Investigating complex patterns of blocked intestinal artery blood pressure signals by empirical mode decomposition and linguistic analysis

Jia-Rong Yeh[1], Tzu-Yu Lin[1,2], Jiann-Shing Shieh[1], Yun Chen[2], Norden E. Huang[3], Zhaohua Wu[4], Chung-Kang Peng[5]

[1] Department of Mechanical Engineering, Yuan Ze University, 135 Far-East Road, Chung-Li, Taoyuan, Taiwan , R.O.C.

[2] Far Eastern Memorial Hospital, Taiwan, R.O.C.

[3] Research Center for Adaptive Data Analysis, National Central University, Taiwan

[4] Center for Ocean-Land-Atmosphere Studies, USA

[5] Beth Israel Deaconess Medical Center, Harvard Medical School, USA

Email: s939205@ mail.yzu.edu.tw

Abstract. In this investigation, surgical operations of blocked intestinal artery have been conducted on pigs to simulate the condition of acute mesenteric arterial occlusion. The empirical mode decomposition method and the algorithm of linguistic analysis were applied to verify the blood pressure signals in simulated situation. We assumed that there was some information hidden in the high-frequency part of the blood pressure signal when an intestinal artery is blocked. The empirical mode decomposition method (EMD) has been applied to decompose the intrinsic mode functions (IMF) from a complex time series. But, the end effects and phenomenon of intermittence damage the consistence of each IMF. Thus, we proposed the complementary ensemble empirical mode decomposition method (CEEMD) to solve the problems of end effects and the phenomenon of intermittence. The main wave of blood pressure signals can be reconstructed by the main components, identified by Monte Carlo verification, and removed from the original signal to derive a riding wave. Furthermore, the concept of linguistic analysis was applied to design the blocking index to verify the pattern of riding wave of blood pressure using the measurements of dissimilarity. Blocking index works well to identify the situation in which the sampled time series of blood pressure signal was recorded. Here, these two totally different algorithms are successfully integrated and the existence of the existence of information hidden in high-frequency part of blood pressure signal has been proven.

1. Introduction

Acute intestinal ischemia as the result of a sudden cessation of mesenteric arterial blood flow is an abdominal catastrophe that carries high morbidity and mortality rates [1]. The poor outcomes of this disease process are caused by the delay in initiating therapy because of difficulties in making an accurate and timely diagnosis [2-5]. In this investigation, we tried to obtain more understanding for mesenteric arterial embolus and thrombus by blood pressure signal. Thus, as a fundamental study, we conducted experimentally surgical operations on two young and healthy pigs to generate the blood pressure signal under designed situations. We also surveyed two innovative digital signal processing and analysis algorithms to provide us with more understanding for the change of blood pressure signal during the designed process.

Recently, empirical mode decomposition (EMD) has been proposed as an innovative method applied to decompose intrinsic mode functions (IMF) from a complex time series [6]. Also, Hilbert transform has been applied to calculate the instantaneous frequency and amplitude of IMFs. The integrated analysis algorithm of EMD and Hilbert transform is named as Hilbert Huang transform (HHT). HHT can be applied to identify the components of the wave spectra [9] and to extract the characteristic and components of signals [10, 11].

Because of the sensitivity of cubic spline, edge effects damage the performance of decomposition [6]. Another serious drawback of the original EMD is the phenomenon of intermittence. Wu and Huang proposed a new noise-assisted data analysis (NADA) method [15] to overcome the phenomenon of intermittence and named it ensemble EMD (EEMD). In this investigation, we found the NADA method causes the residue of added white noises on the decomposed IMFs. For the purpose of removing the residue of added white noises, we modified the EEMD method by using the complementary sets of added white noises to remove residue of added white noises. This modified EEMD named as complementary EEMD (CEEMD) was also developed as a new technique to overcome intermittence. Furthermore, Monte Carlo verification method was applied to verify the significant IMFs in previous study [13]. The main wave of blood pressure signal can be reconstructed by those significant IMFs. IMFs with higher frequencies can be reassembled as the riding wave.

A measurement of similarity between two complex time series was proposed by Yang et al. in 2003 [14]. The method of constructing phylogenetic trees is also applied to arrange different groups of samples on a branching tree to best fit the pair-wise distance measurements. In this study, we extended the method of constructing phylogenetic trees to present the distances among riding waves of blood pressure signals in situations of artery clamping and relaxing for different objects. We assumed that the weighted distance is linear scale and define the blocking index as the difference between non-clamping and non-relaxing indexes. Moreover, this novel blocking index was applied to verify the pattern of time series of blood pressure signal in situation of artery clamping or relaxing.

2. Methdology

2.1. Extracting main wave of blood pressure signal by EMD

The EMD method uses the envelopes defined by the local maxima and minima separately. A cubic spline was applied to connect the identified extrema (e.g. maxima and minima) as envelopes. The difference between data and the mean of envelopes is the decomposed component. The process starts to identify the extrema and ends at obtaining the component called a sifting process. A sifting process should repeat until the component satisfies two conditions [6]: (1) in the whole time series, the difference between numbers of extrema and zero-crossing must equal to zero or one; (2) at any point, the mean value of upper and lower envelopes is zero. When the component satisfies these two conditions it is named an intrinsic mode function (IMF) and noted by c_1. The nth residue noted by r_n and treated as the data for decomposing next IMF. The decomposing process should be repeated to find the nth IMF until the residue becomes monotonic. The original data can be reconstructed by the summation of n IMFs and the nth residue and expressed as follow:

$$X(t) = \sum_{i=1}^{n} c_i + r_n . \tag{1}$$

where $X(t)$ is the original data; c_i is the ith IMF; and r_n is the nth residue.

Couglin et al. mentioned the influence of the end point is a difficulty for EMD [13]. Because of the sensitivity of cubic splines applied for calculating envelops, edge effects happen on the end points and propagate into the interior solution. In this study, we deal with this problem by wave extension method proposed by Couglin et al. Furthermore, in practical applications of EMD, unpredictable and small fluctuations appear in complex time series intermittently and cause the shifting of IMFs. It is named as phenomenon of intermittence. Thus, Li et al. proposed a new filtering method to pre-treats the original data by wavelet to avoid phenomenon of intermittence [10]. On the other hand, Wu [7] and Huang et al. [8] found that EMD is effectively a dyadic filter based on numerical experiments on white noise using EMD method. So, Wu and Huang [15] proposed the ensemble EMD (EEMD) using a noise-assisted data analysis method to overcome the phenomenon of intermittence. For EEMD, the residue of added white noises will be diminished by adding more white noises to produce the averaged IMFs. In fact, it is hard to clear the residue of added white noises. Here, we added 1000 white noises for EEMD to evaluate residue of added white noises. Residue of added white noises is separated by subtracting the reconstructed signal by the original signal. In Fig.1, we found the residue of added white noises is still clear. Thus, we propose a modified EEMD method named complementary ensemble empirical mode decomposition (CEEMD) to eliminate the residue of added white noises.

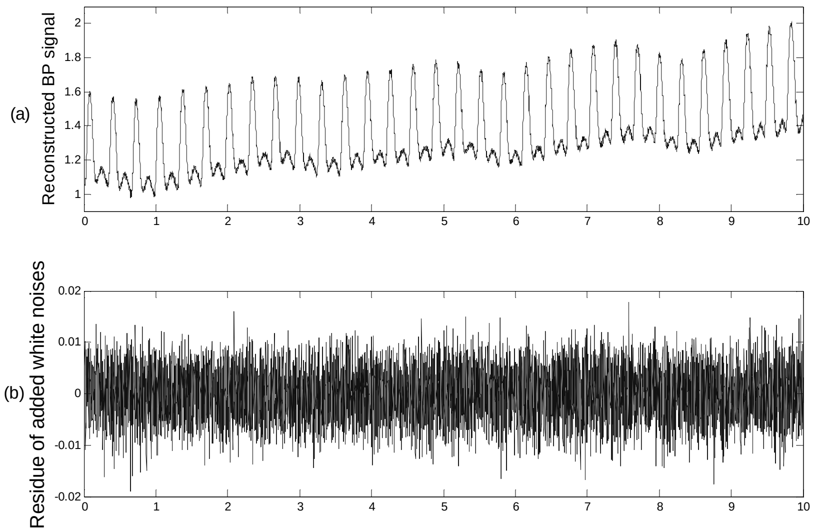

Figure 1. The reconstructed blood pressure signal and residue by EEMD using 1000 added white noises. (a) Reconstructed the blood pressure signal is derived by the summation of the averaged IMFs and residue of original signal after 1000 times of adding white noises to the original signal. (b) Residue of added white noises is the difference between the reconstructed and original blood pressure signals.

CEEMD extents the concept of EEMD method by generating two sets of averaged IMFs, averaged IMFs with positive and negative residues of added white noises. In the process of CEEMD, 20 arbitrary white noises were chosen for added white noises because a single white noise cannot solve all intermittent signals. We produced two mixtures of the original signal and added white noise by following equation:

$$\begin{bmatrix} M_1 \\ M_2 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} S \\ N \end{bmatrix} \tag{2}$$

where, S is the original signal; N is the added white noise; M_1 is the positive mixture and M_2 is the negative mixture. The averaged IMFs decomposed from positive mixtures are the averaged IMFs with positive residue of added white noises. Similarly, the averaged IMFs with negative residue of added white noises are obtained. Then, the averaged IMFs without added residue of white noises can be derived by the following equation.

$$\begin{bmatrix} IMF_s \\ IMF_N \end{bmatrix} = inv\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} IMF_p \\ IMF_n \end{bmatrix} \tag{3}$$

where IMF_p is the averaged IMF with positive residue of added white noises; IMF_n is the averaged IMF with negative residue of added white noises; IMF_S is the averaged IMF without the residue of added white noises; IMF_N is the part of averaged IMF contributed by the added white noises.

The averaged IMF without the residue of added white noises is the final result of CEEMD. Now, we need to reconstruct the main wave of blood pressure signal. The key issue of reconstruction is which IMFs are the main components of blood pressure signal. Here, this problem was dealt with by Monte Carlo verification. Then, we find the IMFs 4-7 are the significant components of blood pressure signal and that the eighth IMF and residue contribute the trend of original signal.

2.2. Monte Carlo verification and signal reconstruction

The averaged IMF without the residue of added white noises is the final result of CEEMD. When we try to reconstruct the main wave of blood pressure signal, the key problem is which IMFs are the main components of blood pressure signal. Here, this problem is dealt with by Monte Carlo verification. In the study of the characteristics of white noise using EMD, the product of energy density and its corresponding averaged period is a constant. For a normalized white noise, the distribution of energy density-correspondent averaged period of IMFs should locate around the diagonal of Monte Carlo plot [7, 13]. For a normalized signal with significant components, the dot represents the relationship between the energy density and averaged period of a significant IMF should locate on the area above the diagonal. So, we can recognize the significant components by the location of averaged period – energy density plot. In Fig.2 the first eight IMFs of blood pressure signal are shown. Then, the IMFs 4-7 are recognized as the significant IMFs of blood pressure signal. Then, the main wave of blood pressure signal can be reconstructed by summing the IMFs 4-7.

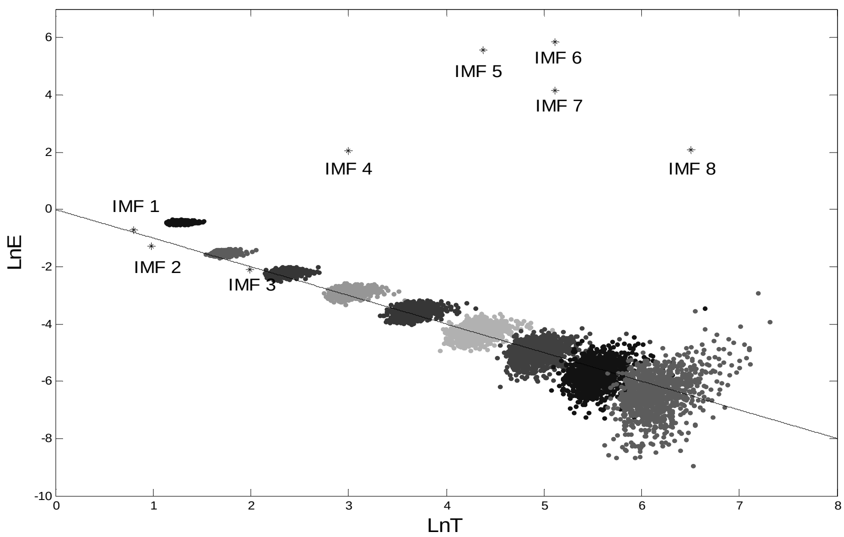

Figure 2. Monte Carlo verification of the relation between the energy density and the averaged period.

2.3. Definition of blocking index

Based on the method of linguistic analysis proposed by Yang et al. [14], we considered that a blood pressure time series, $\{x_0,x_1,x_2,\ldots,x_N\}$, where x_i is the voltage value of the ith sampling point of blood pressure recording. The complex time series can be simplified to binary sequences by a mapping process, where an increase and decrease of voltage values are denoted by 1 and 0. This mapping can be expressed as below:

$$I_n = \begin{cases} 0, & \text{if } x_n \leqq x_{n-1}, \\ 1, & \text{if } x_n > x_{n-1}, \end{cases} \tag{4}$$

When a complex time series signal is simplified via mapping to binary series, the complex analog patterns are transformed to digital patterns. Digitalized patterns are convenient for us to characterize the pattern by a word. By shifting one sampling point at a time, a collection of 8-bit words over the whole time series is derived. This collection contains 256 different digital patterns and their occurrences frequencies. Thus, we obtain the ranks of frequency distribution. This set of ranks of words represents the statistical hierarchy of symbolic words of the original time series.

To define a measurement of similarity between two time series, a weighted distance, D_m, between two symbolic sequences, S_1 and S_2, can be expressed as below [14]:

$$D_m(S_1, S_2) = \frac{\sum_{k=1}^{2^m} \left| R_1(w_k) - R_2(w_k) \right| \cdot p_1(w_k) p_2(w_k)}{\left(2^m - 1\right) \sum_{k=1}^{2^m} p_1(w_k) p_2(w_k)} \tag{5}$$

where $p_i(w_k)$, and $R_i(w_k)$ represent the occurrence frequency and the rank of a specific word, w_k, in time series S_i, $i=1$ or 2.

Two time series with similar patterns of fluctuations have similar probabilities and ranks of words, and result in a smaller distance. Then, we can define the non-clamping and non-relaxing indexes are the distance of similarity between a pattern of a section of time series and the referent patterns of artery clamping or relaxing. Two pairs of referent patterns were extracted from the recording of the first and the second surgical operation. Method of constructing phylogenetic trees is applied to present the results of comparisons among these referent patterns. In Fig. 3, the straightened phylogenetic tree shows the relationship of similarity measurements among these four referent patterns.

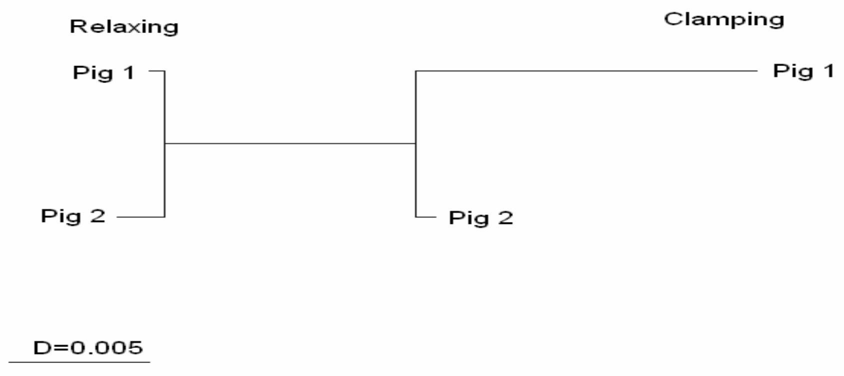

Figure 3. The straightened phylogenetic tree constructed according to the measurements of similarity for four referent patterns.

Here, we tried to design a factor (i.e., blocking index) for identifying the situation of blood flow. Based on the observation in this investigation, weighted distance between two extreme situations for the same object is close to the summation of non-clamping and non-relaxing indexes and the summations are different for diverse objects. For the purpose to reduce the effect of intra-object difference and normalize the index, blocking index should be divided by the summation of non-clamping and non-relaxing indexes. So, the blocking index can be expressed below:

$$I_B = \frac{(I_{NR} - I_{NC})}{(I_{NR} + I_{NC})} \quad (6)$$

where I_B means the blocking index; I_{NR} is non-relaxing index; and I_{NC} is non-clamping index.

3. Results & Discussions

Fig. 4 shows the results of the pattern analysis for the riding wave with high frequency by blocking index. Fig. 4(a) shows the original time series of blood pressure signal and Fig. 4(b) shows the results of blocking indexes using different referent patterns. The black line shows the blocking index calculated by referring the baseline extracted from the first surgical operation. And, the gray line shows the blocking index calculated by the second baseline. The pattern analysis by blocking is clearly dependent on the baseline we use. When the recording of signal and the applied baseline are measured on the same subject, the blocking index is more sensitive.

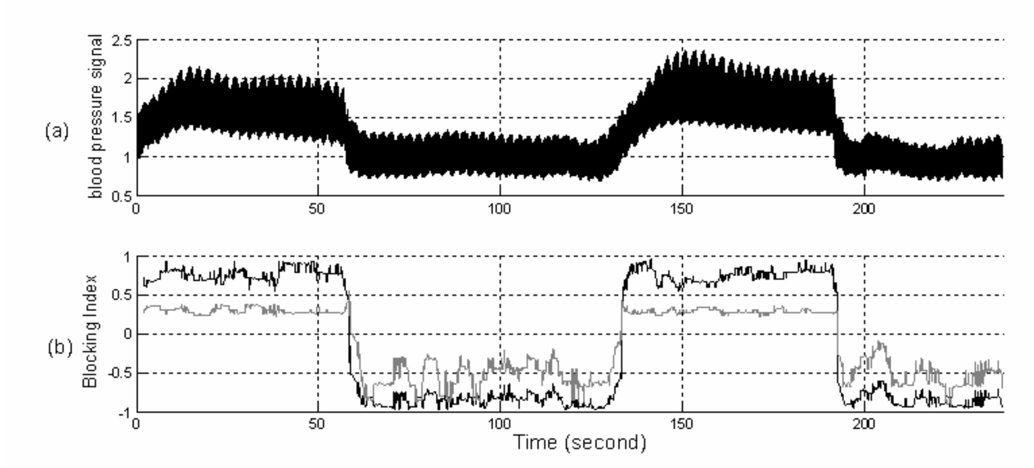

Figure 4. The original blood pressure signal and the results of pattern analysis by blocking indexes using two different baselines. (a) The original blood pressure signal. (b) The results of pattern analysis by blocking indexes using two different baselines.

4. Discussions and limitations

In this investigation, two novel data processing and analysis algorithms (i.e. CEEMD and linguistic analysis) were combined for a new application. We assumed there is some information hidden in the high-frequency part of the blood pressure signal when the intestinal artery is blocked. Two experimentally surgical operations were conducted with the designed procedure to generate the recordings of blood pressure signal. During processes of these surgical operations, the pigs were anesthetized completely. The effects caused by anesthemic drugs are ignored in this investigation. Some medicines have different side effects for different patients. Increasing or decreasing the blood pressure is one of those side effects.

Furthermore, we also ignore the effects caused by the patterns of main wave of blood pressure signal. According to the recordings of blood pressure signal recorded in those surgical operations, unidentified noises usually damage the blood pressure signal unexpectedly. The damages specially are serious in the components with high frequencies. On the other hand, the pattern of reflection wave is also affected by the patterns of main wave. But, the calculation of blocking index using the referent patterns extracted from the same subject always works. In Fig. 4, the results of blocking index for the four-minute recording of the first surgical operation using two sets of referent patterns show the result of blocking index using the referent patterns extracted from the first surgical operation is more sensitive than the other one. It is clear that the fluctuating patterns of riding wave of blood pressure signal can be used to verify the situations of circulatory system. But, the limitation of this application is there are too many factors will affect the pattern of blood pressure signal, such as the cardiac diseases, flexibility of the vessel wall, viscosity of blood, heart beat, the measuring position, the blocking point, and so on.

However, for the purpose of removing the main wave from blood pressure signal, we improved the empirical mode decomposition method and propose the CEEMD method to decompose the components of blood pressure signal. CEEMD solves the phenomenon of intermittence by adding white noises to the original signal but the added white noises will reside on the decomposed IMFs. CEEMD also proposes the solution to remove the residue of added white noises.

The novel blocking index we defined in this study is successfully applied to verify the situation of intestinal artery blocking or relaxing. As the purpose of designing this parameter, the blocking index is positive under situation of artery clamping and negative under situation of artery relaxing. However, the results of blocking index depend on the baseline (i.e., the referent patterns) we use. How to define a general baseline suitable for most of subjects or build up the criterion to select the referent patterns is a crucial issue for pattern analysis using blocking index.

5. Conclusions

In this investigation, we proposed an integrated procedure to verify the pattern of the riding wave of blood pressure signal. The complementary ensemble empirical mode decomposition method (CEEMD) proposed in this study can eliminate the phenomenon of intermittence and generate IMFs with consistence of characteristics. It is the key to separate the main wave and riding wave of the blood pressure signal. Thus, we successfully separate the main wave and riding wave of blood pressure signal by CEEMD. Furthermore, we also extend the method of constructing phylogenetic tree to design the blocking index by those measurements of dissimilarity. This designed index also works to identify the situation under which the sampled time series of a blood pressure signal was recorded. In this investigation, these two totally different algorithms of data processing and analysis for non-linear and non-stationary time series were integrated successfully. Based on the integration of different algorithms, more information hidden in complex system can be observed.

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