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Performance improved method for subtracted blood volume spectrometry using empirical mode decomposition

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Abstract. Subtracted blood volume spectrometry (SBVS) can eliminate the background information in near infrared spectroscopy (NIRS) noninvasive biochemical sensing. However, the spectrum obtained by this method is accompanied by serious noises which are to the disadvantage of the calibration models. Empirical mode decomposition (EMD) was applied to restrict the noises in order to improve the performance of subtracted blood volume spectrometry. Certain criteria were used to evaluate the performance of the method, such as the average correlation coefficient, and the average and standard deviation of the Euclidean distance. EMD was applied to three subtracted spectra with different ΔL, and the criteria were calculated accordingly. All of the criteria were improvement. Especially for the subtracted spectra with ΔL=0.5mm, the correlation coefficient increased from 0.9970 to 0.9999, the average Euclidean distance decreased from 0.0265 to 0.0118, and the standard deviation of the Euclidean distance decreased from 0.0148 to 0.0033 after EMD filtering. The PLS models of the processed spectra were promoted as well. These preliminary results suggest that EMD is a promising means of improving the performance of subtracted blood volume spectrometry.

Keywords: Near-infrared spectroscopy, noninvasive biochemical sensing, subtracted blood volume spectrometry, empirical mode decomposition

1. Introduction

Biochemical blood test is an important means of determining the functions of human body, and also crucial in the diagnosis and prevention of some diseases. Conventional biochemical analysis requires needle jabs to test blood biochemical indices, which is painful and inconvenient. This method also poses some hidden dangers, such as infection [1]. Fortunately, NIRS has the advantages of no pain, safety in use, no reagents, and allows real-time monitoring. Since the 1990s, NIR has been an intriguing concept for noninvasive biochemical sensing and has simulated research in this field [2-5]. However, it is quite difficult to achieve results due to the extremely weak effective signal, strong and varied background of human tissue [6].

Theoretically, SBVS [7] is able to eliminate the background interferences, and obtain effective spectrum of blood. During extremely short periods of time (seconds), human's physiological state,

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including the background of human tissue and blood biochemical indices, barely changes. However, due to pulsation, blood volume changes all the time. Therefore, information on certain-volume blood spectrum can be obtained and the background interferences can be eliminated by subtracting two blood spectra measured during this short period. When the blood spectrum is obtained without background interferences, noises are more evident for the decreasing absorbance by subtracting spectra. This makes the calibration models ineffective. Therefore, it is important to restrict serious noise which exists in the subtracted spectra.

Since the collecting time of the spectral interval lasts only for seconds, it could be supposed that the background interferences generated by the human body remain unchanged. Therefore, a series of optical filters were selected by the authors, which had certain features of absorption in the near-infrared band, of simulating the background interferences of human tissue. The performance of SBVS was analyzed, and EMD filtering was then adopted to suppress the noise in the subtracted spectra. To evaluate the effect of spectra subtraction, criteria such as average related correlation coefficient(R), mean ($\overline{D}$) and standard deviation (δ) of the Euclidean distance between subtracted spectra and their mean spectra were applied. Further analysis of the effect of EMD on SBVS was made using partial least squares (PLS) to establish the calibration model. Through the filtering processes, the effect of spectra subtraction was promoted. It was proved that EMD filtering had an apparent advantage in promoting the performance of SBVS.

2. Materials and method

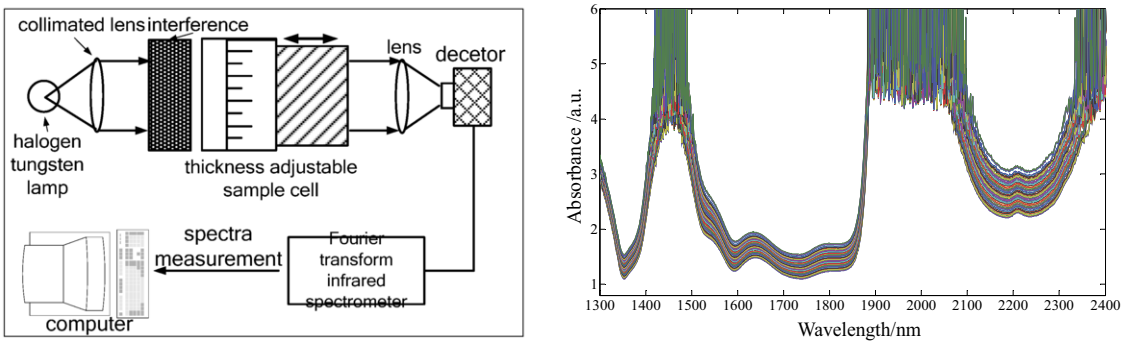
2.1. Sample preparation

As the scattering properties, absorption properties and anisotropic factor of intralipid are similar to the optical parameters of biological tissue, intralipid have been used as biological organization simulation solutions by many scholars [8,9]. In this study, a 2% intralipid was used to prepare the samples. In the experiment, a total of 37 samples were prepared with glucose concentrations ranging from 106mg/dL to 1501mg/dL.

2.2. Spectroscopic measurement

In order to simulate SBVS, several optical filters with different absorption peaks were used to insert into the optical path and imitate the background interferences for the stability of human body over a short period of time, as shown in Figure 1(a). Then, a series of spectra with different pathlength were measured for each sample by tuning the thickness of the adjustable sample cell through which the sample pathlength could be varied from 0.05mm to 0.6mm with 0.05mm intervals. Finally, 444 spectra with the same interference, different glucose concentrations and different pathlength were obtained.

The NIR spectra of all samples at different pathlength were recorded using a Nicolet 6700 Fourier transform infrared spectrometer. All spectra were measured in the region 1300-2400nm by an average of 32 scans at a resolution of 8cm^{-1} using OMNIC software. Figure 1(b) shows the 444 spectra with the same interference. In order to avoid the broad and strong water absorption bands at 1450 and 1920nm, it was theoretically possible to use the combination region and the first overtone region [10]. Compared with the combination frequency region, the first overtone band (1600-1800nm) had a high signal to noise ratio and an appropriate absorbance. In addition, glucose exhibited three absorption bands in this region: 1610, 1690, and 1730nm [11]. Thus, the analysis band was determined at 1600-1800nm in this study.



(a) (b)

Fig. 1.Spectroscopic measurement method and equipment.(a)Diagrammatic sketch of the experimental system; (b) 444 near infrared spectra of intralipid with different glucose concentrations at different pathlength.

2.3. Subtracted blood volume spectrometry

A simplified model of SBVS which was comprised of three compartments was used in this work: background interference, same and different part (ΔL=L2-L1) of the sample with pathlength of L1 and L2, respectively. The background interference indicated the bloodless tissue and veins at positions in the human body. The arterial blood volume changed in a pulsatile manner throughout the cardiac cycle, thereby producing small changes in the transmitted intensity. Similarly, samples with pathlength of L1 and L2were used to simulate different volumes of arterial blood. A light source with incident radiation intensity I_0 irradiated the system. Combined with absorption and scattering afterwards in each compartment, the transmitted radiation intensity I_f, I_{L1} and I_{L2}were obtained. The absorbance of each part can then be calculated as follows:

$$A_{L1} = lg\left(\frac{I_{L1}}{I_0}\right) \tag{1}$$

$$A_{L2} = lg\left(\frac{I_{L2}}{I_0}\right) \tag{2}$$

Subtracting A_{L1} from A_{L2}, the spectra at ΔL pathlength without background interference was obtained,

$$A_{L2} - A_{L1} = lg\left(\frac{I_{L2}}{I_0}\right) - lg\left(\frac{I_{L1}}{I_0}\right) = lg\left(\frac{I_{L2}}{I_{L1}}\right) = A_{\Delta L} \tag{3}$$

2.4. Empirical mode decomposition

EMD [12], which is an important part of Hilbert-Huang Transform (HHT), can eliminate the noises in a signal. It decomposes the signal into a finite number of intrinsic mode functions (IMFs), by their characteristic time scales. Noises are then reduced by removing the IMFs partly through setting an appropriate threshold which contains most of the noises. As the IMFs are adaptive, they usually provide a physically meaningful representation of the processes. EMD is a fully data-driven method that does not need any predetermined information to process the signal. Therefore, EMD is ideally suited for analyzing non-stationary and nonlinear data sets. Given the merits mentioned above, EMD has been extensively applied to detect signal trends, singular points, filtering and characteristic

frequencies in recent years, such as the acquisition of gravity wave characteristics [13], the extraction of solar cycle [14] and ECG peak detection [15, 16]. EMD filtering is adaptive, therefore highly efficient at restricting the noise and identifying useful information in SBVS, even those with small amplitudes.

2.5. Assessment criteria

In order to evaluate the performance of the subtracted spectra before and after EMD filtering, a series of assessment criteria were proposed, such as the average related correlation coefficient (R), mean ($\overline{D}$) and standard deviation(δ) Euclidean distance between subtracted spectra and their mean spectra. The Euclidean distance between subtracted spectra and their mean spectra are defined as follows:

$$D(x_i) = \sqrt{\sum_\lambda \left| x_{\lambda,i} - \bar{x} \right|^2}, i \in n \tag{4}$$

Where x and $\bar{x}$ are the subtracted spectra and mean spectra, respectively. The R, $\overline{D}$ and δ can then be calculated using the following formulas:

$$R = \frac{2}{n(n-1)} \sum_{i,j} \frac{\sum_\lambda (x_{\lambda,i} - \overline{x_{\lambda,i}})(x_{\lambda,j} - \overline{x_{\lambda,j}})}{\sum_\lambda (x_{\lambda,i} - \overline{x_{\lambda,i}})^2 \sum_\lambda (x_{\lambda,j} - \overline{x_{\lambda,j}})^2}, (i, j \in n, i \neq j) \tag{5}$$

$$\overline{D} = \frac{1}{n} \sum_{i=1}^{n} D(x_i), i \in n \tag{6}$$

$$\delta = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [D(x_i) - \overline{D}]^2}, i \in n \tag{7}$$

3. Results and discussion

According to Eq. (3), the spectra with the same glucose concentration and background interference were subtracted, and also a number of pure spectra of intralipid with glucose at ΔL pathlength were obtained. As shown in Figure2, a series of spectra with ΔL of 0.8mm were obtained. It was plausible that the interferences generated by filters were eliminated, and the subtracted spectra were similar to the pure spectra.

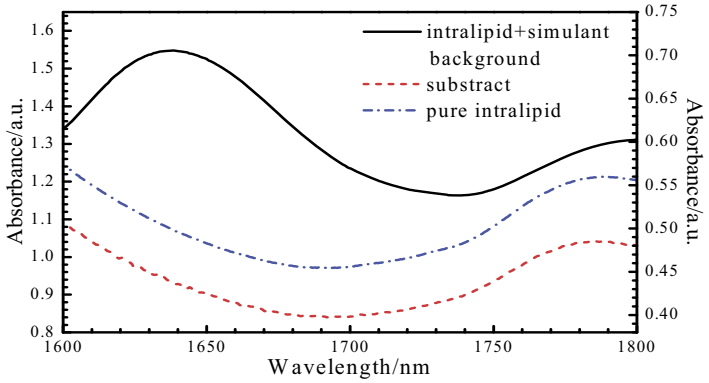
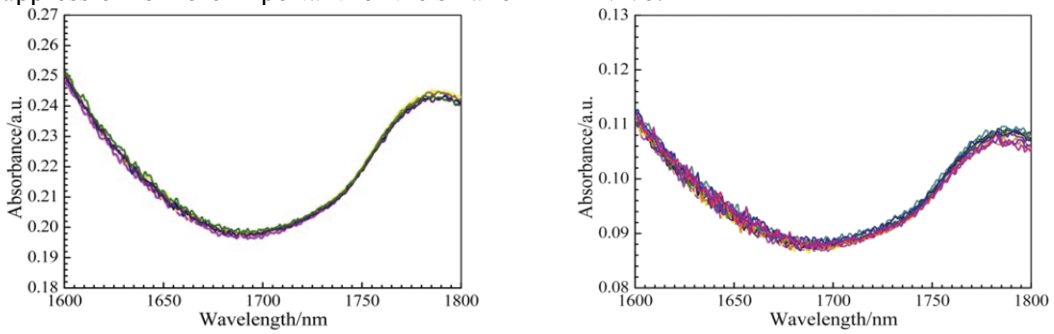


Fig. 2. Results of spectra subtracted (dash-right axis represents the subtracted spectra; dash dot-right axis represents the pure spectra; solid-left axis represents the spectra with interference)

With diminishingly ΔL, the noise in the subtracted spectra was more obvious. As shown in Figure3, the spectra with ΔL=0.5mm is smoother than those with ΔL=0.2mm. It was because the noise from the instrument and environment was roughly equal. The signal decreased in accordance with decreasing ΔL. Hence, with a smaller ΔL, the signal to noise ratio was lower. In biochemical sensing, noise suppression is more important for the smaller ΔL in vivo.



(a) ΔL=0.5mm (b) ΔL=0.2mm

Fig. 3. Subtracted spectra with different pathlength using SVBS.

In this study, EMD filtering was applied to eliminate noise in the subtracted spectra. One of the subtracted spectrum with Δ*L*=0.5mm which was processed by EMD filtering is shown in Figure 4. The spectrum was then decomposed into four IMFs, which represented the characteristic of the spectrum, and the residual. From IMF1 to IMF4, the frequency of the signal which reflected the noise reduced gradually. It was necessary to eliminate the noise in each IMF using the threshold acquired by their characteristic. In this study, adaptive threshold selection strategy [17] was used to separate the signal and noise. The threshold is defined as Eq. (8),

$$thr = \theta\sqrt{2log(N)} \tag{8}$$

Where *N* is the size of the wavelet coefficient arrays and is the noise standard deviation.

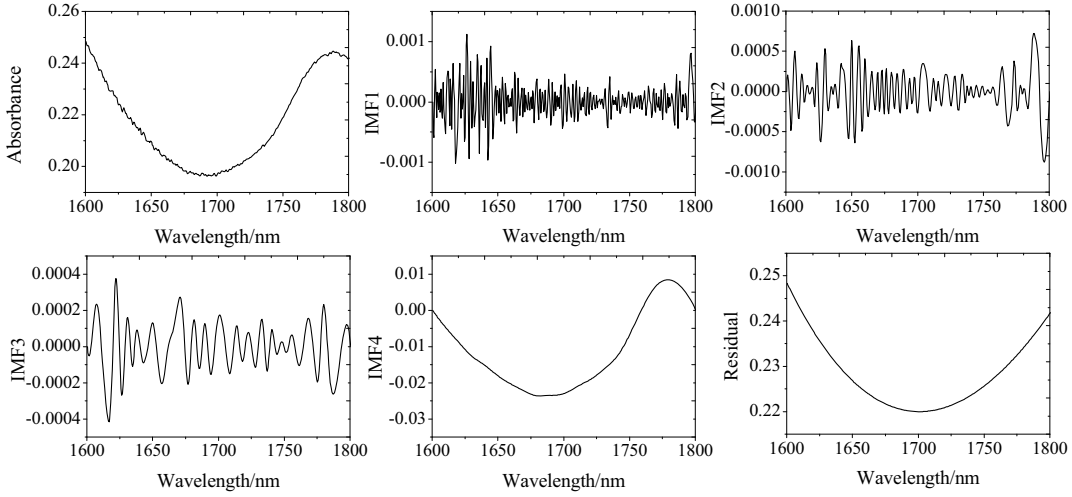


Fig. 4. EMD filtering of the subtracted spectrum with ΔL=0.5mm

The assessment criteria mentioned above were calculated before and after EMD processing. As shown in Table 1, for the subtracted spectra with ΔL=0.5mm, R increased from 0.9970 to 0.9999, decreased from 0.0265 to 0.0118, and from 0.0148 to 0.0033 after EMD processing. All of the three criteria were improved, especially $\overline{D}$ and δ. Similar results were obtained when ΔL=0.3mm and 0.2mm.

Finally, an in-depth analysis of the effect of EMD on SVBS and the calibration models of glucose were calculated using partial least squares (PLS) which was a multivariate calibration method in NIRS. The characters of the models such as regression coefficient, root mean square error of calibration (RMSEC) and root mean square error of cross validation (RMSECV) [18] are also shown in Table 1. It can be seen that, all of these characters are better with EMD filtering than without EMD filtering. These preliminary results suggest that EMD filtering is a promising means of improving the performance of SVBS. For the practical application of SVBS in noninvasive biochemical sensing, large ΔL, which can be realized using "Occlusion Spectroscopy" [19] or other methods, is better for obtaining good results.

Table 1

Comparison of performance before and after EMD filtering with different ΔL

	Method	R	$\overline{D}$(a.u.)	δ(a.u.)	Calibration model		
					Regression Coefficient	RMSEC (mg/dL)	RMSECV (mg/dL)
ΔL=0.5mm	Raw	0.9970	0.0265	0.0148	0.9790	50.65	80.73
	EMD	0.9999	0.0118	0.0033	0.9813	36.72	56.44
ΔL=0.3mm	Raw	0.9930	0.0186	0.0114	0.9633	61.33	87.25
	EMD	0.9958	0.0152	0.0056	0.9712	41.81	76.26
ΔL=0.2mm	Raw	0.9900	0.0164	0.0065	0.9615	65.98	89.07
	EMD	0.9934	0.0136	0.0042	0.9702	44.36	79.96

4. Conclusion

EMD filtering was used to improve the performance of SVBS in NIR non-invasive biochemical detection. EMD filtering was successful in simultaneously eliminating the noise and enhancing the effective information. The performance of the calibration models which was established by the subtracted spectrum was promoted obviously after EMD filtering. Furthermore, the filtering process is simple, fast and inexpensive, due to the adaptive algorithm. This study provides both a theoretical and experimental basis for the application of SVBS in the field of noninvasive biochemical sensing. These findings also set the stage for the practical application of SBVS.

5. Acknowledgment

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