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EEMD and DHT based Solution to Detect Systolic Phase from Doppler Ultrasound Signal

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***Abstract*— This paper concerns the detection of cardiac cycle's systolic phase from underwater construction workers Doppler ultrasound signal based on ensemble empirical mode decomposition (EEMD) and discrete Hilbert transform (DHT). Each Doppler ultrasound signal is decomposed into its individual embedded modes with the EEMD method. Then DHT is applied to the disintegrated intrinsic mode functions (IMF) subsequently to generate the distinct time-dependent Hilbert amplitude, frequency and phase. The mode mixing issue of traditional EMD is addressed and resolved using EEMD. In that case for high graded signal, better visualization to the Hilbert spectrum is obtained. Here, the HS is obtained from the weighted sum of the instantaneous amplitudes of all the IMFs at the frequency bins. In case of sensitivity and positive predictivity, it is illustrated that the proposed algorithm improves the detection rate than the traditional EMD method.**

***Index Terms*— Ensemble empirical mode decomposition, systolic phase, discrete Hilbert transform, instantaneous frequency, decompression-induced gas bubble.**

I. INTRODUCTION

Systolic phase detection is a difficult problem because the Doppler ultrasound signal is too much affected by decompression-induced gas bubbles as well as different types of noises. It is common to separate the single cardiac cycle into two basic phases – systolic phase and diastolic phase. Cardiac cycle is defined as a sequence of mechanical and electrical events that repeats with every heartbeat. For a heartbeat of 75, the cardiac cycle duration is considered to be 800 milliseconds. Systolic phase occupies ~300 milliseconds and diastolic phase occupies ~500 milliseconds. It is observed that decompression-induced gas bubble passes through the pulmonary artery during the systolic phase. The formation of gas bubbles in the blood stream are due to rapid changes in environmental pressure that could happen while carrying out construction work under water (caisson), flying or scuba diving. The bubbles remaining in the body could block many vessels or compress nerves and result in various functional disorders, including strokes and even death. Such disorders are called decompression syndromes (DCS) or caisson disease. The systolic phase detection plays an important role in the field of decompression-induced gas bubble detection.

In this paper, we propose a method to detect systolic phase from Doppler ultrasound signal. Detecting systolic phase from Doppler ultrasound signal is challenging if the signal belongs to high grade in terms of gas bubble detection rate. Doppler ultrasound signal is graded from low to high by Spencer and Johanson in [1] according to the rate of bubble detection. EMD based systolic phase detection algorithm is shown by Chappell and Payne in [2] as an associate algorithm by considering only two types of Doppler ultrasound signals. However, the correspondence between the signals used in [2] and the signal grades defined by Spencer in [1] is not clear. Applying EMD to the electrocardiogram systolic phase can be detected by the detection of QRS complex is published in [3]. In our previous study [6], EMD-DHT based systolic phase detection approach is proposed without addressing the mode mixing problem of EMD. It can also be detected from other types of signals, e.g. cardiac output and arterial pressure signals, are discussed in [11][12]. The detection result from different signals could be different, since there is a time delay in the different signal types. This is due to the fact that the cardiac output and arterial pressures describe the vaso-mechanical properties of the heart while electrocardiogram and Doppler ultrasound describe the electrical activity and mechanical properties respectively.

In this study, the signals are decomposed into a finite number and band-limited IMFs using EEMD. To resolve the mode mixing problem of traditional EMD, EEMD method is employed to estimate the IMFs and then the instantaneous frequency (IF) and instantaneous amplitude is determined for each component. Once IF is determined, it is normalized between 0 and 0.5 and multiplied by a weighting factor. Hilbert spectrum (HS) is generated to represent the instantaneous amplitude, IF and time. The overall HS is defined as the weighted sum of the instantaneous amplitudes of all the IMFs at the frequency bin. Then an alternative visualization to the HS is proposed. This alternative visualization offers a clue to the detection of systolic phase. The properly detection of the systolic phase is the most important task to detect gas bubble associated DCS. The remaining of the paper is organized as follows: section II gives information about experimental setup. Section III A, B, C describes the EEMD, DHT and HS respectively. Section III D shows how to derive the ratio

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between low frequency components energy and high frequency components energy from HS. Section III E presents the systolic phase detection from that ratio derived in previous section. Section IV illustrates the results and discussions in terms of sensitivity and specificity. Finally section V provides the conclusions.

II. Experimental Setup

A pulsed wave (PW) Doppler system comprises a single transducer which emits short bursts of ultrasound and then "listens" from echoes. In our research, a PW Doppler system having 2 MHz carrier frequency is used. Doppler ultrasound signal is radiated targeting the pulmonary artery and the reflected signal is received. The reflected signal is a sound with frequency proportional to the velocity of the reflectors and amplitude according to their acoustic properties. Reflections from moving objects (blood, gas bubble) will have a Doppler shift and will be found in the output signal and the Doppler signal is obtained by band pass filtering through hardware.

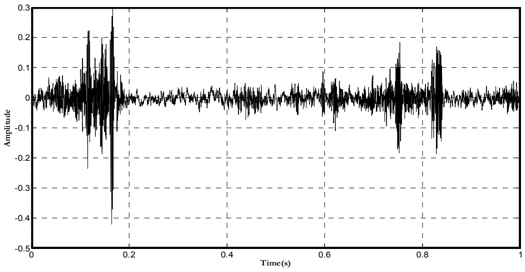

Fig. 1. The underwater construction workers Doppler ultrasound signal.

III. Systolic Phase Detection Approach

The Hilbert spectrum (HS) provides the most detailed information in a time-frequency-energy distribution compared to traditional data processing techniques [4]. In this paper, this distribution is represented and interpreted in a slightly different way for having some valuable information to detect systolic phase. Two steps are required to generate the HS. In the first step, EEMD is employed, which is an adaptive decomposition method [7]. In the second step, DHT is employed to obtain the instantaneous components. HS is generated by the combination of EEMD and DHT. This is an adaptive analysis method, especially useful for nonlinear and non-stationary signal analysis.

A. Ensemble Empirical Mode Decomposition

The principle of the EMD technique is to decompose a signal $s(t)$ into a sum of the band-limited functions $\alpha_m(t)$ or bases called intrinsic mode functions (IMFs). Each IMF satisfies two basic conditions: (i) in the whole data set, the number of extrema and the number of zero crossings must be the same or differ at most by one, (ii) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. There exist many approaches of computing EMD [8]. The following algorithm is employed here to decompose signal $s(t)$ into a set of IMF components. The process of extracting an IMF from a signal is called "the sifting process".

1. Set $u_1(t) = s(t)$
2. Find the extrema (both maxima and minima) of $u_1(t)$
3. Generate the upper and lower envelopes $h(t)$ and $l(t)$ respectively by connecting the local maxima and local minima separately with cubic spline interpolation (e.g., linear, spline, piece-wise spline). In this paper the linear method is chosen.
4. Calculate the local mean as : $\mu_1(t) = [h(t) + l(t)]/2$
5. IMF should have zero local mean; subtract $\mu_1(t)$ from the original signal as: $u_1(t) = u_1(t) - \mu_1(t)$
6. Decide whether $u_1(t)$ is an IMF or not by checking the two basic conditions as described above
7. Repeat steps 2 to 6 until an IMF $u_1(t)$ is found

The sifting process will be continued until the final residue is a constant, a monotonic function, or a function with only one maxima and one minima from which no more IMF can be derived. At the end of the decomposition, the signal $s(t)$ is represented as: $s(t) = \sum_m \alpha_m(t) + \varepsilon_M(t)$ where $\varepsilon_M(t)$ is the final. The EMD (individual IMF) of Doppler signal is illustrated in Figure2.

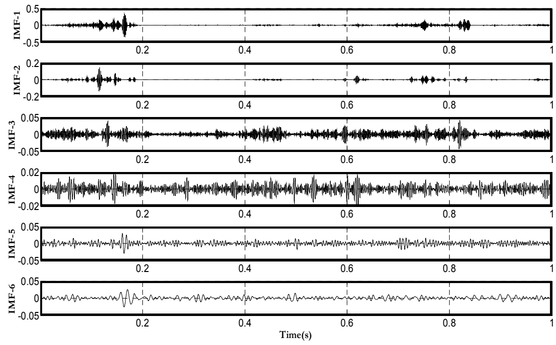

Fig. 2. EEMD of the Doppler ultrasound signal showing the first six IMFs.

The EMD algorithm is very sensitive to noise. This can lead to complications due to mode mixing problem. Mode mixing problem is defined as an IMF that includes oscillations of dramatically disparate scales or a component of similar scale residing in different IMFs, and can also be due to the presence of decompression-induced gas bubble in the signal. EEMD method is proposed in [7] to overcome the mode mixing problem. EEMD defines the IMF components as the mean of an ensemble of trials, each consisting of the signal plus a finite amplitude white noise. At first white noise is added to the analyzed signal and then EMD is used to decompose the noisy signal. These operations produce noisy IMFs. These operations are repeated for a certain number of times by adding different white noise series each time. Since the noise in each trail is different, it is canceled out by averaging corresponding IMFs of each trial. The final average of the corresponding IMFs is treated as EEMD result. Added noise forces for a uniform scale distribution in each trail and the mean of IMFs stay within the natural dyadic filter windows, significantly reducing chance of mode mixing and preserving the dyadic property [7]. Peak of parabolic shape (figure 4) containing systolic phase could be shifted due to the mode mixing problem of EMD. EEMD is used in this paper to stop peak shifting from its original position.

B. Discrete Hilbert Transform

The analytic signal is advantageous in determining the instantaneous quantities such as energy, phase and frequency. The analytic signal is obtained by applying discrete Hilbert transform (DHT) to the IMF. The discrete Hilbert transform $H_D[.]$ corresponding to the m_{th} IMF $\alpha_m(t)$ is defined as

$$H_D[\alpha_m(t)] = \frac{1}{\pi}\sum_{\tau=1,\tau\neq t}^{T}\frac{\alpha_m(\tau)}{t-\tau} \quad (1)$$

Then the analytic signal $Z_m(t)$ corresponding to the m_{th}IMF $\alpha_m(t)$ is defined as

$$Z_m(\mathrm{t}) = \alpha_m(t) + jH_D[\alpha_m(t)] = \delta_m(t)e^{j\theta_m(t)} \quad (2)$$

where $\delta_m(t)$ and $\theta_m(t)$ are the time-dependent amplitude and phase associated with the m_{th}IMF, respectively. The IF of m_{th} IMF is then given as the derivative of the phase $\theta_m(t)$– calculated at *t* i.e.

$$f_m(t) = \frac{\partial\tilde{\theta}_m(t)}{\partial t} \quad (3)$$

where $\tilde{\theta}_m(t)$ represents the unwrapped version of instantaneous phase $\theta_m(t)$. The derivative in equation (3) is evaluated at discrete instant of time *t*. It should be noted that such derivative introduces the abrupt fluctuations of IF and hence nonlinear smoothing is required. Here, the moving average smoothing filter is used to remove such fluctuations.

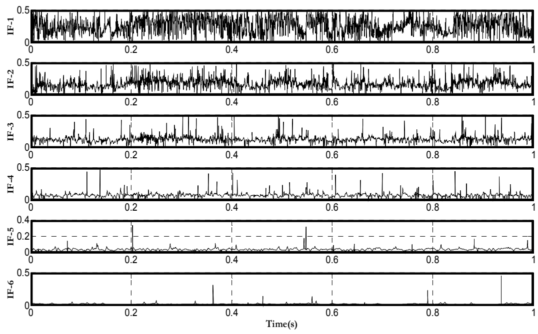

Fig. 3. The IFs of the selected (1st to 6th) IMF components.

The filtering scheme improves the effectiveness of computing IF using discrete derivative. The IF of individual IMF shown in Figure2 is illustrated in Figure3. The concept of IF is physically meaningful only when applied to mono-component signals. In order to apply the concept of IF to arbitrary signals it is necessary to decompose the signals into a series of mono-component contributions. In the recent approaches [4], EMD technique decomposes a time domain signal into a series of mono-component IMFs. Then the IF derived for each component provides the meaningful physical information.

C. Hilbert Spectral Analysis

The HS, or a three dimensional (3D) plot that represents the distribution of the signal energy as a function of time and frequency is generated after having the IMFs as a result of the sifting process of EEMD method and IFs from each IMF through the concept of analytic signal. In this 3D plot time, frequency and energy are plotted on the X-coordinate, Y-coordinate and the Z-coordinate respectively. All the IFs are scaled between 0 and 0.5 and multiplied by the equation $\beta = 0.5/(IF_{max} - IF_{min})$ for simplifying the generation of HS, where IF_{max} and IF_{min} is the maximum and minimum IF calculated from all the IFs. The bin spacing of the HS is 0.5/B, where B is the number of desired frequency bins. The overall HS is defined as the amalgamation of the spectra of each of the IMFs. Hence, each element $H(b,t)$ in the overall HS is defined as the weighted sum of the instantaneous amplitudes of all the IMFs at the b_{th} frequency bin.

$$H(b,t) = \sum_{m=1}^{M}\delta_m(t)\omega_m^{(b)}(t) \quad (4)$$

$$\rho(b,t) = \sum_{m=1}^{M}\theta_m(t)\omega_m^{(b)}(t) \quad (5)$$

where the factor $\omega_m^{(b)}(t)$ is equal to 1 if $\beta \times f_m(t)$is found between two consecutive frequency bins, otherwise it is 0. After computing the elements over the frequency bins, *H* represents the instantaneous signal spectrum in time-frequency (TF) space [9]. Figure 4 illustrates the Hilbert energy spectrum of the Doppler ultrasound signal using 256 frequency bins. In this Figure, only one color is plotted for all the levels of energy except the zero level. For zero level nothing is plotted. Low frequency components energy are contributing more and high frequency components energy are contributing less in the HS. It is noted that the time resolution of *H* is equal to the sampling rate and the frequency resolution can be chosen up to the Nyquist limit [10]. Based on equation (5) the phase matrix $\rho(b,t)$ representing the phase information corresponding to each time-frequency cell of *H*(*b*,*t*) is determined during the construction of the Hilbert spectrum. This phase matrix is used to reconstruct the signal after performing some operations on Hilbert energy spectrum.

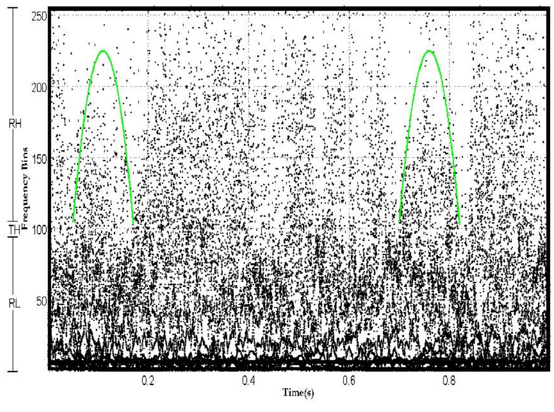

Fig. 4. The Hilbert energy spectrum of the Doppler ultrasound signal.

D. High Frequency Energy to Low Frequency Energy Ratio

The HS is significantly affected by noise and its interpretation is not very easy. However, a correspondence is found between systolic phases in time domain with energy activities in the HS by observing the Figure 1 and Figure 4. Considering this clue a threshold (TH) is determined to divide the HS into two regions, the region of low frequency components energy (RL) and the region of high frequency components energy (RH). The choice of the threshold is performed visually from the HS. It is observed that the RL is visually uniform throughout the spectrum. However in RH, two parabolic shapes are found (Figure 4) which corresponds to the approximate location of two systolic phases in time domain. The systolic phase could be detected within any location of the parabolic shape. This is due to the mode mixing problem of EMD and variation in timing between systolic phase sound and pulmonary valve opening sound. The influence of mode mixing problem on the HS is reduced by employing the EEMD method. The region between two parabolic shapes is also visually uniform. In RL, the low frequency components energy is summed up over the frequency bins at every time instant as $\mathrm{L(t)} = \sum_{b=1}^{TH} HS(t)$. Similarly in RH, $\mathrm{H(t)} = \sum_{b=TH+1}^{B} HS(t)$. Ratio between L(t) and H(t) is defined as RA(t)=H(t)/L(t).

E. Systolic Phase Detection through Signal Reconstruction

In this section, systolic phase is detected by applying the signal reconstruction technique to RA and phase vector $\rho(b, t)$. The time domain signal representing systolic phase is determined by element wise multiplication of *RA(t)* and the cosine of the phase vector $\rho(b, t)$ as

$$sp(t) = RA(t) \cdot \cos[\rho(b, t)] \tag{6}$$

where the signal containing systolic phase is designated by $\mathrm{sp}(t)$. In order to obtain a unique maximum for each systolic phase $\mathrm{sp}(t)$ is filtered through the low pass Butterworth filter of order ten. Having detected the systolic phase from the first block (one second signal) of the Doppler ultrasound, the same detection method is repeated for all other blocks of the signal. The order of the detected systolic phases is maintained and all the blocks are concatenated. The result shows that the detected systolic phases are well represented and well localized in Figure 5.

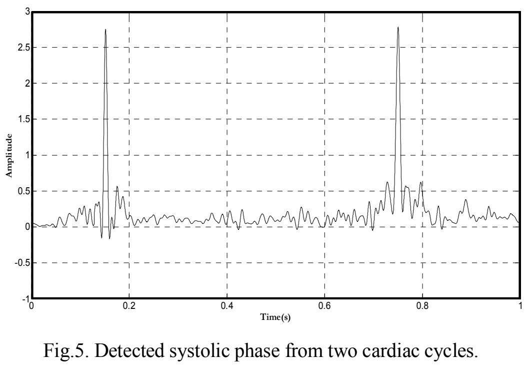

Fig.5. Detected systolic phase from two cardiac cycles.

IV. Results and Discussions

The proposed method is evaluated using four grades of Doppler ultrasound signals. Table 1 summarizes the systolic phase detection performance of the proposed method compared to our previous EMD based method [6]. The sensitivity (SE) and positive predictivity (PP) are used to assess the performance of the methods. The sensitivity reports the percentage of true systoles that are correctly detected. The positive predictivity reports the percentage of detected systoles which are in reality true systoles. The sensitivity and the positive predictivity are normally computed by

$$\mathrm{SE}(\%) = \frac{TP}{TP+FN} * 100 \tag{7}$$

$$\mathrm{PP}(\%) = \frac{TP}{TP+FP} * 100 \tag{8}$$

where TP is the number of true positives, FN the number of false negatives, and FP the number of false positives. In case of grade I and grade II signals, same results are obtained from EMD and EEMD based methods. However, for grade III and grade IV signals better results are obtained by the proposed method. It should be noted that these results may be influenced by the choice of the TH values.

TABLE 1: RESULTS OF EVALUATION OF THE PROPOSED ALGORITHM

Grade	Systolic phase	TP		FN		FP		SE(%)		PP(%)	
		EMD	EEMD	EMD	EEMD	EMD	EEMD	EMD	EEMD	EMD	EEMD
I	20	20	20	0	0	0	0	100	100	100	100
I	20	20	20	1	1	0	0	95	95	100	100
II	20	20	20	0	0	0	0	100	100	100	100
II	20	19	19	1	1	1	1	95	95	95	95
III	20	20	20	0	0	0	0	100	100	100	100
III	20	19	19	1	1	1	0	95	95	95	100
IV	20	14	16	3	2	2	1	83	88	88	94
IV	20	13	14	3	2	3	1	82	87	82	93

V. Conclusions

In this paper, a combination of EEMD and DHT based algorithm is proposed to detect systolic phase. This study shows that how systolic phases are visualized in new time-frequency-energy representations. This representation illustrates the empirical relation between time, frequency and energy which is very advantageous to the detection of systolic phase. It is clear that the presence of parabolic shape in HS domain corresponds to the systolic phase in time domain. It is also possible to conclude that EEMD and DHT is the perfect combination that really could detect systolic phase.

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