A New Complementary Empirical Ensemble Mode Decomposition Method for Respiration Extraction

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***Abstract*—Respiration monitoring is essential for diagnosing and managing a variety of diseases. It is a non-invasive, convenient and effective method to derive breathing from ECG signals. This paper proposes a new complementary ensemble empirical mode decomposition (NCEEMD) method for respiration extraction. By additional ensemble empirical mode decomposition (EEMD) of the auxiliary white gaussian noise, the noise residue of the corresponding respiratory band after the EEMD decomposition of original ECG signal is subtracted. The new IMF was selected for correlation analysis with the measured respiratory signal, and the optimal amplitude noise coefficient was determined adaptively by the principle of maximum correlation increment. Then IMF in the respiratory band is selected to reconstruct the respiratory signal which is ECG-derived respiration (EDR). A comparative experiment of respiration extraction was conducted using the data of the MIT-BIH Polysomnographic database. The experimental results show that compared with the complementary ensemble empirical mode decomposition (CEEMD) method, the proposed EDR extraction method reduces the average MSE by 3.95%, RMSE by 2.74%, and MAE by 2.52% and the physical significance of the IMF component is more explicit. This method has good accuracy, robustness and adaptability, and provides a new solution idea for the extraction of respiratory signals.**

Keywords—ECG; white gaussian noise; complementary ensemble empirical mode decomposition; ECG-derived respiration (EDR)

I. Introduction

Breathing is an important physiological parameter in the human body and is commonly associated with heart disease, sleep apnea syndrome and anxiety [16, 19], and a coupling between breathing and heart rate has been demonstrated [17, 20]. However, monitoring breathing requires bulky equipment that may interfere with natural breathing. ECG-derived respiratory (EDR) from ECG signals can effectively reduce the cost of monitoring, improve user comfort, and be more suitable for outpatient and home monitoring.

Scholars at home and abroad have carried out a lot of explorations and researches on the extraction of EDR based on ECG signals. EDR is extracted from the slope and angle of QRS complex wave of ECG signal, but this method only be used to estimate the respiratory rate, and can not obtain the respiratory waveform [2]. Millimeter wave radar technology is used to obtain ECG and respiratory signals in a non-contact manner, which is capable of real-time monitoring, but the signal quality can be affected by environmental factors, human movement and other interferences, and the scope of application is limited [1, 22]. Linear principal component analysis (PCA) was used to extract EDR signals from ECG signals and extracted the main components by calculating eigenvectors and eigenvalues, but PCA could not capture the nonlinear relationship between ECG and respiratory signals, which resulted in distorted downscaling results [6]. Literature proposed kernel-based principal component analysis to introduce nonlinear feature extraction into PCA by introducing kernel tricks, but the optimization process of kernel parameters is complicated [28]. Researchers have found that the EDR extraction technique based on the principle of empirical mode decomposition (EMD) out-performs the method based on the discrete wavelet transform, and it can be a better alternative method for indirect extraction of respiration [4, 13], but it causes severe mode aliasing in time-frequency distributions, which blurs the physical significance of the individual intrinsic modal functions [11, 14]. Wu and Huang proposed an ensemble empirical mode decomposition (EEMD) method [25], which overcomes the mode mixing problem of EMD, but the superimposed white noise amplitude and the overall average number of iterations of this method rely on human empirical choices [3, 29], and the effect of the residual white noise after signal reconstruction is not negligible [15].

A complementary ensemble empirical mode decomposition (CEEMD) method is mainly used to add a pair of opposite white noise signals to the source signal and performing EMD decomposition. CEEMD reduces the reconstruction error caused by white noise compared to EEMD method [26], but disadvantage is that the operation is doubled, and if the white noise amplitude and the number of iterations are not appropriate, more pseudo-components will be decomposed, which need to be recombined or processed subsequently for the IMF components.

For improved EMD methods, the addition of auxiliary white noise may lead to energy shift and spectrum distortion in the decomposition results, reducing the accuracy and reliability of the decomposition results. For how to eliminate the added auxiliary white noise effect, it is necessary to find an effective method to distinguish and suppress the noise components in order to retain the useful information of the signal. Inappropriate noise amplitude parameters may mask or change the features in the original signal, making the accuracy and interpretability of IMFs decreased [5, 24]. The statistical and distribution characteristics of white noise make the estimation of auxiliary noise level subjective and uncertain [25]. Based on the resonance characteristics of the signal in the time-frequency plane, the noise residue in the corresponding frequency band can be eliminated during the original signal decomposition by leveraging the decomposition characteristics of white Gaussian noise itself, thereby reducing the mutual interference and

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aliasing of energy dispersed between different Intrinsic Mode Functions [8, 12].

This paper proposes a new complementary empirical ensemble mode decomposition (NCEEMD) method for breath extraction. By additional EEMD decomposition of the auxiliary white noise, the noise residue of the corresponding respiratory band after the original ECG decomposition is subtracted. And the optimal amplitude noise factor is selected adaptively.

The structure of this paper is as follows: Section II proposes the EDR method based on NCEEMD and its evaluation performance index. It also introduces the data set. Experimental results in Section III. Finally, the discussion and conclusion are given in Section IV and in Section V respectively.

II. Materials and Methods

A. Datasets

The MIT-BIH Polysomnographic Database (MBPD) includes 18 consecutive records from 16 male subjects diagnosed with sleep apnea syndrome [10]. Slp01a and slp01b are polysomnographic segments of the same patient, slp02a and slp02b are polysomnographic segments of another patient, and the remaining 14 data records belong to 14 different patients. Individual recordings in the database are between two and seven hours in length and are digitized at 250Hz and 12-bit resolution. The recorded physiological signals include electrocardiogram, electromyogram, electrooculogram, arterial blood pressure, respiration, and arterial oxygen saturation.

In this study, we used ECG and respiratory signals measured synchronously by the MBPD. ECG signals measure and record the electrical activity of the heart via electrodes attached to the patient's chest and are used to detect heart abnormalities and assess heart function. Respiratory signals are recorded by an inductive plethysmograph or nasal thermistor, which records the amplitude of abdominal motion and changes in nasal airflow, thereby providing information about respiratory activity. The sampling frequency of the above physiological signals is 250Hz, and the sleep phase is marked every 30s. Fig. 1 is an example of time domain waveform of 60s ECG signal and respiratory signal recorded by slp01a in the database.

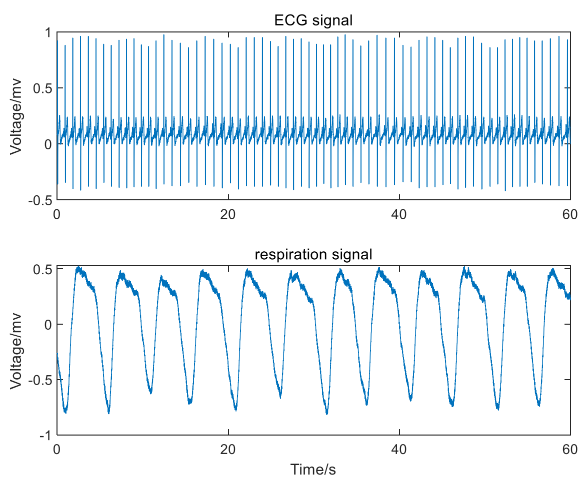


Fig. 1. Examples of waveforms of ECG and respiratory signals recorded by slp01a.

B. The Proposed NCEEMD Method

The EMD method can be used to analyze nonlinear and non-stationary signal sequences, which have a high signal-to-noise ratio and well time-frequency focus [9]. However, the defects of the method make the physical meaning of a single intrinsic mode function ambiguous, which will cause severe mode aliasing in the time-frequency dis-tribution. Compared with the original EMD, CEEMD has been greatly improved [26]. By superimposing multiple EMD decomposition of positive and negative white noise which are negative to each other, the problem of pattern aliasing is effectively solved by using the statistical property of Gaussian white noise with uniform frequency distribution. However, in the CEEMD decomposition method, the setting of the noise amplitude coefficient still depends on the human experience. Although the impact of noise on the results decreases with the increase of the overall average number of iterations, the time cost of the method also increases correspondingly, and the residue of white noise added cannot be ignored. Based on this, an NCEEMD method is proposed in this paper. In order to eliminate the residual white noise in the reconstructed signal to a certain extent, the EEMD decomposition of Gaussian white noise is first subtracted from the EEMD decomposition result of the original signal, and the noise residue in the signal decomposition is diluted or eliminated by using the characteristics of Gaussian white noise to improve the accuracy of the method.

1) Suppose the original signal is $y(t)$, gaussian white noise signal is $g(t)$, the overall average number is preset to m, the noise amplitude coefficient is α;

2) The white noise sequence with standard normal distribution added for the ith time is $n_i(t)$, then the noisy signal of the ith experiment is $y_i(t)$, $g_i(t)$;

$$y_i(t) = y(t) + \alpha n_i(t) \quad i = 1,2, \dots , m \tag{1}$$

$$g_i(t) = g(t) + \alpha n_i(t) \quad i = 1,2, \dots , m \tag{2}$$

3) The i th EMD process is conducted to $y_i(t)$, $g_i(t)$. The obtained multi-resolution features of the original signal can reflect more detailed scale information. Observing the detailed characteristics of gaussian white noise in each frequency band, which is used to simulate the error residue of white noise added by EEMD in reconstruction;

$$y_i(t) = \sum_{j=1}^{n} x_{ij}(t) + r_i(t) \quad j = 1,2, \dots , n \quad g_i(t) \tag{3}$$

$$= \sum_{j=1}^{n} k_{ij}(t) + l_i(t) \quad j = 1,2, \dots , n \tag{4}$$

where, $x_{ij}(t)$ is the average value of the jth IMF component obtained from the EMD decomposition of the original signal. $r_i(t)$ is the average value of the residual item. It is the average value of the j th IMF component obtained by EMD decomposition of gaussian white noise. $l_i(t)$ is the average value of the residual item.

4) Subtract the IMF components obtained in Eq. (3) and Eq. (4) in the corresponding frequency band to obtain a new IMF component $W_{ij}(t)$, which is used to eliminate the white noise residue in the EEMD decomposition of the original signal.

$$W_{ij}(t) = x_{ij}(t) - k_{ij}(t) \quad (5)$$

$$T_{ij}(t) = r_i(t) - l_i(t) \quad (6)$$

where, $W_{ij}(t)$ is the newly obtained average value of the jth IMF component. $T_{ij}(t)$ is the average value of the new residual item.

5) Repeat the process of 3) and 4) until $i = m$, the average value of the jth IMF component and the average value of the residual item obtained after the mth EMD decomposition are calculated, the functions are as follows.

$$A_j(t) = \frac{1}{n}\sum_{i=1}^{n} W_{ij}(t) \quad (7)$$

$$B_n(t) = \frac{1}{n}\sum_{i=1}^{n} T_{ij}(t) \quad (8)$$

6) The final result $C(t)$ after compound noise reduction with gaussian white noise is:

$$C(t) = \sum_{j=1}^{n} A_j(t) + B_n(t) \quad (9)$$

C. NCEEMD-based EDR Extraction Method

To solve the defects of the noise amplitude coefficient in the CEEMD method that need to be set by human experience and reduce the introduced noise interference, considering that the correlation between signals will gradually increase with the decrease of the noise residue in the original signal decomposition, this paper proposes an EDR method based on NCEEMD in Fig. 2. By presetting different noise coefficients, the correlation between the IMF component obtained from CEEMD decomposition and NCEEMD decomposition and the original respiration was compared. The optimal amplitude noise coefficient α in the method was determined by the principle of maximum increment of the correlation coefficient, which was used to reconstruct respiratory signals and automatically adjust parameters according to data characteristics to improve the adaptability of the method.

Selection of the IMF frequency range to reconstruct the respiration. Since respiration and heartbeat are in different frequency bands, respiration can be separated from the ECG signal by filtering or decomposition. Typically, the human respiratory rate ranges from 0.1 to 0.5 Hz, while the heart rate ranges from 0.8 to 2 Hz [7]. Considering that the patient has shortness of respiration or apnea, the respiratory frequency range selected in this paper is 0.07-0.75 Hz [3], and the IMF component in the frequency band is used as the component of reconstructed respiration.

Calculation of the correlation between the IMF and the measured respiration signal. Multiple IMF components are obtained by decomposing the original signal by NCEEMD. In this paper, the Pearson correlation coefficient index is used to measure the correlation between the IMF component and the measured respiration. The size of the correlation coefficient reflects the degree of correlation between two signals. P is a test value, which is used to test whether the two variables have the same correlation as the sample in the population from which the sample comes. If P is less than 0.05, it is considered statistically significant, and the correlation R is considered significant.

$$R(X,Y) = \frac{Cov(X \cdot Y)}{\sqrt{Var[X]Var[Y]}} \quad (10)$$

where, $Cov(X \cdot Y)$ is the covariance of X and Y, $Var[X]$ is the variance of X, $Var[Y]$ is the variance of Y.

Determination of the optimal magnitude noise coefficients. The increment of the correlation coefficient between the CEEMD decomposition component $x_{ij}(t)$, the NCEEMD decomposition component $W_{ij}(t)$, and the measured respiratory signal are compared respectively. The optimal amplitude noise coefficient α is determined by the principle of the maximum increment of the correlation coefficient, which is used to reconstruct the respiratory signal.

D. Evaluation Metrics

To quantify the error between EDR and original respiration, this paper evaluates the method by calculating mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE) accuracy.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (11)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (12)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \quad (13)$$

where, $\hat{y}_i$ is the predicted value and y_i is the actual measured value.

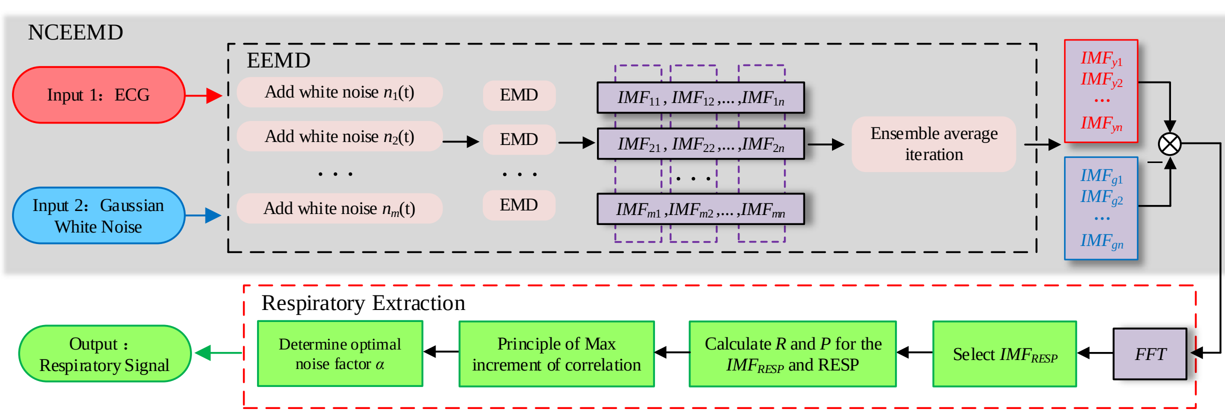


Fig. 2. Overview of the proposed NCEEMD method for respiratory extraction.

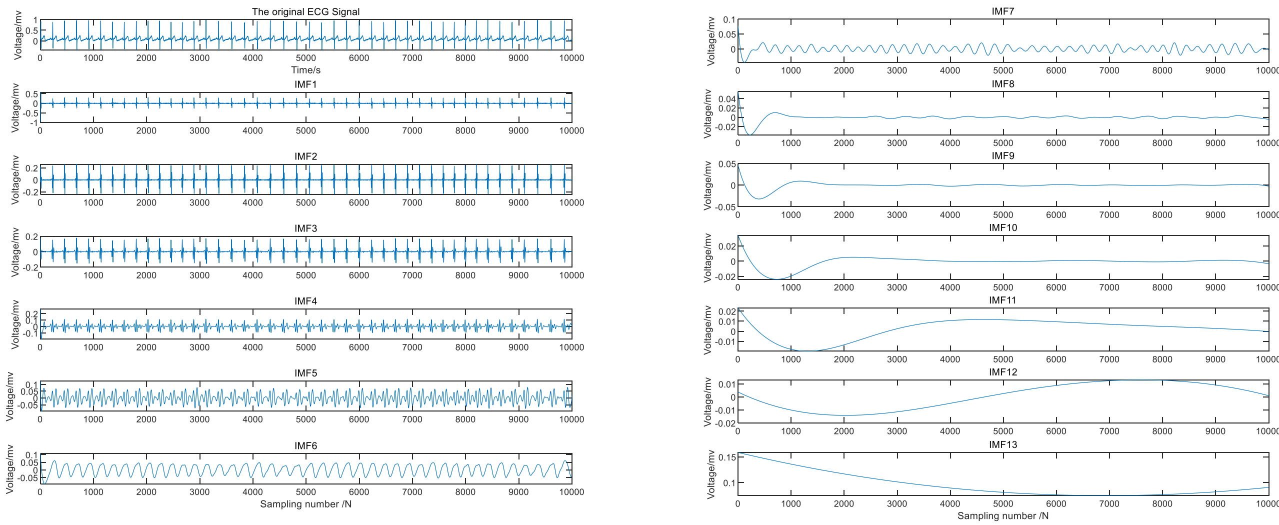
III. Results

A. NCEEMD Method for ECG Signal

Taking the first 60 seconds of slp01a data in MBPD as an example, NCEEMD decomposition of the raw ECG signal was done to obtain different IMF components, as shown in Fig. 3.

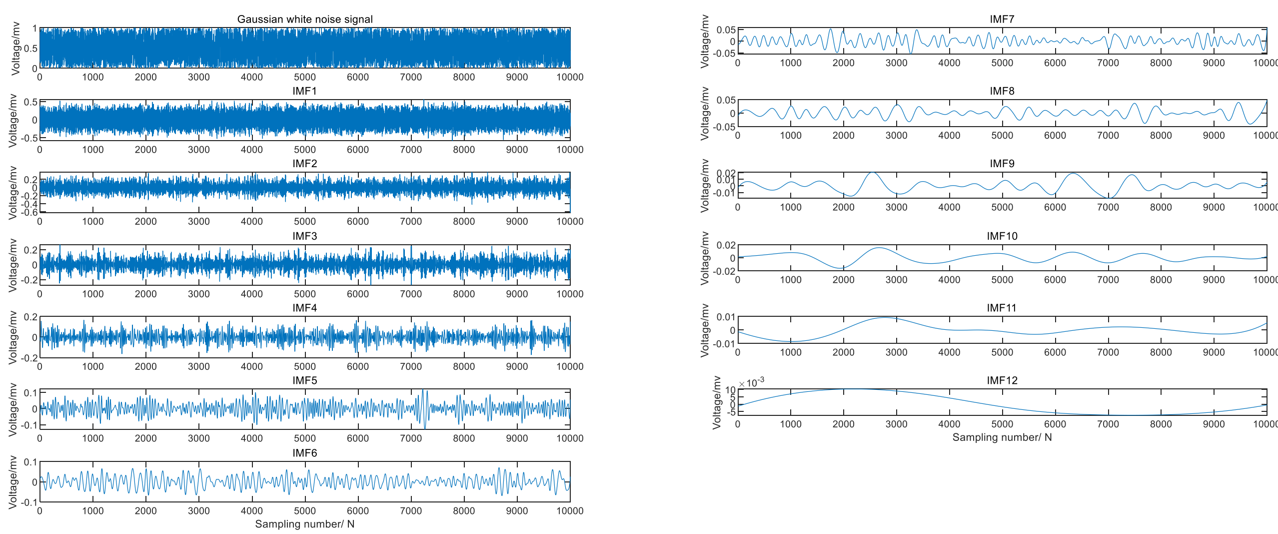
Gaussian white noise is a kind of noise with zero mean in time domain and uniform distribution of power spectral density in frequency domain [5]. Each sample is independent from each other and exhibits Gaussian distribution characteristics. EEMD decomposition of Gaussian white noise is performed below, as shown in Fig. 4.

Subtract the IMF components obtained in EEMD decomposition of ECG signals and Gaussian white noise signal in the corresponding frequency band to obtain a new IMF component, which is used to eliminate the white noise residue in the EEMD decomposition of the original signal, as shown in Fig. 5.



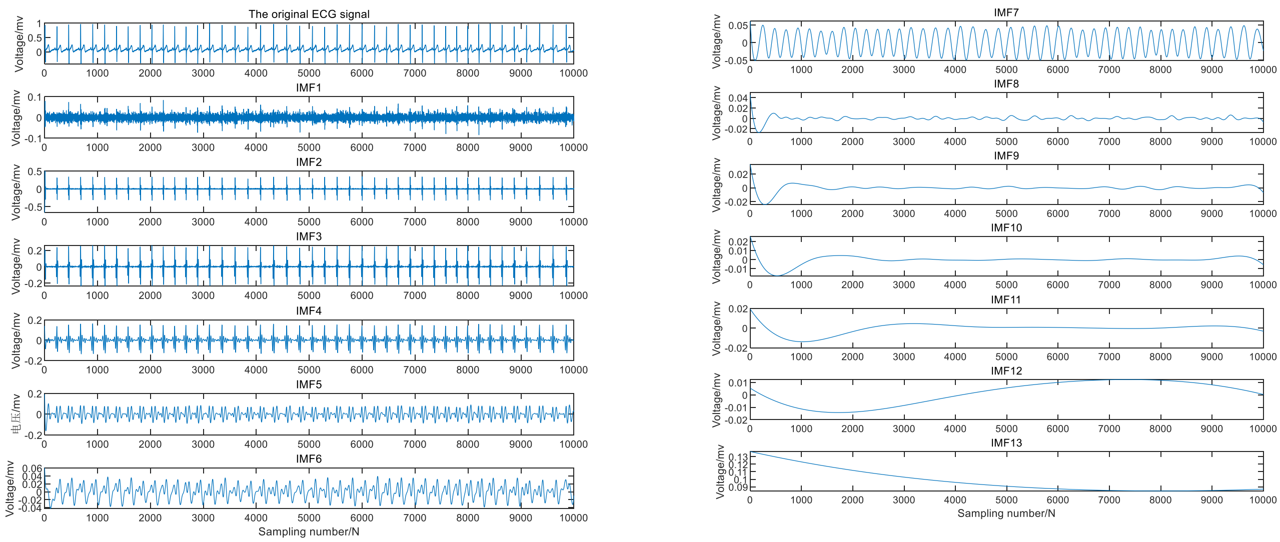
(**a**) Decomposition detail of IMF1~IMF6 (**b**) Decomposition detail of IMF7~IMF13

Fig. 3. EEMD decomposition of ECG signals.



(**a**) Decomposition detail of IMF1~IMF6 (**b**) Decomposition detail of IMF7~IMF13

Fig. 4. EEMD decomposition of Gaussian white noise signal.



(**a**) Decomposition detail of IMF1~IMF6

(**b**) Decomposition detail of IMF7~IMF13

Fig. 5. NCEEMD method decomposition detail diagram.

B. *Respiratory Extraction Method*

The original ECG signals were decomposed by EMD, EEMD, CEEMD and NCEEMD methods to obtain different IMF components, and the IMF components in the respiratory band (0.07 ~ 0.75 Hz) were calculated by FFT technology as shown in Fig. 6 and Table I below. In the NCEEMD decomposition results, the maximum centre frequency of IMF8~IMF10 is within the range of 0.07-0.75Hz in the respiratory band.

As can be seen from Table I, the components in the respiratory band obtained by EMD decomposition are: IMF5~ IMF 8; The components in the respiratory band obtained by EEMD/CEEMD/NCEEMD decomposition are IMF8~IMF 10.

The P and R values of IMF and measured respiratory signals in the respiratory band were calculated in Table II and Table III. The increment of the correlation coefficient between the CEEMD decomposition component, the NCEEMD decomposition component and the measured respiratory signal are compared respectively. The optimal amplitude noise coefficient α is determined by the principle of the maximum increment of the correlation coefficient, the optimal amplitude coefficient is used for the final reconstruction of the respiratory signal.

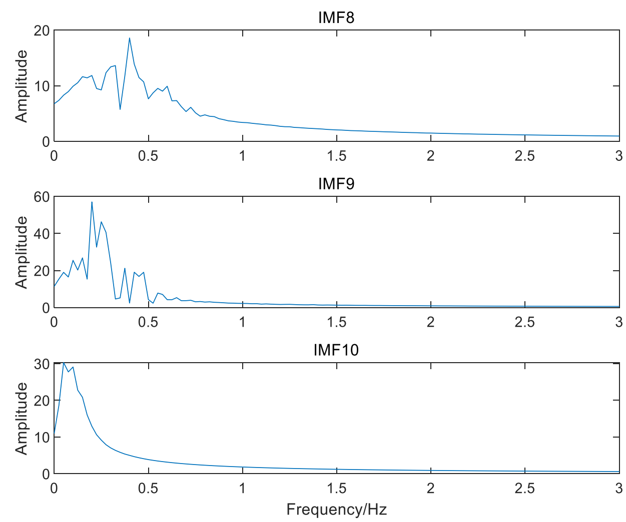


Fig. 6. The Spectrum of IMF_RESP of NCEEMD method.

TABLE I. CORRESPONDING RESPIRATORY BAND FREQUENCY IMF

Method	Frequency (Hz)					
	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10
EMD	**0.45**	**0.3**	**0.15**	**0.075**	0.025	/
EEMD	3.3	1.125	1.125	**0.4**	**0.15**	**0.075**
CEEMD	3.3	1.125	1.125	**0.4**	**0.15**	**0.075**
NCEEMD	3.3	1.125	1.125	**0.325**	**0.2**	**0.1**

TABLE II. COMPARISON OF P VALUES BETWEEN DIFFERENT IMF COMPONENTS AND ORIGINAL RESPIRATION

Method	Significance *P* value					
	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10
EMD	0.2033	0	0	0	0.5684	/
EEMD	0.5411	0.4435	0.0252	0	0	0
CEEMD	0.4646	0.1196	0.6107	0	0	0
NCEEMD	0.5412	0.4385	0.0234	0	0	0

TABLE III. COMPARISON OF R VALUES BETWEEN DIFFERENT IMF COMPONENTS AND ORIGINAL RESPIRATION

Method	Correlation coefficient *R* value					
	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10
EMD	**0.0127**	**0.0826**	0.0889	0.0416	0.0057	/
EEMD	-0.0061	-0.0077	-0.0067	0.1628	0.2198	0.0787
CEEMD	0.0073	0.0156	-0.0051	0.1413	0.1945	-0.174
NCEEMD	0.0111	-0.0136	**-0.1635**	**0.2261**	**0.2338**	**0.0876**

With a statistically significant P-value<0.05, the correlation coefficient R-value of NCEEMD with original respiration was the largest among components IMF7 to IMF10 (see the bolded portion in Table III), indicating that the IMF component decomposed by this method had the strongest correlation with original respiration. The changes in the incremental correlation coefficients of NCEEMD-IMF with original respiration were calculated comparing the CEEMD decomposition method under different amplitude noise factor α, as shown in Fig. 7 below.

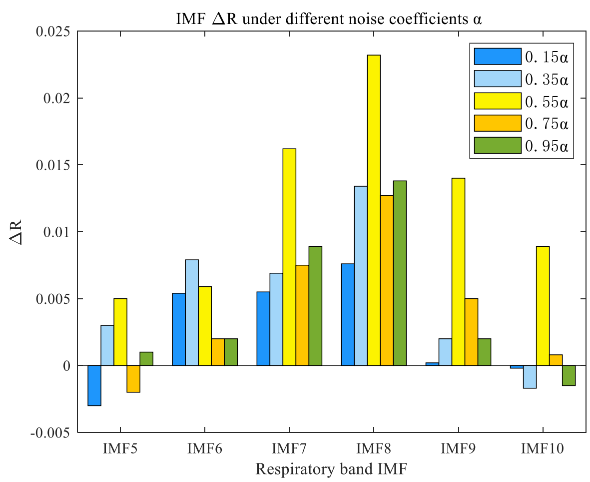


Fig. 7. IMF correlation coefficient increment at different noise coefficient α.

As shown in Fig. 7, under the noise amplitude coefficient $\alpha = 0.55$, the correlation coefficient of each component is increased and the correlation coefficient of IMF8 component has the largest increment. The frequency of IMF8 component is 0.4Hz, which is also the closest to the original respiratory frequency of 0.3Hz, indicating that the decomposed component of this method highlights the respiratory feature information more. Under other different noise coefficients, the correlation between IMF5 and IMF10 decreases, which may be since the IMF5 component carries the characteristic information of the ECG signal, and the IMF10 component carries part of the characteristic information of the baseline drift, which makes its correlation with the respiration weakened, which is manifested in the decreasing increment of the correlation coefficient [23]. The method proposed in this paper has good adaptability in determining the noise amplitude coefficient.

C. Compare EDR Extraction with Other Methods

As can be seen from Table I, the components in the respiratory band obtained by EMD decomposition are: IMF5~ IMF 8; The components in the respiratory band obtained by EEMD/CEEMD/NCEEMD decomposition are IMF8~ IMF 10. Based on the above determination of the optimal noise amplitude coefficient, slp01a data in the first 60 seconds of MBPD is taken as an example to compare EDR signals obtained by EMD, EEMD, CEEMD, and NCEEMD decomposition methods, respectively, and compare them with the measured raw respiration in the database in Fig. 8**.**

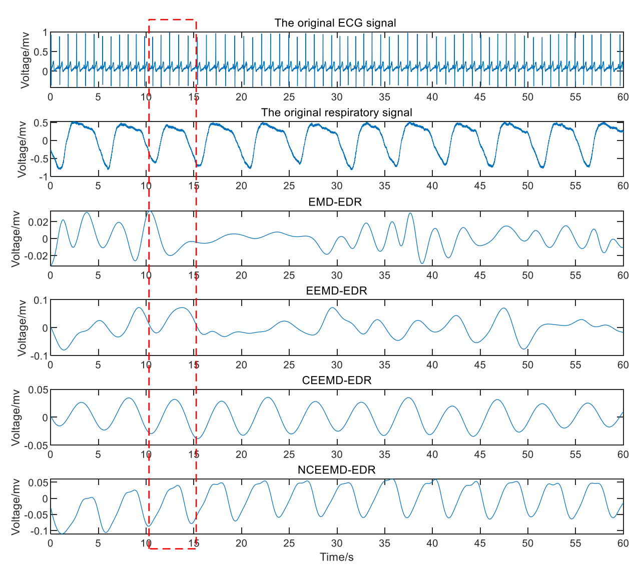


Fig. 8. Example of a comparison of the different EDRs recorded by slp01a with the original respiration.

Fig. 8 shows an example of an abdominal respiration fragment recorded using slp01a over a period of 60 seconds. Each of the above EDR techniques provides information on the peaks and valleys of inhalation and exhalation, as well as respiration rates. In the red box in the figure above, firstly, the respiratory peaks and trills of EMD-EDR and EEMD-EDR are inconsistent with the original respiratory signals, and the respiratory waveforms of the whole minute are incomplete, resulting in poor respiratory extraction effect. Second, although CEEMD-EDR retains part of the characteristics of the respiratory cycle, the overall waveform is too smooth, and the detailed information between the crest and the trough is covered, and the characteristic information of the respiratory rhythm cannot be highlighted. The respiration extracted based on the NCEEMD-EDR method is more morphologically like the original respiration. This means that the NCEEMD algorithm can retain the morphological characteristics of the original breathing signal more accurately when extracting EDR. The NCEEMD method significantly reduces noise residue by incorporating additional EEMD decomposition of white noise, which effectively separates signal and noise, reducing mode mixing. Compared to traditional techniques like low-pass filtering or wavelet transform, NCEEMD excels in handling non-stationary and nonlinear signals, preserving the physical significance of the signal more accurately. Our experimental results indicate that NCEEMD maintains high signal extraction accuracy even in noisy environments.(Q3: Can you elaborate on the advantages of the noise residue removal process in the NCEEMD method compared to other noise removal techniques? Specifically, how does this method compare with other recent noise removal techniques?)

After the ECG derived respiratory EDR is obtained by different decomposition methods, Hilbert-Huang transform is applied to the original time-domain sequential signal in Fig. 9, and the obtained Hilbert spectrum represents the distribution and characteristics of the signal in time-frequency domain [9]. In the Hilbert spectrum, the main frequency variation is restricted to a narrow range of about 0 to 1.5Hz. By analysing the Hilbert spectrum, the characteristics and variation modes of the signal in the time-frequency domain can be obtained. It can help reveal features such as frequency components, frequency jumps, harmonics, nonlinear vibrations, and resonances in the signal.

In Fig. 10, EMD-EDR has the sparsest Hilbert spectrum, meaning that the breathing related waveforms in the signal have fewer discrete frequency components in a specific frequency range. The frequency of the Hilbert spectrum of EEMD-EDR and CEEMD-EDR is within the range of 0 to 1.5Hz, but the signal amplitude remains constant throughout the period, there is no significant amplitude modulation, and the energy distribution in the frequency space is weaker. The Hilbert spectrum energy of NCEEMD-EDR has a good locality in both frequency domain and time domain, and the extracted EDR signal has a similar instantaneous frequency change to the original breathing signal, reflecting the local characteristics of important events and sudden activities of the signal.

Compared with other algorithms, NCEEMD is more accurate and effective in extracting respiratory features from ECG signals.

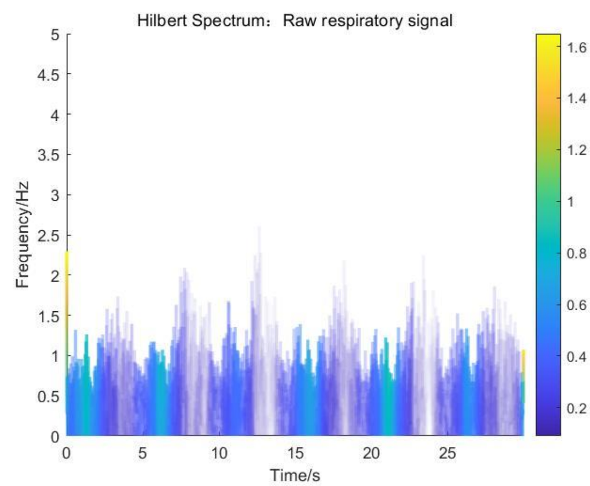
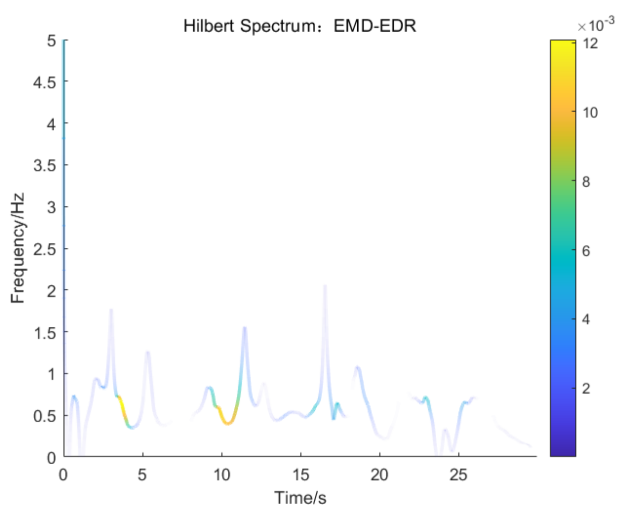
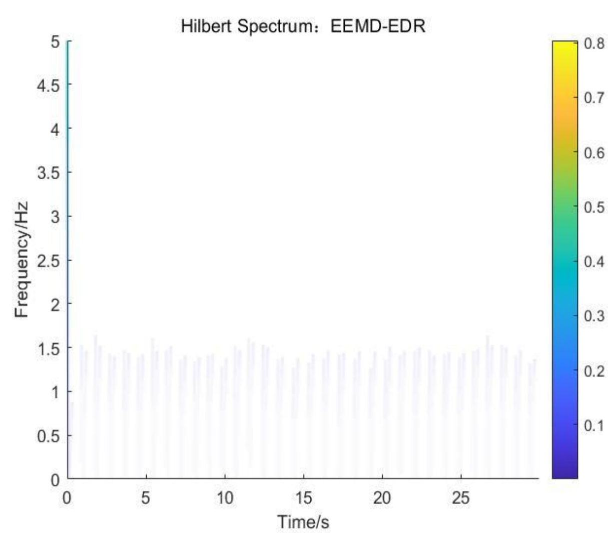


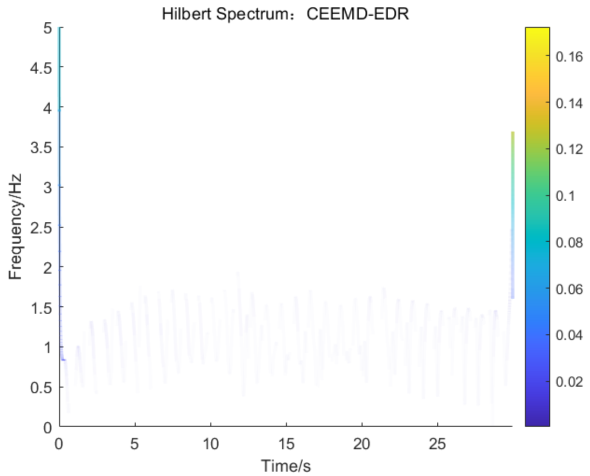
Fig. 9. Hilbert spectrum of raw respiratory signals by slp01a data.



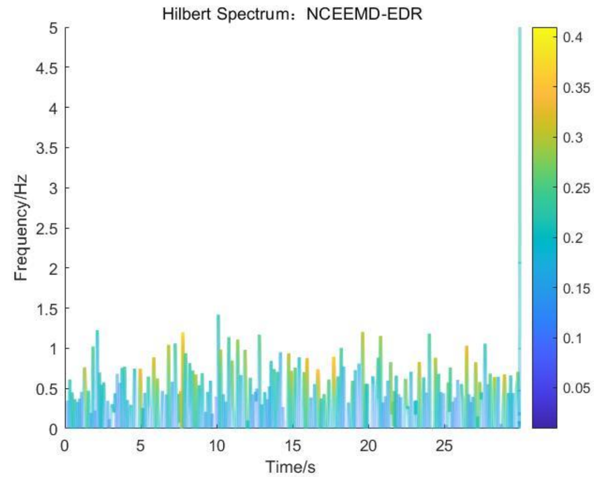
(a) Hilbert Spectrum of EMD-EDR



(b) Hilbert Spectrum of EEMD-EDR



(c) Hilbert Spectrum of CEEMD-EDR



(d) Hilbert Spectrum of NEEMD-EDR

Fig. 10. Compare the Hilbert Spectrum of different EDR extraction methods.

The error comparison of all records is listed below in Table IV. In Table IV, taking the slp01a record in MBPD as an example, the EDR extracted by this method has the smallest error in MSE, RMSE, and MAE of the original breath, and compared with CEEMD method, the average MSE is reduced by 3.95%, the average RMSE is reduced by 2.74%, and the average MAE is reduced by 2.52%. In most cases, the EDR extracted by the NCEEMD method minimizes all kinds of errors with respect to the original respiration (see the bolded part in Table IV), and the NCEEMD-based EDR method has a higher accuracy.

TABLE IV. COMPARISON BETWEEN DIFFERENT EDR AND MEASURED RESPIRATION ERRORS FOR ALL RECORDS

Record	EMD			EEMD			CEEMD			NCEEMD		
	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE	MSE	RMSE	MAE
Slp01a	0.1674	0.4091	0.3696	0.1686	0.4106	0.3704	0.1682	0.4101	0.3704	**0.1668**	**0.4084**	**0.3681**
Slp01b	0.2518	0.5018	0.4314	0.2521	0.5021	0.4315	0.2528	0.5027	0.4322	**0.2431**	**0.4931**	**0.4313**
Slp02a	0.2206	0.4697	0.3898	0.2176	0.4665	0.3881	0.2178	0.4667	0.3877	**0.2158**	**0.4645**	**0.3861**
slp02b	0.1946	0.4411	0.3821	0.1945	0.441	0.3816	0.194	0.4404	0.3816	**0.1932**	**0.4395**	**0.3816**
Slp03	0.0604	0.2458	0.196	0.0616	0.2482	0.1991	0.061	0.2469	0.1971	**0.06**	**0.2449**	**0.1948**
Slp04	**0.0223**	**0.1493**	0.1204	0.0313	0.1769	0.1412	0.0259	0.161	0.1314	0.024	0.1549	**0.1143**
Slp14	0.0296	0.172	0.1451	0.0313	0.1769	0.1424	0.0285	0.169	0.1414	**0.0266**	**0.1651**	**0.1321**
Slp16	0.0414	0.2035	0.1719	0.0468	0.2163	0.1766	0.0415	0.2038	0.1712	**0.0406**	**0.2015**	**0.1697**
Slp32	**0.098**	0.313	0.2524	0.1063	0.326	0.2641	0.1021	0.3196	0.2577	0.1002	**0.3112**	**0.2487**
Slp37	0.0322	0.1794	0.1697	0.0337	0.1836	0.1707	0.0321	0.179	**0.1692**	**0.0281**	**0.1619**	0.1696
Slp45	0.0616	0.2482	**0.218**	0.0769	0.2773	0.2394	0.0707	0.2658	0.2315	**0.0588**	**0.2425**	0.2282
Slp48	0.0899	0.2998	0.2587	0.092	0.3033	0.2617	0.091	0.3016	0.2608	**0.0805**	**0.2837**	**0.2408**
Slp60	0.0313	0.1769	0.1478	0.0338	0.1838	0.1515	0.0335	0.1831	0.151	**0.0304**	**0.1744**	**0.1369**
Slp61	0.0544	0.2332	0.1939	0.0551	0.2347	0.1946	0.0546	0.2336	0.194	**0.0542**	**0.2328**	**0.1919**
Slp66	0.0176	0.1327	**0.1114**	0.0191	0.1382	0.1153	0.0183	0.1354	0.1134	**0.0165**	**0.1285**	0.1136
Slp67x	0.0265	0.1628	0.1539	0.0278	0.1667	0.1513	0.0264	0.1624	0.1526	**0.0249**	**0.154**	**0.1424**
Average Error	0.0875	0.2711	0.232	0.0905	0.2783	0.2362	0.0887	0.2738	0.234	**0.0852**	**0.2663**	**0.2281**

TABLE V. COMPARISON OF EEMD, CEEMD AND NEEMD INDICES RECORDED BY SLP01A

Method	Added noise amplitude：α	Number of added noises：Ne	Method computation time /s	Orthogonality index [27]
EEMD	0.2	100	**21.01**	0.21
CEEMD	0.2	100（50×2）	40.23	0.26
NCEEMD	0.2	100	25.14	**0.01**

The methods were run on a computer with a CPU model i7-11800H, 16GB of memory, and an RTX3050Ti graphics card. In Table V, under the same noise amplitude coefficient and number of noises, the computation time of this method is 25.14s, which is 37.5% faster than the CEEMD method. The orthogonality index of this method is only 0.01, and its decomposition components have higher independence, which can effectively extract the independent features or components in the data, and the physical meaning of IMF components is more explicit.

IV. Discussion

A. Significance Test of IMFs of White Noise

"Significance test of IMFs of white noise" aims to determine if the IMFs extracted from a given signal exhibit characteristics that can be attributed to random white noise or if there is a significant departure from randomness [24]. The IMF significance test for white noise has several purposes:

1) Verify the IMF extraction method: By resolving the IMF from white noise, it is possible to assess whether the chosen method can accurately decompose the signal into its inherent components.

2) Assess the randomness of the IMF: White noise is a random signal of equal intensity across all frequencies. If the IMF of white noise is found to be statistically significant, it indicates that the extracted components have some characteristics that deviate from random behaviour. This could indicate a non-random pattern or underlying structure in the signal. If the significance test shows that the IMF of white noise is not statistically significant, this means that the extracted components are likely random and do not contain any meaningful patterns or structures. Despite the increased computational complexity of the proposed NCEEMD method compared to existing EEMD and CEEMD methods, optimizations such as parallel computing and efficient programming techniques can significantly reduce computation time. Our experiments indicate that while the complexity is higher, the NCEEMD method remains manageable in terms of computational resources and offers significant advantages in accuracy and robustness, which are crucial for practical applications.(Q1: The proposed NCEEMD method adds complexity compared to existing EEMD and CEEMD methods. How do you address the increased computational cost and practical applicability of this method?)

The relationship between energy density and average period of Gaussian white noise. The horizontal coordinate is the natural logarithm of the mean period of IMFs, the curve is the natural logarithm of the mean energy of the significance line, and the red dot is the natural logarithm of the mean energy of all IMFs.

As can be seen from the figure, the natural pair value of the average energy of all IMF (the midpoint in the Fig. 11) is near the natural logarithm of the average energy of the significance lines (95% and 99% confidence intervals), and the IMF is statistically significant, that is, it is not produced by pure randomness. This shows that IMFs derived from Gaussian white noise decomposition contain some non-random patterns or structures. The residual of auxiliary white noise added to the original signal affects the decomposition results and physical significance of different IMFs. Based on the above analysis, the same decomposition of Gaussian white noise and the elimination in the frequency band of the IMFs corresponding to the original signal can eliminate or reduce the influence of noise residue on the reconstructed EDR.

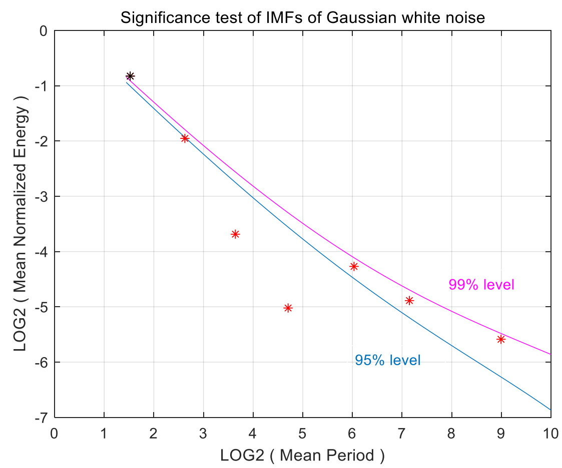


Fig. 11. Significance test of IMFs of white noise.

B. Cycle Comparison of NCEEMD-EDR and Original Respiration

The time of breath detected in the EDR signal is compared with the time of the corresponding reference breath signal in Fig. 12. The time window for determining the reference breath corresponding to the EDR is two seconds. Each breathing peak or trough is labelled to define the breathing beat.

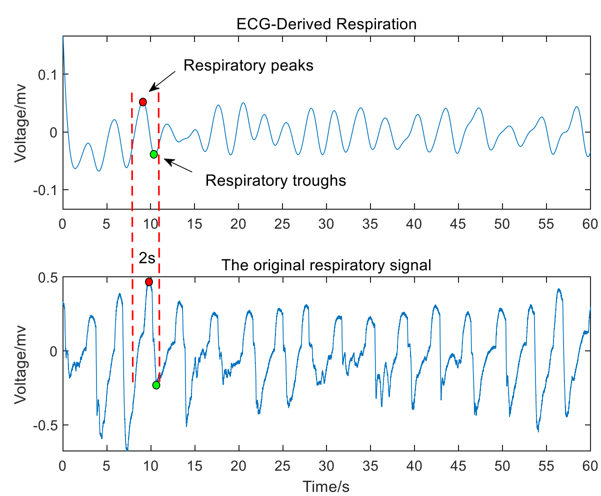


Fig. 12. Comparison of NCEEMD-EDR recorded by Slp03 with original respiration.

Based on the NCEEMD-EDR method, the number of respirations was extracted and compared with the measured number of respirations in the database in Table VI.

TABLE VI. CYCLE COMPARISON OF NCEEMD-EDR AND ORIGINAL RESPIRATION

Record	Age	Gender	This method respiration times/min	Measured respiration times/min	Errors/min
Slp01a	44	M	13	12	1
Slp01b	44	M	11	10	1
Slp02a	38	M	20	21	-1
slp02b	38	M	19	21	-2
Slp03	51	M	17	16	1
Slp04	40	M	9	10	-1
Slp14	37	M	13	15	-2
Slp16	**35**	**M**	**22**	**21**	**1**
Slp32	**54**	**M**	**7**	**7**	**0**
Slp37	39	M	18	18	0
Slp45	42	M	12	12	0
Slp48	56	M	13	11	2
Slp60	49	M	13	13	0
Slp61	32	M	17	18	-1
Slp66	33	M	15	18	-3
Slp67x	/	M	14	15	-1
Average error					-0.3125

As can be seen from Table VI, compared with the respiration cycle of NCEEMD-EDR and the original measured respiration, the error times were all less than two times/min, except for some data with large deviations. For patients with shortness of respiration (Slp16 record: 21 times/min) and slow respiration (Slp32 record: 7 times/min), the error times were 1 time/min and 0 times/min, and the total average error was about ±0.31 times/min. The EDR method based on NCEEMD had stronger robustness.

The respiratory signals extracted based on the method in this paper can be used in respiratory-related research and clinical applications. The analysis of respiratory signals can reveal respiratory rhythm and variability, help evaluate respiratory function and abnormalities, and monitor the progress and treatment effects of respiratory diseases. The NCEEMD-EDR method was applied to the extraction of ECG-derived breathing signals, and the accuracy and reliability of the method were evaluated by comparing the error accuracy and breathing period with the real breathing signals. The effectiveness of this method for measuring respiratory cycles has been proven and does not hinder its use in patient populations. In addition, it is an easy method to implement. The method proposed in this paper is feasible and effective in extracting respiratory rate and detecting respiratory activity during sleep, but the limitation is that this method cannot distinguish between obstructive apnea and central apnea, and can only provide reference guidance such as AHI index. A significant decrease in EDR signalling during apnea events is a sensitive feature for identifying obstructive apnea [18, 21]. The use of EDR technology to distinguish obstructive apnea from central apnea needs further research in the future.

The NCEEMD method offers several advantages in practical medical applications, including non-contact monitoring, which enhances patient comfort and compliance, and its robustness in detecting respiratory abnormalities such as sleep apnea. However, the method's higher computational complexity requires high-performance computing resources, potentially increasing costs. Implementing this method in hospital or home settings requires consideration of real-time data processing capabilities and system portability. Additionally, training medical personnel is essential to ensure accurate usage and interpretation of results. （Q4: What are the benefits and limitations of applying the proposed method in real-world medical environments? For instance, what additional considerations are needed when implementing this method in hospitals or homes?)

V. CONCLUSION

We compared four different methods to calculate EDR and found that they lead to different results. In this paper, a new complementary empirical ensemble mode decomposition respiration extraction method for deriving respiration signals from ECG signals is proposed, which does not require preprocessing of ECG data to obtain good EDR signals. As analyzed by experimental comparison, the NCEEMD decomposition yields more detail scales than the EMD decomposition and less residual noise in the IMF component than the EEMD and CEEMD decompositions. The NCEEMD-based breath extraction method proposed in this paper reduces the average MSE by 3.95%, the average RMSE by 2.74%, and the average MAE by 2.52%, while the computational time consumed is reduced by 37.5%, and the orthogonality of the obtained IMF decomposition components is better when compared with the CEEMD method. The EDR signal obtained by this method has a high similarity to the respiratory signal synchronously recorded by commercial instruments, which can be used for different applications such as sleep apnea detection and home-based respiratory monitoring.

Currently, our research is primarily based on the MIT-BIH database. However, we acknowledge the necessity of validating the method across various datasets to ensure its broad applicability and generalization. Future work will include testing the NCEEMD method on different physiological signal datasets to further evaluate its performance under diverse conditions. In the initial phase of our research, we focused primarily on comparing the NCEEMD method with the most commonly used EEMD and CEEMD methods to validate its effectiveness. However, we plan to extend the scope of comparisons to include other recent respiration signal extraction methods, such as those based on machine learning and deep learning techniques, in future studies. This will help establish the relative superiority of the NCEEMD method in various scenarios and applications. (Q2: Have you validated the performance of the proposed method on datasets other than the MIT-BIH database? If not, do you think it is necessary to validate it across a variety of datasets? Q5: Why did you not include additional performance comparisons with other recent respiration signal extraction methods? Do you have any plans to provide more comparisons to better establish the relative superiority of the proposed method?)

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