International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.7, No.5 (2014), pp.207-216
http://dx.doi.org/10.14257/ijsip.2014.7.5.18

Systolic Phase Detection from Pulsed Doppler Ultrasound Signal using EMD-DHT based Approach

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Abstract

A new algorithm is developed to detect cardiac cycle's systolic phase from the underwater construction workersDopplerultrasound signal. The method is on the basis of empirical mode decomposition (EMD), in combination with the discrete Hilbert transform (DHT). The EMD combined with DHT constitutes the Hilbert spectrum (HS) which is a fine-resolution time-frequency-energy representation of a nonstationary signal. Here EMD is used to calculate the intrinsic mode functions (IMFs), and thenthe DHT is employed to the IMFs to obtain three instantaneous components- frequency, amplitude and phase. Therefore, the HS is constructed from the normalized instantaneous frequencies and weighted sum of instantaneous amplitudes of the IMFs at the frequency bins. A new representation and interpretation of high graded signal is given to the time-frequency-energy distribution using HS. Finally systolic phase detection performance is evaluated in terms of sensitivity and positive predictivity.

Keywords: *Systolic phase, Empirical mode decomposition, Hilbert spectrum, Instantaneous frequency*

1. Introduction

Systolic phase detection is challenging if the signal contains decompression-induced gas bubbles. The sequence of mechanical and electrical events that repeats with every heartbeat is called the cardiac cycle. A single cycle of cardiac activity can be divided into two basic phases – systolic and diastolic phase. 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 gas bubble monitoring relies upon the detection of individual systolic phase.

The aim of this study is 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. Spencer and Johanson in [1] defined Doppler ultrasound signal grades according to the rate of bubble detection. In another study by Chappell and Payne in [2],where only two types of Doppler ultrasound signals are considered to detect systolic phase using EMD. However, the correspondence between the signals used in [2] and the signal grades defined by Spencer in [1] is not clear. Using EMD systolic phase can be detected from the electrocardiogram by the detection of QRS complex, is published in [3].It can also be detected from other types of signals, e.g. cardiac output and arterial pressure

ISSN: 2005-4254 IJSIP

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 pressure describe the vaso-mechanical properties of the heart while electrocardiogram and Doppler ultrasound describe the electrical activity and mechanical properties respectively.

In this paper, an efficient algorithm is proposed for the purpose of systolic phase detection from the high graded Doppler ultrasound signal. In the literature, very often systolic phases are detected in time domain analysis. In the case of low graded signals, a simple time domain algorithm can be used to detect systolic phase. However, it cannot provide a description of how systolic phase energy evolves over time. Whereas, in the case of high graded signals, the analysis is not simple and identification of the systolic phase shape and the time when it occurs are difficult. Such an analysis is proposed in the current study using time-frequency-energy representation of the Doppler ultrasound signal. In this study, the signals are decomposed into a finite number and band-limited IMFs using EMD then the instantaneous frequency IF is derived for each component. All the IFs are scaled between 0 and 0.5 and multiplied by a weighting factor and the bin spacing of the HS is selected. The overall HS is defined as the weighted sum of the instantaneous amplitudes of all the IMFs at the frequency bin. Therefore a new time-frequency-energy representation is determined from the IMFs using HS. This new representation offers a clue to the detection of systolic phase. The properly detection of the systolic phase is the most important task to detect gas bubbles associated DCS. Regarding the organization of this paper, the experimental setup is discussed in section 2, the EMD, DHT and HS are described in section 3.1, 3.2 and 3.3 respectively, the determination of the ratio between low frequency components energy and high frequency components energy from HS is described in section 3.4, systolic phase detection from the ratio is presented in section 3.5, in section 4result and discussions are illustrated in terms of sensitivity and specificity. Finally concluding remarks are given in section 5.

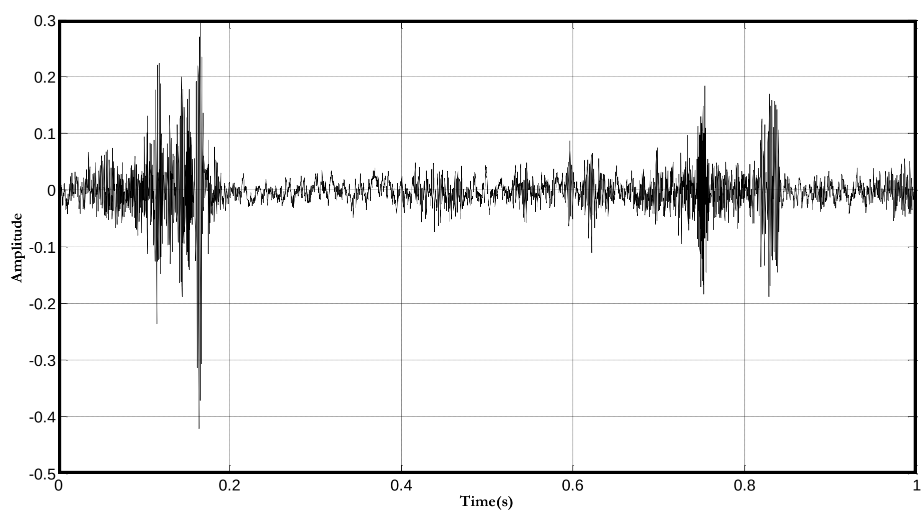

Figure 1. The Underwater Construction Workers Doppler Ultrasound Signal

2. 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 bandpass filtering through hardware.

3. Method of Systolic Phase Detection

The Hilbert spectrum (HS) is a relatively new joint time-frequency representation introduced in [4]. Two phases are required to generate the HS. In the first phase, EMD is employed, which is an adaptive decomposition method [5]. Then DHT is employed in the second phase. HS is generated by the combination of EMD and DHT. This is an adaptive analysis method, especially useful for nonlinear and non-stationary signal analysis.

At a normal heart rate (80 beats per minute), a period is considered to be 0.8 seconds. A trial systole, ventricular systole, and diastole take approximately 0.1 second, 0.3 seconds and 0.4 seconds respectively. One period Doppler signal must contain 4000 samples (N) if the sampling frequency is 5000 Hz and heart rate is 80 beats per minute. Since heart rate of the Doppler signal during the recording time could not be at such rate, one period of the obtained signal could be longer or shorter than 4000 samples. Therefore, the sample duration considered in the study is one second and it is thought that within that limit there should be at best two systolic phases.

3.1. EMD Basics

Empirical mode decomposition (EMD) focuses on the level of local oscillations and decomposes the signal into a finite set of AM-FM oscillating components which are bases of the decomposition. The bases into which the signal is decomposed are obtained from the signal itself, and they are defined in the time domain. 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. The first condition is similar to the narrow-band requirement for a stationary Gaussian process and the second condition is a local requirement induced from the global one, and is necessary to ensure that the instantaneous frequency will not have redundant fluctuations as induced by asymmetric waveforms.

3.1.1. Univariate EMD (uEMD): The univariate EMD (uEMD) is used to decompose the univariate signal into a finite set of IMFs. There exist many approaches of computing EMD [6]. 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

Once the first IMF is derived, we define$\alpha_1(t) = u_1(t)$, which the smallest temporal scale is ins(t). In order to find out the rest of the IMF components, the residue $\varepsilon_1(t)$ of the data is generated by subtracting $\alpha_1(t)$ from the signal s(t)as$s(t) - \alpha_1(t) = \varepsilon_1(t)$. 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.

The subsequent basis functions and the residues are as $\varepsilon_1(t) - \alpha_2(t) = \varepsilon_2(t), \ldots, \varepsilon_{M-1}(t) - \alpha_M(t) = \varepsilon_M(t)$ where $\varepsilon_M(t)$ is the final residue. 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 residue which can be either the mean trend or a constant, and functions $\alpha_m(t)$ are not guaranteed to be mutually orthogonal, but often are close to orthogonal, and all have zero means [4]. The EMD (individual IMF) of Doppler signal is illustrated in Figure2. More specifically, the first component has the smallest time scale which corresponds to the fastest time variation of the data. As the decomposition process proceeds, the time scale increases, and hence, the mean frequency of the mode decreases [6]. Since the decomposition is based on the local characteristic time scale of the data to yield adaptive basis, it is applicable to nonlinear and non-stationary data in general and in particular.

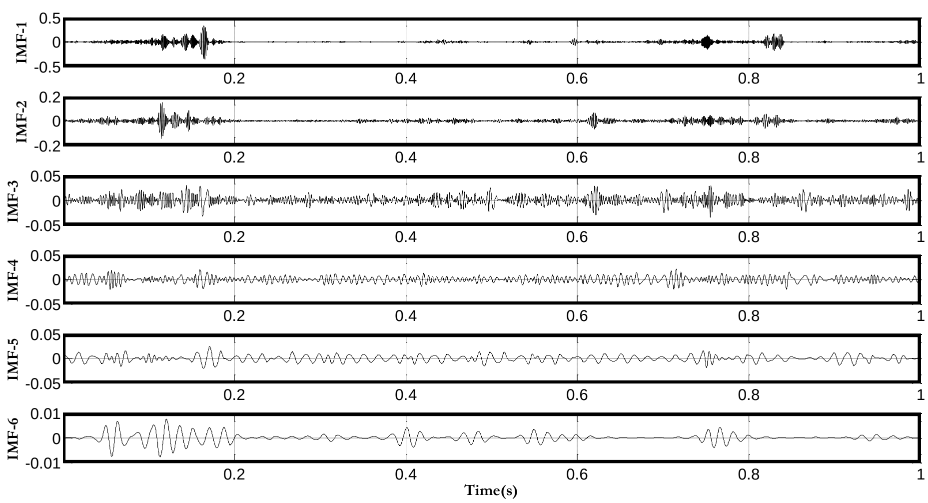

Figure 2. EMD of the Doppler Ultrasound Signal Showing the Selected (1st to 6th) IMF Components out of 13

3.2. Discrete Hilbert Transform

The notion of frequency and energy for each IMF is obtained by employing the concept of analytic signals. The discrete Hilbert transform (DHT) is used to compute the analytic signal for an IMF. The analytic signal $Z_m(t)$ corresponding to the m_{th}IMF $\alpha_m(t)$ is defined as

$Z_m(\mathrm{t}) = \alpha_m(t) + jH_D[\alpha_m(t)] = \gamma_m(t)e^{j\theta_m(t)}$(1)

where $\gamma_m(t)$ and $\theta_m(t)$ are instantaneous amplitude and phase respectively of the m_{th}IMF. The discrete Hilbert transform $H_D[.]$ is defined as

$$H_D[\alpha_m(t)] = \frac{1}{\pi}\sum_{\tau=1,\tau\neq t}^{T} \frac{\alpha_m(\tau)}{t-\tau} \quad (2)$$

The analytic signal is advantageous in determining the instantaneous quantities such as

energy, phase and frequency. The IF of m_{th} IMF is then given as the derivative of the phase $\theta_m(t)$–calculatedat *t i.e.*, $f_m(t) = \frac{\partial \tilde{\theta}_m(t)}{\partial t}$(3)
where $\tilde{\theta}_m(t)$ represents the unwrapped version of instantaneous phase$\theta_m(t)$. The derivative in Eq. (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. The filtering scheme improves the effectiveness of computing IF using discrete derivative. The IF of individual IMF shown in Figure 2 is illustrated in Figure 3. 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.

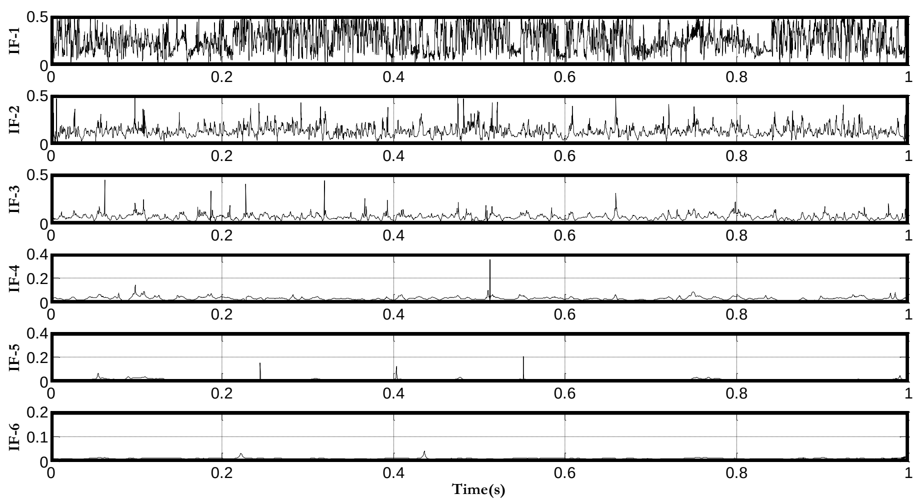

Figure 3. The IFs of the Selected (1st to 6th) IMF Components

Although the IMFs may have frequency overlaps but at any time instant, the instantaneous frequencies represented by each IMF are different. This phenomenon can be well understood in Figure 3 which shows the instantaneous frequencies of the first 6 IMFs of the Doppler signal shown in Figure 2. Therefore, EMD is an effective decomposition of non-linear and non-stationary signals in terms of their local frequency characteristics. With such property, each frequency component of the signal is clearly identified and localized in both time and frequency scales yielding spectra at each sampling point.

3.3. Hilbert spectrum

Having obtained the IMFs as a result of the sifting process and IFs from each IMF, it is possible to generate the HS, or a three dimensional (3D) plot that represents the distribution of the signal energy as a function of time and frequency. In the Figure 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$\lambda = 0.5/(IF_{max} - IF_{min})$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.

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

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

where the factor $\omega_m^{(b)}(t)$ is equal to 1 if $\lambda \times f_m(t)$lies between two consecutive frequency bins, otherwise is 0. After computing the elements over the frequency bins, H represents the instantaneous signal spectrum in time-frequency (TF) space [7]. Figure 4 illustrates the Hilbert spectrum of the Doppler ultrasound using 256 frequency bins. 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 [8]. During the construction of the Hilbert spectrum, the phase matrix$\varphi(b,t)$ representing the phase information corresponding to each time-frequency cell of $H(b,t)$ is saved. In Figure4, 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.

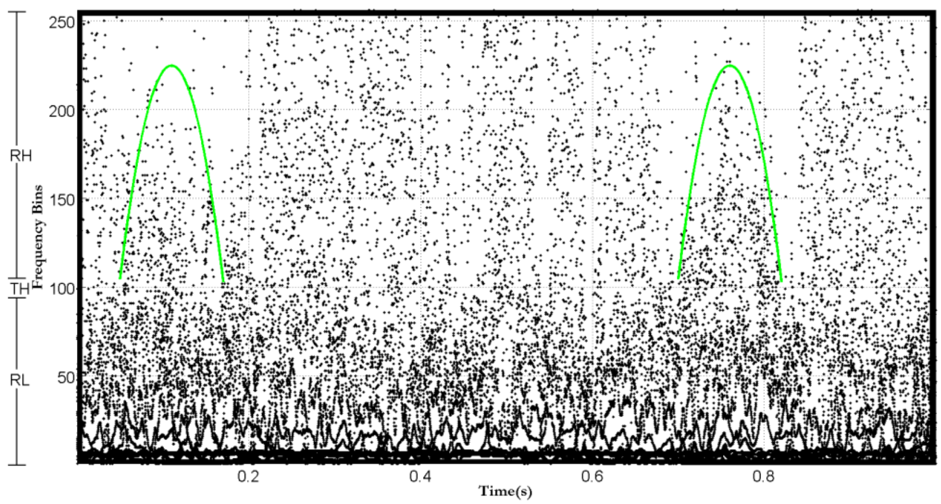

Figure 4. Hilbert Spectrum of the Doppler Ultrasound Signal

3.4. High Frequency Energy to Low Frequency Energy Ratio

Our aim is to observe the synchrony between systolic phases in time domain with energy activities in the HS. With the intention of easing the interpretation of the HS, a threshold (TH) is determined to separate 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 variation in timing between systolic phase sound and pulmonary valve opening sound. 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 $\mathrm{L(t)} = \sum_{b=1}^{TH} HS(t)$. Similarlyin 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) and plotted in Figure5.

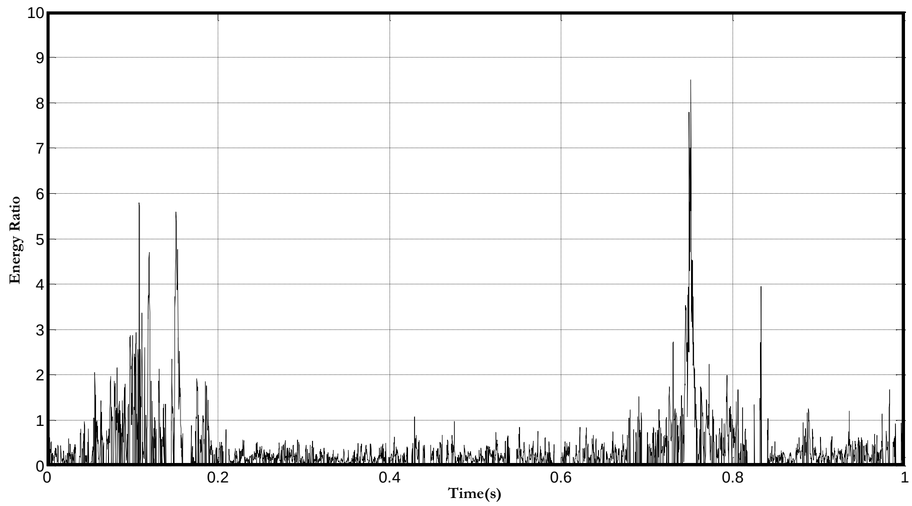

Figure 5. Ratio between High Frequency Energy and Low Frequency Energy

3.5. Signal Reconstruction

Systolic phase detection from RA(t) is obtained by signal reconstruction. Since RA(t) is derived from HS, distribution of RA(t) and HS is similar. Regarding the distribution of RA(t) and HS the main difference between those two terms is that one is represented by the energy ratio at every instant of time, whereas the other is represented by energy over all the frequency bins at every instant of time. The time domain signal representing systolic phase is calculated by element wise multiplication of *RA(t)* and the cosine of the phase vector$\varphi(b,t)$as
$sp(t) = RA(t) \cdot \cos[\varphi(b,t)]$(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 localized in the Figure. In Figure 6 two systolic phases are detected which appear to be correct as detected by medical specialist.

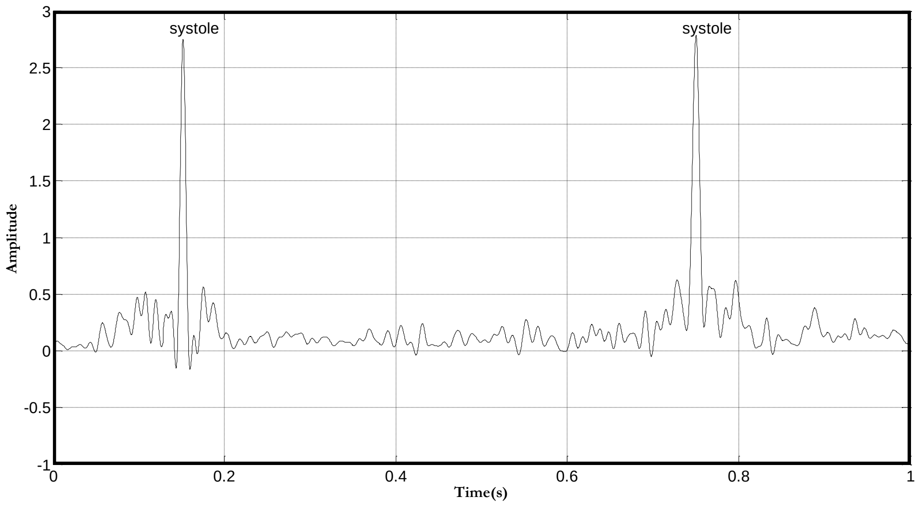

Figure 6. Two Systolic Phases are Detected

4. Result and Discussions

In the experiment, four levels (grades) of signal are considered to demonstrate the performance of the proposed method. In case of low graded signals very simple algorithm is required to detect systolic phase. On the other hand very efficient algorithm is required to detect systolic phase from high graded signals. Such algorithm could be used in the first phase to the detection of gas bubble.

The studies in [2], there are two parts. In the first part systolic phases are detected from Doppler ultrasound but the performance of this detection algorithm is not discussed. This makes it difficult to compare the method with our proposed method. Some algorithms are proposed in [9, 12, 10] to detect systolic phase from ECG, cardiac output and arterial pressure signals but variation is found between the times of occurrence of successive systolic phase in the different signal types. Moreover, these signals are derived in an entirely different manner to the signal used here. Hence, again it is difficult to compare this to the method presented here.

Therefore, the two most essential parameters used here for describing the overall performance of the systolic phase detection are: sensitivity SE and positive predictivity PP. 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 positive predictivity of the detection algorithms are computed by

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

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

Where TP is the number of true positives, FN the number of false negatives, and FP the number of false positives. The systolic phase detection result is illustrated in Table 1. Over 97 percent of the systolic phases are detected from grade 0 and grade 1 signal. In case of grade 2 signals, over 97percent of the systolic phases are detected. However, for grade 3, the detection performance of our proposed algorithm is not as efficient as that for grade 2. All the grades of the signal are divided into two groups. In the first group first three grades are considered and the remaining grades are considered in another group. 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(%)
0	20	20	0	0	100	100
0	20	20	1	0	95	100
1	20	20	0	0	100	100
1	20	19	1	1	95	95
2	20	20	0	0	100	100
2	20	19	1	1	95	95
3	20	14	3	2	83	88
3	20	13	3	3	82	82
4	20	0	0	0	0	0
4	20	0	0	0	0	0

5. Concluding Remarks

The results presented in this study are based on Doppler ultrasound signals for the purpose of detecting systolic phase of cardiac cycle. For this investigation EMD, DHT and new representation of HS is very adequate. 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 frequency domain corresponds to the systolic phase in time domain. Detecting gas bubble by utilizing proposed systolic phase detection algorithm is the main concern for our future works.

Acknowledgements

The authors would like to thank Mr. Tohru Mochizuki, Diving Technology Center Company Limited, Tokyo, Japan for providing the Doppler ultrasound signals. The authors wish to acknowledge and thank Mr. K. Ishida for his assistance.

References

[1] M. P. Spencer, “Decompression limits for compressed air determined by ultrasonically detected blood bubbles”, J. Appl. Phys., vol. 40, no. 2, **(1976)**.

[2] M. A. Chappell and S. J. Payne, “A method for the automated detection of venous gas bubbles in humans using empirical mode decomposition”, Annals of Biomedical Engineering, vol. 33, no. 10, **(2005)**.

[3] Z. E. H. Slimane and A. Nait-Ali, “QRS complex detection using empirical mode decomposition”, Digital Signal Processing, vol. 20, no. 4, **(2010)**.

[4] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. -C. Yen, C. C. Tung and H. H. Liu, “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis”, Proc. Roy. Soc. of London, vol. 454, no. 1971, **(1998)**.

[5] P. Flandrin, G. Rilling and P. Gonqalves, “Empirical mode decomposition as a filter bank”, IEEE Signal Processing Letters, vol. 11, no. 2, **(2004)**.

[6] B. Z. Wu and N. E. Huang, “A study of the characteristics of white noise using empirical mode decomposition method”, Proc. Roy. Soc. of London, vol. 460, no. 2046, **(2004)**.

[7] M. K. I. Molla and K. Hirose, “Single-mixture audio source separation by subspace decomposition of hilbert spectrum”, IEEE Transactions on Audio, Speech and Language Processing, vol. 15, no. 3, **(2007)**.

[8] N. E. Huang, M. –L. Wu, W. Qu, S. R. Long and S. S. P. Shen, “Application of Hilbert-Huang transform to non-stationary financial time series analysis”, Applied Stochastic Model in Business and Industry, vol. 19, no. 3, **(2003)**.

[9] S. A. Taouli and F. Bereksi-Regig, "Detection of QRS complexes in ECG signals based on empirical mode decomposition", Global Journal of Computer Science and Technology, vol. 11, no. 20, **(2011)**.
[10] M. Aboy, J. McNames, T. Thong, D. Tsunami, M. S. Ellenby and B. Goldstein, "An automatic beat detection algorithm for pressure signals", IEEE Transactions onBiomedical Engineering, vol. 52, no. 10, **(2005)**.
[11] M. L. Schmidt, L. Johannesen, J. S. Sorensen, K. Lundhus, S. E. Schmidt and N. H. Staalsen, "Detection of systole and diastole start in cardiac and arterial pressure recordings", Computing in Cardiology, **(2010)** September 26-29, Belfast, Northern Ireland.
[12] W. Zong, T. Heldt, G. B. Moody and R. G. Mark, "An open-source algorithm to detect onset of arterial blood pressure pulses", Computing in Cardiology, **(2003)** September 21-24, Thessaloniki Chalkidiki, Greece.

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