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Doppler Ultrasound Blood Flow Velocimetry Based on the Optimization of Effective EEMD Components

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DOPPLER ULTRASOUND BLOOD FLOW VELOCIMETRY BASED ON THE OPTIMIZATION OF EFFECTIVE EEMD COMPONENTS

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***Abstract*—A new approach based on the optimization of effective blood components using the ensemble empirical mode decomposition (EEMD) and normalized fluctuation index (EEMD_N) is proposed to overcome the limitations of short-time Fourier transform (STFT) in processing non-stationary blood flow signals. Firstly, blood flow Doppler signals are decomposed by the EEMD method to get a group of intrinsic mode functions (IMFs). Next, the normalized fluctuation index (NFIs) of all IMFs are calculated. Then, the normalized root mean square errors (NRMSEs) of blood flow velocities, which are measured by IMFs with different NFI thresholds, are fitted by the Fourier function to determine the optimal threshold of NFI. Then, using the optimal threshold, the effective components in blood flow signals are chosen. Finally, blood flow velocities are computed by the Doppler frequency shift formula. Simulations show that the NRMSEs of blood flow velocity profiles estimated by the EEMD_N method were reduced by 24.46 % in comparison with these by the traditional STFT method. In summary, the EEMD_N method could effectively improve the measurement accuracy of blood flow velocity profiles, especially low velocities close to vessel walls, which is potential to provide more accurate diagnostic information for cardiovascular diseases.**

Keywords-ultrasound Doppler signal of blood flow; Doppler frequency shift; ensemble empirical mode decomposition; fluctuation index; blood flow velocity profile

NOMENCLATURE

BFVP	Blood flow velocity profile
BFDS	Blood flow Doppler signal
STFT	Short-time Fourier transform
WT	Wavelet transform
EMD	Empirical mode decomposition
EEMD	Ensemble empirical mode decomposition
EEMD_N	The optimization of effective blood components using the EEMD and normalized fluctuation index
NFI	Normalized fluctuation index
IMF	Intrinsic mode functions
NRMSE	Normalized root mean square error
RJR	Rate of judged region

I. INTRODUCTION

A large number of clinical studies[1-3] show that atherosclerosis is the main cause of cerebrovascular disease. Doppler color flow imaging technology can explore the changes in radial blood flow velocity profiles (BFVPs) caused by atherosclerosis. The BFVPs estimation are depend on the accuracy of time-frequency analysis of blood flow Doppler signals (BFDSs)[4]. Owing to the traditional Fourier transform cannot simultaneously display the complete information of signals in the time domain and frequency domain[5]. Therefore, short-time Fourier transform (STFT) become a common method to estimate the frequency of BFDSs[6]. However, the STFT method used a fixed window function and could not consider both time and frequency resolution[7]. Multi-resolution analysis of wavelet transform (WT) had good spatial and frequency domain localization characteristics. It was suitable for non-stationary signals[8, 9]. And Zhang et al[10-12] achieved good-performance in analysis of Doppler signals by using the WT method. The disadvantage of the WT method is the lack of systematic and standard methods of selecting the optimal wavelet basis function. Huang et al[13] proposed a self-adaptive strategy decomposition method, which called empirical mode decomposition (EMD). Compared with the WT method, the EMD was more suitable for processing non-linear and non-stationary signals. However, EMD had its shortcomings such as mode aliasing, endpoint effects, and stopping conditions[14]. To this end, Wu and Huang *et al*[15] proposed a noise-assisted data analysis method called ensemble empirical mode decomposition (EEMD). The EEMD method widely applied to nonlinear and non-stationary signals due to its intuitive, direct and posteriori characteristics[16].

In this work, a new approach based on the optimization of effective blood components using the EEMD and normalized fluctuation index (EEMD_N) is proposed to overcome the limitations of short-time Fourier transform (STFT) in processing non-stationary blood flow signals. BFDSs are decomposed by EEMD to get a group of intrinsic mode functions (IMFs). From this group, normalized fluctuation index (NFIs) of IMFs are calculated. The optimal threshold of NFIs are found using the Fourier function fitting method. Then, the optimal threshold is chosen by the decomposed blood flow signals. Blood flow velocities are finally computed by the Doppler frequency shift formula. The proposed method is verified via simulation experiments. Results show that the EEMD_N method can effectively improve the accuracy of the low-velocity blood flow which close to the vessel wall.

II. METHOD

A. The Doppler technique

The frequency deviation between echo signals received by transducer and transmitted signals is called Doppler frequency shift. Echo signals received by ultrasound probe

carry a large amount of Doppler frequency shift information. According to the Doppler effect proposed by Lichen John Doppler[18]. Blood flow velocity can be measured by the Doppler frequency shift of echo signals. Based on the Doppler frequency shift formula, the echo signal received by the ultrasound probe can be calculated as,

$$f' = \left(\frac{c + 2v\cos\theta}{c} \right) f_0 \tag{1}$$

where v is blood flow velocity, c represents ultrasonic sound velocity, f_0 represents ultrasonic emission frequency, and θ is angle between ultrasonic probe and blood flow direction ($30° \le \theta \le 60°$). Then the relation between Doppler frequency shift and blood flow velocities is,

$$f_d = f' - f_0 = \frac{2v\cos\theta}{c} f_0 \tag{2}$$

From the Doppler frequency shift f_d, velocity values can be calculated from the following Doppler equation as,

$$v = \frac{cf_d}{2 f_0 cos\theta} \tag{3}$$

B. EEMD

The most important features of the BFDSs are its nonstationary nature and randomness. EEMD proposed by Wu and Huang[15] is an effective method to process non-linear and non-stationary signals. It not only decomposes a signal into multiple components of intrinsic mode functions (IMF) and a residual component, but also inhibits mode fixing and improves accuracy of signal analysis by adding white noises[20].

EEMD decomposition includes the following steps[21].

(a) Z times of Gaussian white noise with a mean value of 0 and amplitude standard deviation constant $n_z(t)$ are added to the original signal $x(t)$,

$$x_z(t) = x(t) + n_z(t) \quad 1 \le z \le Z \tag{4}$$

(b) Then, the signals are decomposed into K groups of IMFs components $C_{(z,k)}(t)$ and residual components $r_z(t)$ by EMD,

$$x_z(t) = \sum_{k=1}^{K} C_{(z,k)}(t) + r_z(t) \quad 1 \le k \le K \tag{5}$$

(c) The mean value of all IMF components and residual components are calculated to obtain the IMF component $c_k(t)$ and the residual component $r(t)$ as,

$$c_k(t) = \frac{1}{Z} \sum_{z=1}^{Z} C_{(z,\ k)}(t) \tag{6}$$

$$r(t) = \frac{1}{Z} \sum_{z=1}^{Z} r_z(t) \tag{7}$$

Finally, several relatively steady IMF components and a remainder term component are obtained as,

$$x(t) = \sum_{k=1}^{K} c_k(t) + r(t) \tag{8}$$

C. EEMD_N

Color Doppler flow imaging system uses an ultrasonic probe integrating transceiver transmit pulse at a fixed frequency to scan the blood flow region of interest. T times echoes on the same detection position are taken to obtain the Doppler signals which containing frequency shift information. The EEMD_N method proposed in this paper, the NFI of each IMF is calculated after EEMD decomposing the BFDSs. Then, an IMF is reasonably selected to calculate the blood flow velocity according to the NFI threshold. NFI denotes the fluctuating intensity of the signal, which can be used to measure the change in the signals. Due to the parabolic distribution of blood flow velocity, the fluctuation of the signal in the center area of blood flow will usually be stronger than that in the marginal area of blood flow.

Three groups of IMFs components and one remainder components are obtained after processing BFDS by the EEMD. NFIs of all IMF_1 are calculated and compared with the NFIs of the original signal in Figure 1. It shows that the NFIs' changes of them are basically same. The NFIs of the signals in the center area of blood flow are generally greater than these of the signals in the marginal area of blood flow. According to laminar flow characteristics of blood flow, the blood flow velocities are highest at the center of the blood vessel and close to zero at the blood vessel walls. The blood flow velocities of IMF_1 are basically consistent with the velocities of the original signals in the center area of blood flow , so the IMF_1 are selected to calculate blood flow velocities in the the center area of blood flow. Blood flow velocities of IMF2 and IMF3 are close to the standard blood flow velocity curve in the marginal area of blood flow. Thus, the IMFs who with smaller NFIs are selected to calculate blood flow velocities in the marginal area of blood flow.

The EEMD_N method includes the following steps.

(a) Doppler signals $x_i(t)$ $(1 \le i \le I, 1 \le t \le T)$ are original signals of the EEMD decomposition, which are extracted in I detection positions from upper to inferior vascular walls.

(b) Original BFDSs $x_i(t)$ are decomposed by using EEMD decomposition into K groups of IMF components $\left\{ \mathrm{IMF}_{(i,1)}, \mathrm{IMF}_{(i,2)}, \cdots, \mathrm{IMF}_{(i,K)} \right\}$ and a residual component $r_i(t)$.

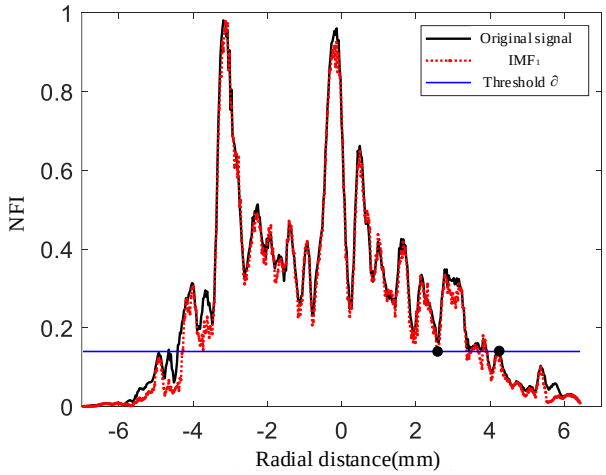

Figure 1. The comparison between NFI of IMF1 and original signals

(c) Fluctuation indexes (FIs) of $\mathrm{IMF}_{(i,k)}$ are calculated as,

$$FI_{(i,k)} = \frac{1}{t}\sum_{1}^{t-1}\left|b(t+1)-b(t)\right| \tag{9}$$

where T is the number of time sampling points of IMF components. $b(t)$ is signal strength of the t-th time sampling point. The NFI is obtained by normalizing the FI,

$$NFI_{(i,k)} = \frac{FI_{(i,k)} - FI_{min}}{FI_{\max} - FI_{min}} \tag{10}$$

where $FI_{\max}$, $FI_{\min}$ represent the largest and the smallest NFI, respectively.

(d) The $NFI_{(i,1)}$ of each IMF_1 is calculated to compared with NFI-threshold ∂ for determining whether the current detection position belongs to the center area of blood flow or the marginal area of blood flow. That yields result of threshold determination results $\phi_{(i)}$ as following,

$$\phi_{(i)} = \begin{cases} 1, NFI_{(i,1)} \geq \partial; \\ 2, NFI_{(i,1)} < \partial; \end{cases} \tag{11}$$

when $\phi_{(i)}$=1, BFDSs belong to the center area of blood flow, and when $\phi_{(i)}$=2 , the signals belong to the marginal area of blood flow.

(e) BFDSs are in a hypoechoic region. Its low amplitude is easy to be disturbed by noise. There will be misjudged after using equation (11), such as P_1 and P_2 in Figure 1. In order to reduce the misjudgment, signals around a certain area S_0 are taken to be detected. It can improve accuracy of using threshold to divide the center area of blood flow or the marginal area of blood flow. The S_0 is defined as the judged region. The spatial position of the signal to be judged are taken as the center of S_0 . Mean value $\overline{NFI_{(i)}}$ of NFIs from all signals in judged region is calculated as follows,

$$\overline{NFI}_{(i)} = \frac{1}{m}\sum_{i-\left[\frac{m}{2}\right]}^{i+\left[\frac{m}{2}\right]} NFI_{(i)}, 1+\left[\frac{m}{2}\right] < i < I-\left[\frac{m}{2}\right] \tag{12}$$

where m is the number of all signals in S_0 .

(f) The signals that belong to the the center area of blood flow or the marginal area of blood flow are judged by comparing $\overline{Nf}_{(i)}$ and ∂ as follows,

$$\phi_{(i)} = \begin{cases} 1, \overline{NF}_{(1,\ i)} \geq \partial; \\ 2, \overline{NF}_{(1,\ i)} < \partial; \end{cases} \tag{13}$$

(g) Formula of BFDSs $f_{\mathrm{imfd}(i)}$ is judged with ∂ as follows,

$$f_{\mathrm{imfd}(i)} = \begin{cases} \phi_{(i)} = 1, \mathrm{IMF}_{(i,1)}; \\ \phi_{(i)} = 2, \mathrm{IMF}_{\min}; \end{cases} \tag{14}$$

where IMF_{min} is IMFs with smaller NFIs are selected between IMF_2 and IMF_3.

(h) Blood flow velocity formula of the EEMD_N method is calculated by putting $f_{\mathrm{imfd}(i)}$ into Doppler frequency shift formula as follows,

$$v_{(i)} = \frac{cf_{\mathrm{imfd}(i)}}{2 f_0 cos\theta} \tag{15}$$

III. EXPERIMENTS AND RESULTS

A. Carotid artery blood flow model

Blood flow velocities of human body change with heart beat as shown in Figure 2. Therefore, the change of blood flow velocities (i.e. the maximum blood flow velocities $v_{\max}$) on central line of vascular lumen changes with time. Overall BFVPs in blood vessel show a parabolic distribution from upper to inferior vessel walls. Blood flow velocities will decrease until it approaches zero when they approach vessel walls. The formula of blood flow velocity parabola is as follows,

$$v_r = v_{\max}(1-\frac{r^2}{R^2}) \tag{16}$$

where r is radial distance of blood flow and R is geometric radius of blood vessel.

B. BFDS

BFDSs are obtained by use Field II ultrasound simulation software to scan the carotid artery blood flow model. Doppler acoustics and transducer parameters during scan are shown in Table 1. F-point, which shown in Figure 2, has the fastest change of BFDSs and the most significant nonstationarity signals. Therefore, the BFDSs of F-point are selected for simulation experiment. The BFDSs of 20 time sampling points were extracted on 100 detection positions of vascular lumen. The EEMD method is used to process BFDSs. Auxiliary noise intensity is 0.2 and 300 times of Gaussian white noise are added in decomposition. A Doppler signal of the center area of blood flow were decomposed by the EEMD method in Figure 3. The result shows that IMFs are arranged in order from high to low frequency. IMF_1 are composed of high-frequency signals and main components of original signals. IMF_2 and IMF_3 are mainly composed of low-frequency signals.

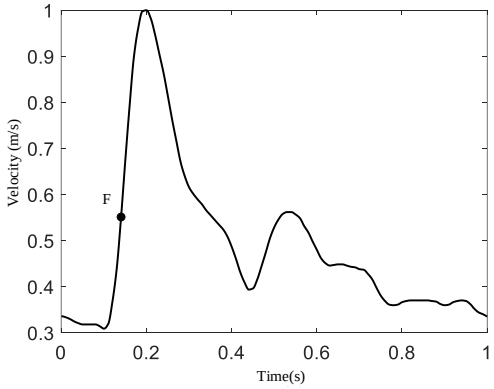

Figure 2. The pulsating blood flow velocities of human body

C. *Optimal rate of judged region (RJR) and NFI-threshold*

The accuracy of BFVP measured by the EEMD_N method is closely related to two key parameters judged region and NFI-threshold. Normalized root mean square error (NRMSE) between standard BFVP and the measurement result of the EEMD_N method in F-point are calculated to find optimal RJR and NFI-threshold. Figure 4 shows the average NRMSE under different the RJR and NFI-threshold. The optimal threshold of NFIs are found by using Fourier function fitting method. The results show that BFVP measured by the EEMD_N method is more accurate according to the smallest NRMSE value when $RJR = 13.6\%$ and $\partial = 0.14$. Consequently, $RJR = 13.6\%$ is optimal RJR, $\partial = 0.14$ is optimal NFI-threshold.

Table 1. Parameters used in computer simulation of blood vessel model

Type	Parameter	Value
Blood vessel model	Geometric radius [mm]	5
	Length [mm]	80
	Width [mm]	10
	Height [mm]	10
	Doppler angle [°]	45°
Doppler acoustic	Center frequency [MHz]	5.0
	Pulse repetition frequency [kHz]	6.7
	Sample frequency [MHz]	100
	Sound velocity [m/s]	1540
	Wavelength [m]	3.08×10^{-4}
Transducer	Type	Linear array
	Number of elements	128
	Array element spacing [m]	0.5×10^{-3}
	Array element width [m]	5.133×10^{-4}
	Array element depth [m]	5×10^{-3}

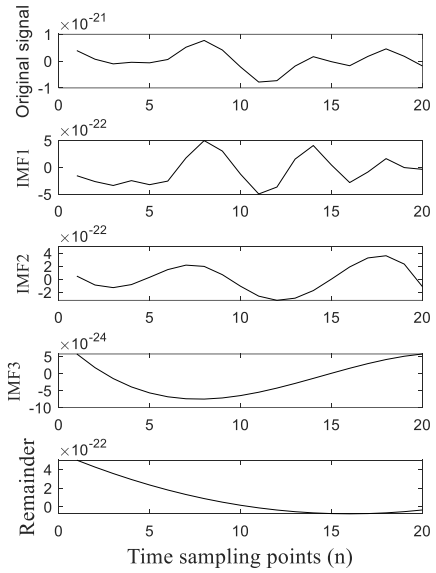

Figure 3. A Doppler signal decomposed by the EEMD method.

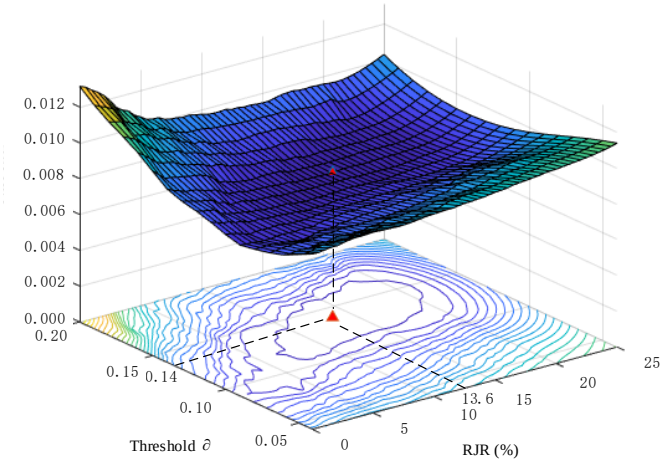

Figure 4. The comparison of Average NRMSE between RJR and NFI-threshold

D. *Result*

NRMSEs of BFVP measured by the EEMD_N method were reduced by 24.46 % in comparison with these calculated by the traditional STFT method. In general, the traditional STFT method directly calculates blood flow velocities using the original signals. Figure 5 shows the comparison of BFVP of the traditional STFT method and the EEMD_N method in F-point when using the optimal RJR and NFI-threshold. It can be seen from Figure 5 that the EEMD_N method can effectively improve blood flow velocities distribution in the marginal area of blood flow and improve the detection accuracy of low-speed blood flows closed to vessel walls.

IV. CONCLUSION

The EEMD_N method based on EEMD method can overcome the limitations of traditional methods in dealing with non-stationary blood flow signals. And it can solve the problem of low accuracy of blood flow from traditional time-frequency analysis method. From IMF groups decomposed by the EEMD method, NFIs of IMFs are calculated to choose the decomposed blood flow signals by NFI threshold. Finally, blood flow velocities are computed by the Doppler frequency shift formula. Simulated results imply that NRMSEs of BFVP measured by the EEMD_N method were reduced by 24.46 % in comparison with these calculated by the traditional STFT method. The EEMD_N method can measure low velocity blood flow near vessel walls more accurate. However, the real-time performance of the method will be greatly limited because N is required to be large enough to eliminate the interference of white noise, which will result in longer decomposition time. Secondly, EEMD_N has no significant improvement on blood flow velocities in the center area of blood flow compared with the traditional method. Therefore, The EEMD_N method could to be improved. How to solve these two problems is the focus of next step.

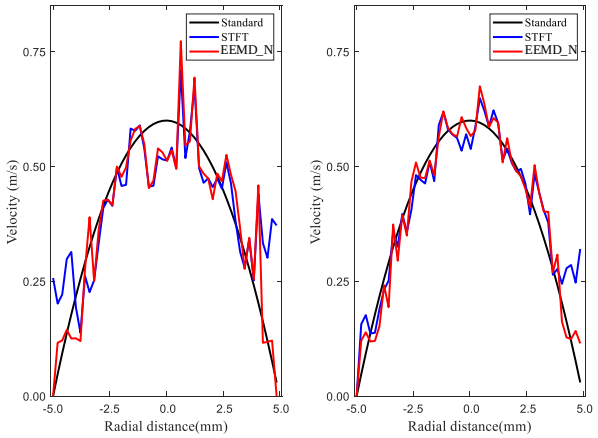

Figure 5. The comparison of BFVPs between the EEMD_N method and the STFT method

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