is the empirical mode decomposition method. The signal is decomposed according to the time scale of the data, and there is no need to set the basis function in advance. The first method is effective for removing some non-physiological noises, but requires a good reference channel. The second requires an appropriate noise identification method, and the number of acquisition channels must be greater than the number of signal sources. The third has multi-resolution characteristics, which is a good de-noising method for non-stationary signals. In practical application, it is necessary to select the appropriate wavelet base and decomposition layers [10, 11]. The last is completely data-driven and suitable for non-stationary and nonlinear random signals. However, it is sensitive to noise and easy to cause modal aliasing [12].

At present, many scholars have proposed some methods to improve the traditional wavelet threshold (WT) de-noising method [13] for the noisy ECG and EEG signals. In 2017, Yu et al. proposed a method to remove the environmental noise and power frequency noise in EEG signals based on the nonlinear continuous attenuation of wavelet coefficient. Their experiment results proved that signal-to-noise ratio (SNR) and mean square error (MSE) were superior to the traditional WT de-noising method [14]. In 2019, Xu et al. extracted EEG signal features by means of wavelet transform and fuzzy entropy algorithm, and further used fisher linear discriminator to classify the filtered signals, thus improving the classification accuracy of motor image EEG signals [15]. In 2020, Wang et al. proposed an improved WT de-noising algorithm, adaptive adjusting threshold and threshold function, which can effectively suppress ECG noise [16]. Although the above method improves the de-noising effect to a certain extent, the selection of undetermined coefficients and de-noising components in these methods mainly relies on experience, which requires a lot of time.

For the improvement of the waveform distortion and the oscillation caused by the traditional WT de-nosing methods and their de-noising efficiency, a new threshold and threshold function containing undetermined coefficients are proposed based on the WT method. SNR, MSE and smooth factor (S) are taken as the combined fitness function, meanwhile the undetermined coefficients in the threshold and threshold function are determined by fruit fly optimization algorithm (FOA), so as to remove the noise components of EEG signals and obtain the best de-noising effect. The paper's structure is as follows. Sect. 1 and Sect. 2 present the introduction and the experimental principle and design respectively. The experimental result and discussion are reported in Sect. 3. Sect. 4 is the conclusion.

2 EXPERIMENTAL PRINCIPLE AND DESIGN

Suppose the EEG signal with noise $f(t)$ is shown as formula (1),

$$f(t) = s(t) + g(t) \tag{1}$$

where $s(t)$ denotes the standard EEG signal and $g(t)$ represents the Gaussian white noise whose mean value is 0, variance is δ^2, obeying a normal distribution of $N(0, \delta^2)$.

The experiment is based on the WT de-noising method whose principle is to threshold the high-frequency noise signal and reconstruct it. The main steps including:

1. In the "wavelet decomposition" step, select the appropriate wavelet basis function and decomposition layer number for treating the processed noisy EEG signals.
2. In the "threshold processing" step, select the appropriate threshold and threshold function to quantify the high frequency part of the wavelet coefficients obtained in Step1.
3. In the "wavelet reconstruction" step, recombine the processed wavelet coefficients to form the reconstructed signal.

2.1 Traditional Wavelet Threshold De-Noising Method

In WT de-noising method, the appropriate threshold and threshold function play an important role. If the value of threshold is too small, the noise removal is incomplete; on the contrary, there is a lot of loss of useful signals. In general, a fixed threshold λ is selected as shown in formula (2).

$$\lambda = \sigma\sqrt{2\ln(N)} \tag{2}$$

Where σ denotes the standard deviation of the global noise, and N is the number of sampling points.

Comparing the decomposed wavelet coefficients with the threshold, they can be transformed according to the threshold function. There are two main traditional WT function, namely hard threshold function (as shown in formula (3) and figure 1(a)) and soft threshold function (as shown in formula (4) and figure 1(b)).

$$\hat{\omega} = \begin{cases} \omega, & |\omega| \geq \lambda \\ 0, & |\omega| < \lambda \end{cases} \tag{3}$$

$$\hat{\omega} = \begin{cases} sgn(\omega)(|\omega| - \lambda), & |\omega| \geq \lambda \\ 0, & |\omega| < \lambda \end{cases} \tag{4}$$

Where, ω and $\hat{\omega}$ denote the original wavelet coefficient and the processed wavelet coefficient respectively, $sgn(\cdot)$ denotes the symbolic function. It can be seen from the formulas and graphs that the wavelet coefficients processed by the hard threshold function are discrete at $|\lambda|$, where is prone to appear the Pseudo-Gibbs artifacts [17]. Soft threshold function avoids the above problem, but the constant error that it creates will leads to fuzzy distortion of reconstructed signal.

2.2 Improved Wavelet Threshold De-Noising Method

Since the general threshold is a specific value, the wavelet decomposition coefficients of each layer are processed the same, which will affect the de-noising effect. Therefore, a new combination of threshold and threshold function is proposed in this paper to solve the above problem. Our proposed threshold and threshold function both contain undetermined coefficients, which can be adaptively adjusted according to the actual signals and noises to get the best de-noising effect. Their definitions are respectively shown in formula (5) and formula (6).

$$\lambda = \sigma_p\sqrt{2\ln N}/p \times \ln(j + \alpha) \tag{5}$$

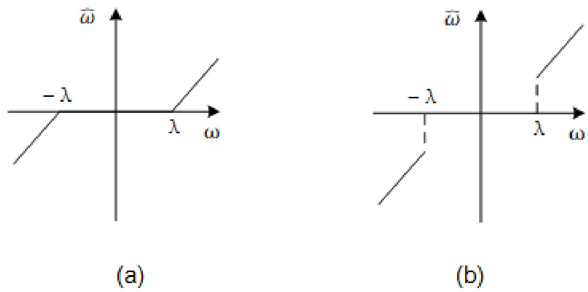

Figure 1: Threshold function de-noising image. (a) Hard threshold function;(b) Soft threshold function.

Where σ_p denotes the noise standard deviation of the wavelet coefficient in the p-th decomposition layer, N is the sampling points, j denotes the total decomposition layers, and α denotes the regulatory factor. The new threshold changes dynamically with the number of decomposed layers and the specific located layers, while is adjusted by the regulator factor. The deeper the layer is, the smaller the threshold is. The actual phenomenon accords with the law of proportional distribution of signal and noise in different decomposition layers after wavelet decomposition.

$$\hat{\omega} = \begin{cases} sgn(w)\left(|w| - \lambda e^{-\frac{h|w|}{\lambda}}\right), & |\omega| \geq \lambda \\ 0, & |\omega| < \lambda \end{cases} \tag{6}$$

From formula (6), h is the regulatory factor: when $h \to 0$, the threshold function is equivalent to the soft threshold function; When $h \to \infty$, the threshold function is equivalent to the hard threshold function; When $h \in (0, \infty)$, the threshold function has the characteristics of both hard threshold function and soft threshold function.

2.3 Evaluation Indicators

Three assessment indicators are selected to evaluate the de-noising effect of our method, namely SNR (as shown in formula (7)), MSE (as shown in formula (8)) and S (as shown in formula (9)).

$$SNR = 10\lg \frac{\sum_{i=1}^{N} s^2(i)}{\sum_{i=1}^{N} (s(i) - \bar{s}(i))^2} \tag{7}$$

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (s(i) - \bar{s}(i))^2} \tag{8}$$

$$S = \frac{\sum_{i=1}^{N-1} (\bar{s}(i+1) - \bar{s}(i))^2}{\sum_{i=1}^{N-1} (s(i+1) - s(i))^2} \tag{9}$$

Where i denotes the i-th samples, N denotes the total number of samples, $s(i)$ denotes the source EEG signal, and $\bar{s}(i)$ denotes the reconstructed EEG signal. The larger the SNR, the smaller the proportion of noise in the reconstructed signal, and the better the de-noising effect. MSE represents the difference between the standard EEG signal and the reconstructed EEG signal, and a smaller MSE means less distortion. S represents the smoothness of the reconstructed signal, and the smaller value means the better smoothness.

2.4 Optimization Algorithm Determining the Undetermined Coefficient

In this paper, FOA is used to determine the undetermined coefficient contained in our threshold and threshold function.

We propose a fitness function that jointly considers SNR, MSE and S to evaluate the de-noising effect. The expression is as follows,

$$fitness(SNR,\ RMSE,\ S) = W_1 \times SNR + W_2 \times RMSE + W_3 \times S \tag{10}$$

where W_1, W_2 and W_3 respectively represent the weight of SNR, MSE and S. There is $\sum_{i=1}^{3} W_i = 1,\ 0 \leq W_i \leq 1$.

FOA is a group optimization algorithm, whose basic idea comes from fruit flies foraging behavior [18]. Due to the superiority of its sense of smell and vision, fruit flies first search for food sources through their sense of smell, and then use vision to accurately find where the food is and where their companions gather. The basic steps are as follows:

1. Set Parameter: including the maximum number of iterations, target accuracy, population number, search radius of the algorithm and the initial positions of the fruit fly population.

$$(Xaxis, Yaxis) = (initX,\ initY) \tag{11}$$

$(Xaxis, Yaxis)$ represents the coordinates of the fruit fly population, $(initX,\ initY)$ represents the initial coordinates set.

1. Individual flies use their sense of smell to search for food.

$$\begin{cases} X_i = Xaxis + RV \\ Y_i = Yaxis + RV \end{cases} \tag{12}$$

(X_i, Y_i) represents the coordinates of an fruit fly individual, where RV represents a random value. The whole represents the direction and distance in which the individual flies forage for food

1. Calculate the distance L_i between the ith fruit fly and the food source and other flies populations, the taste concentration determination values S_i, and the flavor concentration of the ith $Smell_i$.

$$\begin{cases} L_i = \sqrt{X_i^2 + Y_i^2} \\ S_i = 1/L_i \\ Smell_i = fitness(S_i) \end{cases} \tag{13}$$

2. Look for individual flies with the best concentration of flavor $bestSmell$.

$$[bestSmell, bestIndex] = max(Smell) \tag{14}$$

Table 1: De-noising evaluation in different basic functions

Basic Function	Decomposition Level	SNR	MSE	S
sym4	2	8.5464	0.0232	0.2155
sym4	3	9.3879	0.0211	0.1840
sym4	4	8.6736	0.0229	0.0358
db4	2	8.8158	0.0225	0.2237
db4	3	8.7806	0.0226	0.1392
db4	4	8.8336	0.0225	0.0401
db5	2	8.7365	0.0227	0.2117
db5	3	8.8935	0.0223	0.1489
db5	4	8.7394	0.0227	0.0491
db6	2	8.9097	0.0223	0.2348
db6	3	8.5728	0.0231	0.1360
db6	4	8.6530	0.0229	0.2026
coif3	2	8.7236	0.0227	0.2134
coif3	3	9.2573	0.0214	0.1495
coif3	4	8.9163	0.0222	0.0422

Where $bestIndex$ represents the individual with the optimal concentration.

1. Flies use vision flying to the best individual flies.

$$\begin{cases} Smellbest = bestSmell \\ Xaxis = X\,(bestIndex) \\ Yaxis = Y\,(bestIndex) \end{cases} \tag{15}$$

2. Determine whether the maximum number of cycles or target accuracy is achieved. If not, Step3~Step6 are cycled. If achieved, return the optimal individual in the fruit fly population.

3 EXPERIMENTAL RESULTS AND DISCUSSIONS

According to the characteristics of real EEG waveform, we generate original standard EEG signal with sampling rate $F_s = 250$ Hz, time interval T $= 0 : \frac{1}{F_s} : 4$, and frequency range from 2 Hz to 30 Hz. The added noise signal is Gaussian white noise with S_n decibel (dB).

3.1 Establishment of Wavelet Basis Function and Decomposition Layer Number

Under the condition that Gaussian white noise is $S_n = 3\ dB$, the fixed threshold and soft threshold function are applied, we choose the wavelet basis function and the number of decomposition layers. The experimental results are shown in Table 1

Five common wavelet basis functions are selected, and we set three different decomposition layers in our experiment. Our main intention is to maximize noise elimination, so we pay more attention on SNR. Through observation about the above tables, we can find that when the number of decomposition layers is set as 3 and the wavelet basis functions are selected as 'sym4' and 'coif3', SNR in both situations reaches over 9 dB. However, this value in other cases is lower than 9 dB. We set up two experimental conditions for subsequent tests. The first condition is that the wavelet basis functions is 'sym4' and the number of decomposition layers is 3, and the other condition is that the wavelet basis functions is 'coif3' and the number of decomposition layers is 3.

3.2 Comparison in Different Threshold Values and Threshold Functions

Using FOA, we can get the undetermined coefficients in our threshold and threshold function. We compare the improved method proposed in this work with the combination of the fixed threshold and soft threshold function or hard threshold function, and improved threshold or threshold function in other literatures [14, 15, 19]. For reaching the maximum SNR, the population size is set as 20, the number of iterations is set as 200, and $W_1 = 1$, $W_2 = 0$, $W_3 = 0$ of the fitness function in FOA. The experimental results are as follows. Figure 2 (a) shows the optimization process of FOA and the flight path of the fruit fly population, and figure 2 (b) shows the original signal, the added noise signal and the reconstructed signal respectively.

In different wavelet basis functions, SNR increases with the increase of added noise on the whole. Under the different experimental setup, our proposed de-noising method has the highest SNR and the lowest MSE in all cases. In the case that the wavelet basis function is 'coif3' and the decomposition layer is 3, SNR of the proposed method can reach 18.0297 dB, which is 31.58%, 43.53%, 20.04%, 16.23% and 12.90% higher than the traditional hard threshold function method, soft threshold function method and reference methods respectively. In the same case, MSE of the proposed method can falls to 0.0078, which is 39.06%, 46.58%, 29.09%, 25.00% and 21.21% lower than the above comparative methods respectively. It can be observed that with different basis functions and decomposition layers, the improvement effect of the reference method is unstable, and the smoothness of the reconstructed signal is greatly reduced, whose S is almost 1.00. It obviously that our method not only improves the indictors of SNR and reduces the MSE, but also keeps the smoothness of the reconstructed signal, making it between the traditional hard threshold function method and soft threshold function method.

Table 2: In Condition 1, de-noising evaluation to remove different noise situations

Added Noise (dB)	Method	SNR (dB)	MSE	S
3	Fixed Threshold, Hard Threshold Function	11.4126	0.0167	0.2092
3	Fixed Threshold, Soft Threshold Function	10.9796	0.0175	0.1403
3	Improvement Method 1	8.8042	0.0225	0.9887
3	Improvement Method 2	12.2395	0.0152	0.1660
3	Improvement Method 3	12.9181	0.0140	0.2728
3	Our Method	13.5619	0.0130	0.1771
6	Fixed Threshold, Hard Threshold Function	12.5118	0.0147	0.3435
6	Fixed Threshold, Soft Threshold Function	11.4463	0.0166	0.2589
6	Improvement Method 1	11.9957	0.0156	0.9895
6	Improvement Method 2	13.1598	0.0136	0.2656
6	Improvement Method 3	15.7067	0.0102	0.3669
6	Our Method	15.9345	0.0100	0.3135
9	Fixed Threshold, Hard Threshold Function	13.0121	0.0139	0.4981
9	Fixed Threshold, Soft Threshold Function	11.7582	0.0160	0.4168
9	Improvement Method 1	15.0235	0.0110	0.9918
9	Improvement Method 2	14.5417	0.0116	0.4272
9	Improvement Method 3	15.8524	0.0100	0.8347
9	Our Method	17.7763	0.0080	0.5415

Table 3: In Condition 2, de-noising evaluation to remove different noise situations

Added Noise (dB)	Method	SNR (dB)	MSE	S
3	Fixed Threshold, Hard Threshold Function	12.3122	0.0150	0.1795
3	Fixed Threshold, Soft Threshold Function	11.9541	0.0157	0.1326
3	Improvement Method 1	8.8075	0.0225	0.9878
3	Improvement Method 2	13.2641	0.0135	0.1792
3	Improvement Method 3	13.3795	0.0133	0.2529
3	Our Method	14.2233	0.0121	0.1735
6	Fixed Threshold, Hard Threshold Function	13.1826	0.0136	0.3347
6	Fixed Threshold, Soft Threshold Function	12.4494	0.0148	0.2482
6	Improvement Method 1	11.9921	0.0156	0.9902
6	Improvement Method 2	14.2997	0.0120	0.2731
6	Improvement Method 3	15.7617	0.0101	0.3783
6	Our Method	16.2203	0.0096	0.3177
9	Fixed Threshold, Hard Threshold Function	13.702	0.0128	0.4892
9	Fixed Threshold, Soft Threshold Function	12.5616	0.0146	0.3965
9	Improvement Method 1	15.0197	0.0110	0.9925
9	Improvement Method 2	15.5122	0.0104	0.4320
9	Improvement Method 3	15.9697	0.0099	0.8137
9	Our Method	18.0297	0.0078	0.5271

Taking condition 2 and adding 3 dB noise as an example, SNR of our method is 14.2233 dB, which is higher than the traditional hard threshold function method, soft threshold and reference methods 15.52%, 18.98%, 61.49%, 7.23% and 6.31% respectively. The MSE is 0.0121, which is lower than the above comparative methods 19.33%, 22.93%, 46.22%, 10.37% and 9.02% respectively. The smoothness is 0.1734, which improved 3.34%, 82.44%, 3.18% and 31.40% respectively compared with the traditional hard threshold function method and the reference methods. It indicates the improvement difference between the improvement method 3 in SNR and MSE is only less than 10%, but S is very different. In summary, our method has the best overall performance.

3.3 Comparison in Different Optimization Algorithms

The threshold and threshold function defined in this work are optimized in Condition by particle swarm optimization algorithm (PSO) [20] and artificial fish swarm algorithm (AFSA) [21] to compare with our selected FOA. The comparison results are respectively shown in Table 4

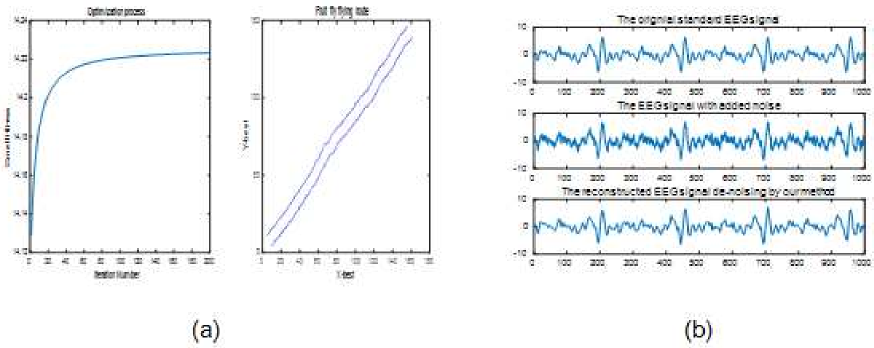

Figure 2: The experimental results of adding S_n=3 dB noise in Condition 1. (a) FOA optimization process; (b) Comparison of EEG signals in different states.

Table 4: De-noising evaluation to remove different noise situations

Added Noise (dB)	Method	SNR (dB)	MSE	S
3	PSO	13.2874	0.0135	0.2313
3	AFSA	13.5869	0.0130	0.1970
3	FOA	13.5619	0.0130	0.1771
6	PSO	15.9775	0.0099	0.3442
6	AFSA	15.9647	0.0099	0.3427
6	FOA	15.9345	0.0100	0.3135
9	PSO	17.8349	0.0080	0.5415
9	AFSA	17.8051	0.0080	0.5529
9	FOA	17.7763	0.0080	0.5386

The above tables respectively represent the de-nosing evaluation in different optimization algorithms under different added noises in Condition 1. By observing the results of different optimization methods, it can be seen that their SNR and MSE are similar, but FOA has the lowest value of S, which indicates FOA method can help to get smoother reconstructed EEG signals. When adding noise is 3 dB, the reconstructed signal of FOA optimization has 30.60% and 11.24% better smoothness than PSO and AFSA respectively; When adding noise is 6 dB, the result is 9.79% and 9.31% respectively; When adding noise is 9 dB, the result is 0.54% and 2.66% respectively.

4 CONCLUSION

In this paper, based on WT de-noising algorithm, a new combination of threshold and threshold function is proposed as the preprocessing step of BCI to remove the noise components in EEG signals. The new threshold and threshold function both contain undetermined coefficients, which are determined by FOA with SNR, MSE and S as the combined fitness function, finally removing the noise in EEG signals. The experimental results show our method has better de-noising effect than the fixed threshold in combination with the basic hard threshold function or soft threshold function, and other improved WT de-noising methods, and FOA optimization can help to get a smoother reconstructed signal. Our method can obtain the purer EEG signal, which can help to better apply to BCI. Furthermore, the improved de-noising method can also be extended to other kinds of signals.

ACKNOWLEDGMENTS

This work was supported by National Natural Science Foundation of China (Grant No. 51675389) and the Excellent Dissertation Cultivation Funds of Wuhan University of Technology (2018-YS-053). It is also supported by the Fundamental Research Funds for the Central Universities (WUT: 203109001).

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