

# Journal of Coastal Life Medicine

## Heart Sound Segregation from Breath Sound Using Hilbert Variational Decomposition

**Received:** 20 August 2022, **Revised:** 19 September 2022, **Accepted:** 20 October 2022

**1Swarup Nandi, 2Shivam Parashar, 3Madhusudhan Mishra, 4Swanirbhar Majumder**

1,4 Department of Information Technology, Tripura University

2,3Department of Electronics & Communication Engineering, North Eastern Regional Institute of Science and Technology, Nirjuli, India.

1swarupnandi@gmail.com,

2shivam98.ece@gmail.com,

3ecmadhusudhan@gmail.com,

swanirbhar:majumder@gmail.com

**Keywords**— Biomedical Signals, Heart sound, HVD, Segregation, Suppression of Lung Sound.

**Abstract**— As the cardiovascular ailments are among the top causes for increasing deaths around the globe, a hustle free heart sound (i.e., without the disturbance which is created by interfering lung sounds) is significant. The objective of this study is to segregate the lung sound from the breath sound in order to get a distraction-free heart sound for medical purposes. Quite often even the most experienced clinicians make mistakes in recognizing the heart sounds (HS) which may lead to a misdiagnosis of HS for ailments while some innocent murmurs may be diagnosed as a severe threat which leads to the expensive and many a time tiresome medical test. In this study, the Hilbert Variational method (HVD) is employed for the suppression of lung sounds (LS) from heart sounds. The HVD decomposes the signal in  $p$  number of sub-signals (modes), without altering the phase information of the signal. Then the modes with lower frequency are summed up to get HS, as the heart sound energy has low-frequency components. A total of 40 pairs of HS and LS signals are analyzed to estimate the efficiency of the algorithm. These signals are appropriated from online available resources. The signals are pre-processed and then decomposed by using HVD method. To reinforce the performance of the algorithm, the results were verified with an impartial panel of 2 doctors and calculated the correlation coefficient amongst the original HS signal and reconstructed HS signal.

### 1. Introduction

Cardiovascular diseases (CVD) are a dominant cause of fatalities throughout the globe. As per a report published by the 'World Health Organization', 31% of the total deaths worldwide are due to CVDs [1],[29]. These numbers are even worse in developing countries. There are many reasons behind this increasing graph of death related to CVDs, the prominent ones being the lack of hospitals with basic medical facilities and the poor ratio of doctors to the population [2]. The WHO started a global heart initiative in 2016, which helped to build the primary health care centres worldwide in backward areas of developing countries.

The identity of a physician is stethoscope around his neck. Auscultation is the initial step in the diagnosis of cardiovascular and pulmonary ailments. It has roots from ancient Egypt [3]. The modern-day stethoscope was invented in 1816 by Rene Laennec. The stethoscope has been undergoing many developments, since. The digital stethoscope, introduced recently, is capable of not only capturing the phonocardiogram (PCG) signals but at the same time can decrease the noise and even analyse the sound for various diseases. The PCG signal is the graphical representation of HLS [28]. While auscultation, the diaphragm is put near the heart region if the physician is trying to listen to HS [31]. Traditional auscultation is a knowledge which is

# Journal of Coastal Life Medicine

purely based on the experience and hearing prowess of the person using the device [4]. So, for interpretation of HS can be only done by clinicians [33]. According to the American heart association, even well-trained physicians might skip some sounds during auscultation process [5]. In this case, clinician's error will change the actual result and cause pointless medical tests and inconvenience to the patients.

The production of a heart sounds is associated with the pumping blood in and out of heart which helps to circulate the blood throughout the body [6],[32] and the closure of the heart valves [30]. When a stethoscope is placed close to heart, there are two prominent sounds viz first heart sound (S1) and second heart sound (S2), generally heard by the physicians. There are two more sounds, they are third heart sound (S3) and fourth heart sound (S4), generally absent in a healthy adult and only audible when there is a chance of heart failure. The pregnant woman and infants could have third heart sound even in normal conditions [4]. Both the third and fourth heart sound has very low amplitude and hence get ignored in many heart sound analysis techniques. For the first and second heart sounds, Dr Aurther C. Guyton in his book "Textbook of Medical Physiology" mentioned that the S1 is caused due to the closing of the atrioventricular valves at the time of contraction of ventricles. The S1 is long lasting and low pitched. The S2 is of the short time period and caused due to the aortic and pulmonary valve closure, at the end of systole [7].

Presently, there are several techniques for the segregation of heart and lung sounds. A Low Pass Filter (LPF) can be applied on the mixed Heart Lung Sound (HLS) signal for segregation process. But as there is an overlap of spectrum amongst the heart sound signal (HSS) and the lung sound signal (LSS), some useful data is lost in this process. In [8], a novel technique of Least mean square (LMS) filter has been introduced for LS segregation. The major drawback of the LMS filter is the need of prior knowledge about the HS signal, which is not the case in normal conditions. To overcome this problem, the intended signal is chosen as the reference signal for the LMS adaptation [9]. However, the noiseless outcome cannot be assured using this method too. The empirical mode decomposition (EMD) has been proposed in [10] for the segregation of HS and LS. It is good for studying the non-linear and non-stationary signal but its

application is limited because of the mode mixing problem [11]. Mishra et al. [4] have introduced Variational Mode Decomposition (VMD) based filter technique for segregation of HS and LS from breath sound. The VMD decomposes the applied input into sub-signals (modes) and then adds the lower frequency modes to reconstruct the heart sound signal and the higher frequency modes are added to get the lung sound signal [4]. As [4] provides evidence of VMD technique being superior to the rest of the segregation techniques like EEMD, EMD, R-CEEMDAN, M-CEEMDAN, etc., in this study, the results will only be compared with the VMD technique.

This section is followed by Section II that discusses tools employed in this study. Section III deals with the system overview and gives an insight into the purposed method. The experimental methodology is dealt with in Section IV and Section V discusses the results in brief. The concluding remarks are in Section VI.

## 2. Tools

### A. Hilbert Variational Decomposition

The HVD is used to decompose the applied HLS into  $p$  number of sub-signals. These sub-signals vary in terms of their frequency and instantaneous amplitude. These sub-signals vary in terms of their frequency and instantaneous amplitude. The phase information is not get deformed during this process. The HVD is a very useful tool in maintaining the time-space data in all decomposed sub-signals.

$$y_{mul}(t) = \sum_p A_p(t) \cos(\int \omega_p(t) dt) \quad (1)$$

The above equation shows that the signal,  $y_{mul}(t)$  where  $A_p(t)$ , refers to instantaneous amplitude and  $\omega_p(t)$  refers to the frequency of the  $p^{th}$  sub-signals. Here,  $p$  shows the total number of decomposed sub-signals.

In HVD, a low pass filter (LPF) of instantaneous frequency is used to get the slowly changing frequency element and the filtrate after each recursion is low energy section.

There are 3 steps involved in HVD algorithm. They are

Instantaneous Frequency (IF) approximation: From the composite signal, the major IF component (element) is considered. For the approximation of IFs, a signal  $x(t)$  is considered and by the addition of signal

# Journal of Coastal Life Medicine

$q(t)$  and  $\tilde{q}(t)$  where  $\tilde{q}(t)$  is the Hilbert transform of the  $q(t)$ [12].

$$x(t) = q(t) + i\tilde{q}(t) \quad (2)$$

Let the instantaneous phase of the signal  $x(t)$  be represented by  $\alpha(t)$ . Thus, the intermediate frequency of  $x(t)$  is the first derivative of the phase. It is denoted by  $\omega(t)$ . The following expression expresses  $\omega(t)$ .

$$\omega(t) = \alpha'(t) = \frac{d}{dx} \text{Im}[\text{In } q(t)] = \text{Im} \frac{q'(t)}{q(t)} \quad (3)$$

In (2)  $y(t)$  has a universal notation where the notation ranges from  $-\infty$  to  $+\infty$ , as per the definition of Hilbert transform in (4). It is evident from this that  $q(t)$  varies with  $t$  from  $-\infty$  to  $+\infty$ , should be considered for the calculation of  $x(t)$

$$q(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{q(s)}{t-s} ds \quad (4)$$

Theoretically, by only using (3) and (4), IF cannot be calculated within a short time interval. Hence, for computing the IF in a short time interval, the method given by Vakman is implemented [13],[14]. The real signal is transferred to the analytical signal using the digital filter in computer processing. Thus, using the digital or analogous form of finite impulse response filter, the Hilbert transform can be implemented [15].

In this study, the park-McClellan method [16] is used to design the filter. In designing it the Remez exchange algorithm and Chebyshev approximation have been employed [17]. Synchronous detection: In synchronous detection, the corresponding largest envelop component is detected. Using synchronous detection, we can extract the amplitude details of oscillating components with known frequency. This leads to the generation of two projections which are the in-phase and the HT phase signals. The square root sum of the following two projection will lead to the derivation of the amplitude component. There are slightly varying vibrations present which are obscured by a large number of additional components and the synchronous detection technique can be used to detect them.

Mathematically,

Let's consider a single element

$g_{m=r}(t) = A_{m=r}(t) \cos(\int \omega_{m=r}(t) dt)$ , which is blended with another  $m$  components.

The  $g_{m=r}(t)$  has the same frequency as  $(\cos(\int \omega_r(t) dt))$ , i.e same as the reference signal.

Now,

$$g_{m=r}(t) = \sum_m [A_m(t) \cos(\int \omega_m(t) dt + \alpha_m(t))] * \cos(\int \omega_r(t) dt) \frac{1}{2} A_m(t) [\cos(\alpha_m(t)) + \cos(\int \omega_m(t) + \omega_r(t) dt + \alpha_m(t))] \quad (5)$$

Where  $A_m(t)$ ,  $\alpha_m(t)$  and  $\omega_m(t)$ , respectively, stands for amplitude, phase angle and IF of the  $m$  component and the IF of the largest component is  $\omega_r(t)$  in  $r$ -reference. The phase shifted portion can be written in the same manner, like

$$\tilde{y}_{m=r}(t) = \frac{1}{2} A_m(t) [\sin(\alpha_m(t)) - \sin(\int (\omega_m(t) + \omega_r(t) dt + \alpha_m(t)))] \quad (6)$$

There are two part in (5) and (6), the first part is of the slowly changing function with phase and amplitude information. And the other part deals with fast changing function with 2 frequency components. Thus, by implementing a LPF, the first, i.e. slow part can be extracted.

The calculations regarding phase and amplitude of (5) and (6) is executed below: -

$$\langle y_{m=r}(t) \rangle = \begin{cases} \frac{1}{2} A_m(t) \cos(\alpha_m(t)), & \text{if } \omega_m = \omega_r \\ 0, & \text{if } \omega_m \text{ is not equal to } \omega_r \end{cases} \quad (7)$$

$$\langle \tilde{y}_{m=r}(t) \rangle = \begin{cases} \frac{1}{2} A_m(t) \sin(\alpha_m(t)), & \text{if } \omega_m = \omega_r \\ 0, & \text{if } \omega_m \text{ is not equal to } \omega_r \end{cases} \quad (8)$$

$$\text{And, } A_{m=r}(t) = 2\sqrt{\langle y_{m=r}(t) \rangle^2 + \langle \tilde{y}_{m=r}(t) \rangle^2} \quad (9)$$

$$\alpha_m(t) = \tan^{-1} \left( \frac{\langle \tilde{y}_{m=r}(t) \rangle}{\langle y_{m=r}(t) \rangle} \right) \quad (10)$$

Even the slight change in the vibration can be measured using synchronous detection technique which is in this HVD method [18]. As we know all the inherent synchronous component has an importance [19].

Signal segregation method: -

As HVD is based on feedback process, so at each cycle, by using LPF of Ifs, the corresponding slowly changing component is extracted and at the end of each feedback/iteration cycle, the lowest energy component is left as residue. By this process, the several slowly changing oscillating elements get formed from the initial composition as a gradual and automated process. The identification of the largest element

# Journal of Coastal Life Medicine

(component) can be done easily with the help of synchronous detection technique. At last the identified largest element will be deducted from the preliminary structure.

$$y_{m-1}(t) = y_m(t) - y_1(t) \quad (11)$$

In the next recursion cycle the difference i.e.  $y_{m-1}(t)$  can be decomposed. As we have discussed, HVD is a recursive process. In this process, as the previous frequency get subtracted, the next one is the current frequency as the deducted part between the two frequencies is larger than the cut-off frequency.

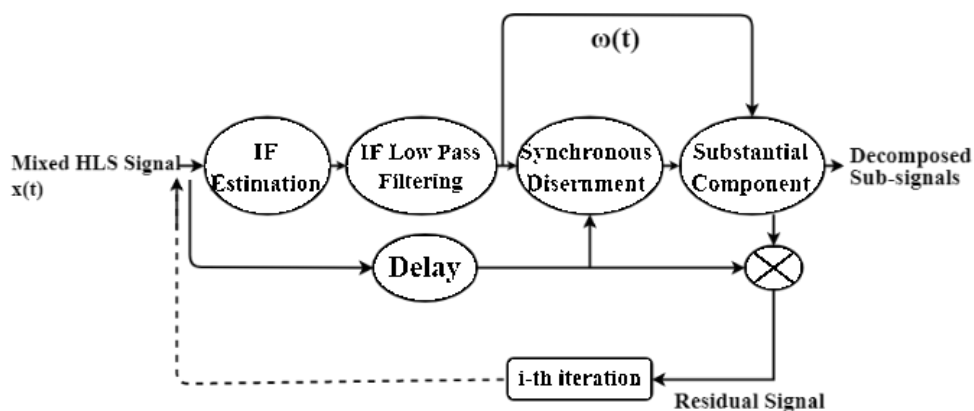


Figure 1 HVD Block Diagram [18],[19],[20] .

The figure above shows the block diagram of HVD method. It has four major sub blocks- IF estimation, IF low-pass filtering, synchronous detection and substantial component. First the IF estimation takes place which is followed by IF low- pass filtering. The synchronous detection with envelop extraction is performed by using the delayed initial signal as reference signal. After this construction and subtraction of the largest component from the initial signal composition is done. Here, the residual signals become the input signal.

## B. Kappa Score

Cohen's kappa coefficient ( $\kappa$ ) is a robust method to measure than a simple percent concurrence (agreement) calculation for measuring the concurrence among two raters for a qualitative item. Cohen's kappa computes the settlement among two raters who each classify N objects into C jointly distinct classes. Galton was the first who mentioned a kappa like method in the year 1892[21].

$\kappa$  is expressed as

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \quad (12)$$

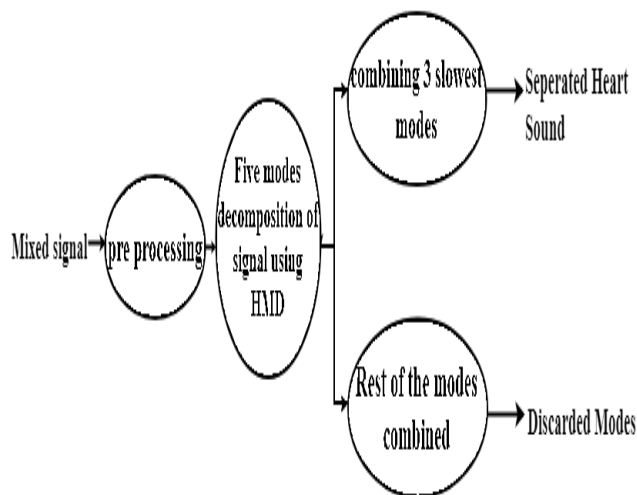
Where,

$p_0$  = relative observed concurrence between participants and

$p_e$  = hypothetical probability of chance concurrence,

By using the data which is obtained from the observers, the probabilities  $p_0$  and  $p_e$  can be calculated. The value of  $\kappa$  will be one if the raters agrees with each other. If the raters are in complete no concurrence besides by chance concurrence ( $p_e$ ), then the value of  $\kappa$  will be zero. When the concurrence among the pair of raters is even inferior than the random concurrence, the value of  $\kappa$  can even be negative [22],[23].

## 3. System Overview



**Figure 2** system flow diagram [4]

Fig. 2 gives an overview of the system. The purpose of this system is to inhibit the lung sound signal in order to get denoised hear sound signal. The input to the system is a mixture of synthetic heart sound and lung sound which is sampled at 44.1 kHz. This merged input signal is further reduced (decimated) by 50, reducing sampling rate to 882 Hz [4]. The low pass Butterworth filter with a cutoff frequency of 2000 Hz is used for pre-processing of the input. It denoises the input signal. Since in our case the input is taken from online sources, the probability of noise or glitches is very low but the probability of noise is high when the input is taken in hospitals, because of the surroundings. So, pre-processing has been done considering the input

to be taken by a clinician in a non-ideal condition. The pre-processing is vital in practical circumstances for a glitch free input and subsequently a precise result. Further analysis on the processed signal is done by applying HVD. The signal is decomposed into 5 sub-signals. The first three sub-signals which have less frequency and considered slow are summed up to get separated heart sound. The choice of three sub-signals is based on the correlation values. The reconstructed heart sound has been inspected by an impartial panel of doctors. The kappa coefficient [21],[22],[23] and correlation coefficient has been obtained for further justification of the results.

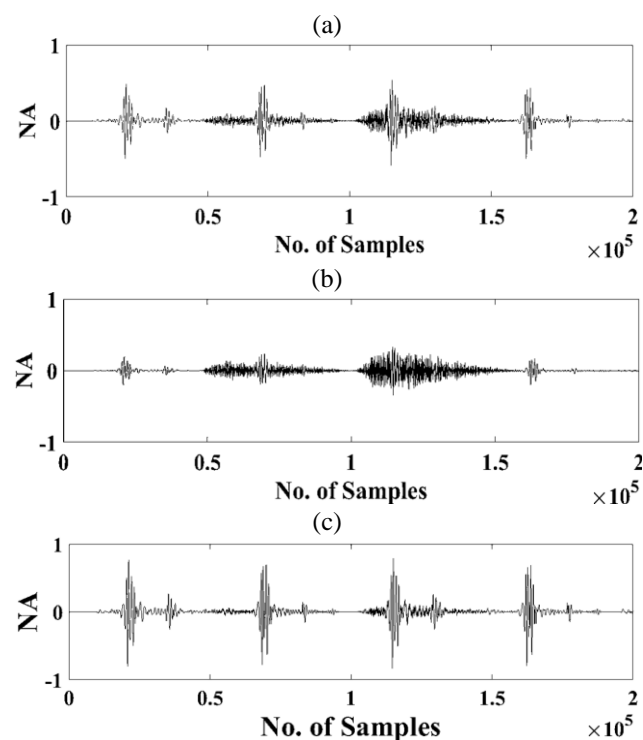
| No. of Modes(p) | Parameters for Different Modes |                |           |        |
|-----------------|--------------------------------|----------------|-----------|--------|
|                 | Correlation Coefficient        | Execution Time | CPU Usage | MSE    |
| 2               | 0.9263                         | 2.7865         | 53.6326   | 0.0007 |
| 3               | 0.9432                         | 3.2934         | 53.8157   | 0.0006 |
| 4               | 0.9475                         | 3.5937         | 53.9683   | 0.0005 |
| 5               | 0.9509                         | 4.0699         | 54.0904   | 0.0005 |
| 6               | 0.9511                         | 4.4144         | 54.2736   | 0.0005 |
| 7               | 0.9517                         | 4.72           | 54.4262   | 0.0005 |
| 8               | 0.9521                         | 4.9742         | 54.5788   | 0.0005 |
| 9               | 0.9529                         | 5.4053         | 54.7314   | 0.0005 |

|    |        |        |         |        |
|----|--------|--------|---------|--------|
| 10 | 0.9531 | 5.7467 | 54.884  | 0.0005 |
| 11 | 0.9533 | 5.8256 | 55.0366 | 0.0005 |
| 12 | 0.9534 | 6.2485 | 55.1892 | 0.0005 |
| 13 | 0.9536 | 6.524  | 55.3418 | 0.0005 |
| 14 | 0.954  | 6.8608 | 55.4944 | 0.0005 |
| 15 | 0.9541 | 7.0711 | 55.647  | 0.0005 |

**TABLE I.** PARAMETER VARIATION IN DIFFERENT NUMBER OF MODES

## 4. Experiment

### A. Data Procurement



**Figure 3** Input HLS Signal (a) 50% HS and 50% LS. (b) 20% HS and 20% LS. (c) 80% HS and 20% LS. Label: In these graphs NA symbolizes normalized amplitude.

The experiment is done on a merged signal of heart and lung sounds. These synthetic signals have been acquired from different online sources [24],[25],[26] including Littman database [25] and Michigan HS and Murmur library [26]. As we had 40 mixed signals with

### B. Experiment

MATLAB has been used for execute the computations. The pre-processing of the mixed sound

unique pair of heart and lung sound, these signals were further mixed in three different ratios (a) 50% heart and 50% lung sounds, (b) 20% heart and 80% lung sounds, and (c)80% heart and 20% lung sounds. Thus, we obtained a total number of 120 samples.

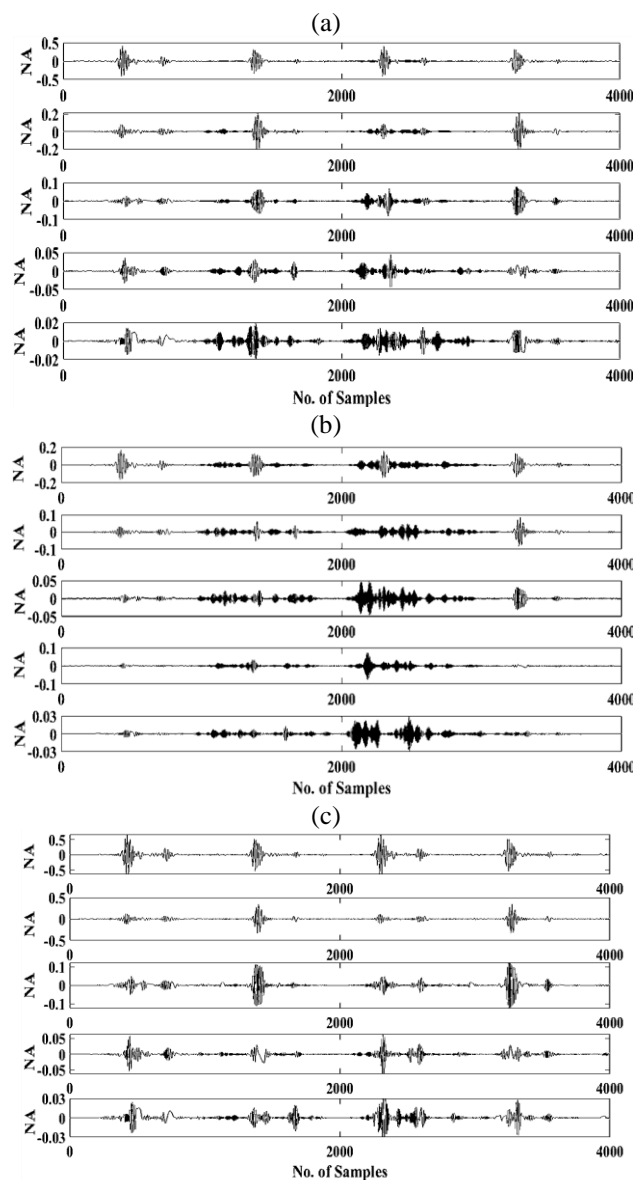
signals is done using Butterworth filter having cut-off frequency of 2000 Hz. A total number of 120 samples are obtained for tests as mentioned already. The mixed signal is then decomposed into 5 sub-signals using

# Journal of Coastal Life Medicine

HVD algorithm. The first 3 sub-signals are used for the reconstructing the heart sound signal. The choice of 3 slower frequency is based on the values of correlation coefficient. These coefficients are obtained from the reconstructed HS signal and the original HS signal which are obtained from online resources.

$$MSE = \frac{1}{n} \sum_{i=1}^n Y_i - \hat{Y}_i \quad (13)$$

the MSE is the mean  $(1/n \sum)$  of the squares of the errors  $Y_i - \hat{Y}_i$ .



**Figure 4** Decomposed modes for input signals (a) 50% HS and 50% LS. (b) 20% HS and 20% LS. (c) 80% HS and 20% LS. Label: In these graphs NA symbolizes normalized amplitude.

## 5. Result and Discussion

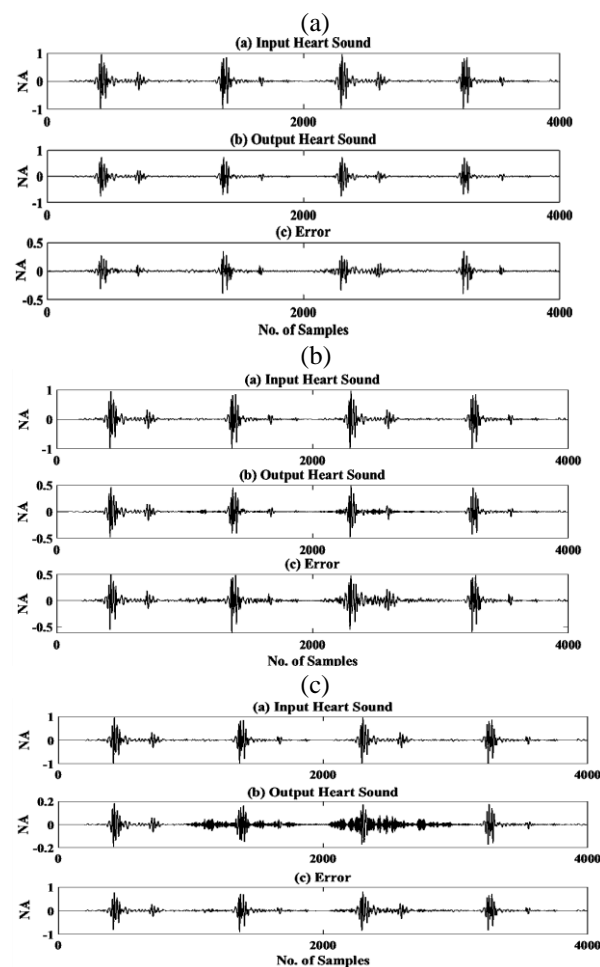
The pre-processed original combined signal is decomposed into various number of sub-signals

$(2 < p < 15)$  using HVD. The correlation coefficient and mean-square-error/MSE between the primary and reconstructed signal i.e., sum of decomposed modes was obtained for each case. The execution time and

# Journal of Coastal Life Medicine

CPU memory usage were also obtained to have a clear assessment/evaluation of different modes. Table (1) shows the comparison between the different number of modes on the basis of their correlation coefficient, MSE, execution time and the CPU usage. The same thing is also explained using the figure 5 (a) –(d). The data shown in table 1 is recorded by executing the code with 3 samples (1 from each proposed ratios) at once. As it is shown that the MSE is almost the same in all cases except when  $p=2$  and  $p=3$ . Considering the

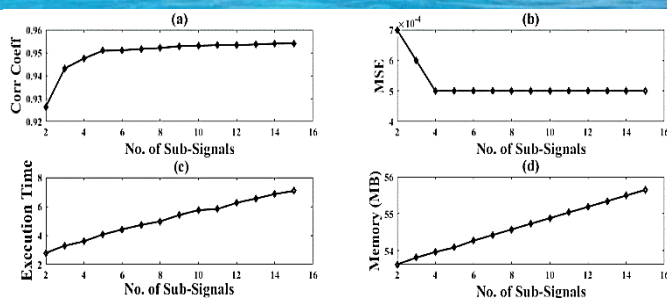
correlation coefficient, execution time and CPU usage, we come to a conclusion that the disintegration of signals in 5 modes using HVD gives an optimal result. As it is already shown in the table, though the correlation coefficient is greater in a higher number of decomposed modes the difference is not significant and comparable when compared to the  $p=5$  i.e., 5 modes. The execution time, as well as CPU usage, shows that the  $p=5$  is most efficient in terms of the execution of the algorithm.



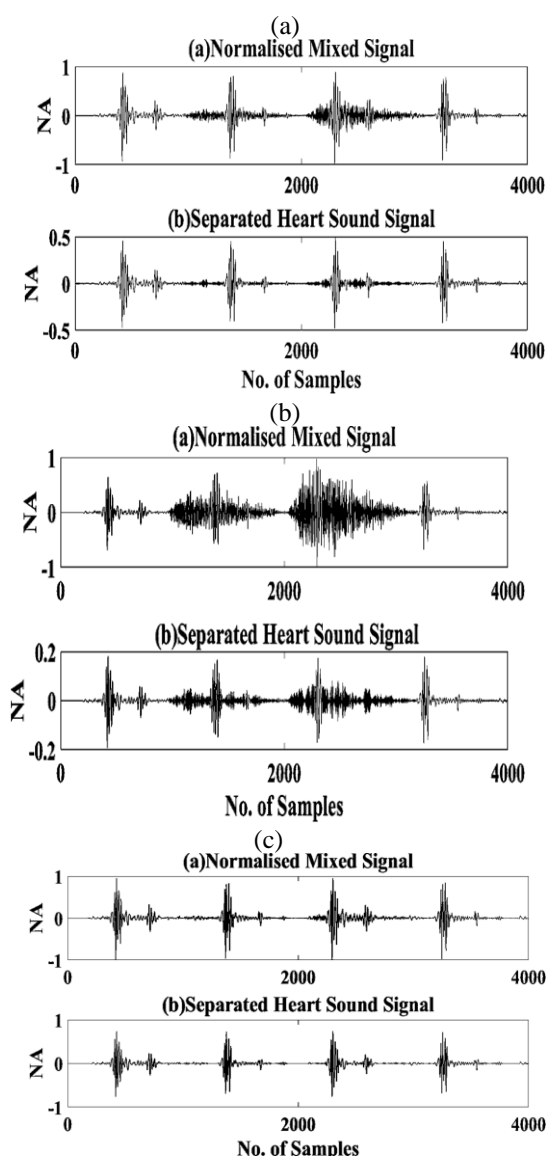
**Figure. 5** Input HS versus Output HS versus Error (a) 50% HS and 50% LS. (b) 20% HS and 20% LS. (c) 80% HS and 20% LS. Label: In these graphs NA symbolizes normalized amplitude.



# Journal of Coastal Life Medicine



**Figure 6.** Number of Sub-Signals versus (a) Correlation Coefficient, (b) MSE, (c) Execution Time, (d) Memory Required. Label: In graph (b), MSE symbolizes mean square error.



**Figure 7** Normalized HLS versus Separated HS (a) 50% HS and 50% LS. (b) 20% HS and 20% LS. (c) 80% HS and 20% LS. Label: In these graphs NA symbolizes normalized amplitude.

# Journal of Coastal Life Medicine

If we only consider the execution time and CPU usage  $p=2$  and  $p=3$  would also be a good choice, but the correlation coefficient and the MSE is not up to mark. So, the 2 and 3 modes-based decompositions is discarded. And for the higher number of decompositions, it is evident from the table (1) that the execution time is way higher than the 5-mode decomposition and the correlation coefficient is also not that much higher. When the mixed signal is decomposed in 5 sub-signals by using HVD algorithm, the next step is to create a heart signal from these sub-

signals which varies from each other on the basis of their frequencies and instantaneous amplitude. For the reconstruction of heart sound signal, we summed up the 3 sub-signals with fewer frequencies, as the heart sound signal energy constitutes of low-frequency components [4]. Table 2 shows the summation of different sub-signals and their effect on the correlation between reference heart sound signal and the reconstructed heart sound signal.

| Serial No. | Average Mean Correlation Coefficient |        |               |
|------------|--------------------------------------|--------|---------------|
|            | Ratio of HS and LS in a Sample       | VMD    | HVD           |
| 01         | 80:20                                | 0.8789 | <b>0.9453</b> |
| 02         | 20:80                                | 0.7352 | 0.6038        |
| 03         | 50:50                                | 0.9164 | 0.9016        |

**TABLE II.** CORRELATION COEFFICIENT FOR 5 MODES

From Table (2) it is evident that when the 4th and 5th sub-signals are added, they contain the maximum amount of lung sound signal i.e., 8.79% (i.e., correlation). So, as we required the lung sound free heart sound signal so we discard these 2 sub-signals and summed up the 1st, 2nd and 3rd sub-signal to reconstruct the heart sound signal. The correlation

coefficient that we got by summing up 3 slowest sub-signals is 0.9595 which is not that low from the correlation coefficient that we got when added all the 5 sub-signals and also the lung sound interference is now excluded as we choose 3 sub-signals. So, the optimum number of sub-signals chosen for the reconstruction of the heart sound signal in this study is 3.

## A. Error Analysis

| Serial No. | Correlation Coefficient for 5 Modes |                         |                        |
|------------|-------------------------------------|-------------------------|------------------------|
|            | $\Sigma$ of Modes                   | Heart Sound Correlation | Lung Sound Correlation |
| 01         | 1                                   | 0.8769                  | 0.0217                 |
| 02         | 1,2                                 | 0.9469                  | 0.0409                 |
| 03         | 1,2,3                               | 0.9595                  | 0.0498                 |
| 04         | 1,2,3,4                             | 0.9604                  | 0.0555                 |
| 05         | 1,2,3,4,5                           | 0.9611                  | 0.0582                 |
| 06         | 2,3,4,5                             | 0.4503                  | 0.0913                 |
| 07         | 3,4,5                               | 0.2004                  | 0.0909                 |
| 08         | 4,5                                 | 0.1131                  | 0.0879                 |
| 09         | 5                                   | -0.0307                 | 0.0484                 |

**TABLE III.** AVERAGE MEAN SQUARE ERROR

The table (3) shows the average mean square error (AMSE) of the VMD and the HVD with respect to the nature of the sample. As it is evident from the

above data, the HVD is having less AMSE than the VMD.

# Journal of Coastal Life Medicine

| Serial No. | Average Mean Square Error      |        |               |
|------------|--------------------------------|--------|---------------|
|            | Ratio of HS and LS in a Sample | VMD    | HVD           |
| 01         | 80:20                          | 0.0035 | <b>0.0015</b> |
| 02         | 20:80                          | 0.0089 | 0.0093        |
| 03         | 50:50                          | 0.0046 | <b>0.0042</b> |

AVERAGE MEAN CORRELATION COEFFICIENT

| Serial No. | Average Execution Time |                                     |
|------------|------------------------|-------------------------------------|
|            | Algorithm              | Average execution time (in seconds) |
| 01         | VMD                    | 16.84                               |
| 02         | HVD                    | <b>4.23</b>                         |

TABLE IV. AVERAGE EXECUTION TIME

### B. Comparative Analysis of VMD and HVD

The Table (4) shows the comparison of HVD and VMD on the basis of their correlation coefficient with various ratio of heart and lung sound ratios. The information in table (4) makes it evident that the correlation of HVD algorithm is better than VMD when the noise is less (i.e., lung sound is in lesser quantity). The correlation coefficient is comparable in 50:50 ratio case. But very less when compared in 20:80 case. The HVD completely over performs the VMD in terms of execution time but VMD has less CPU usage. The table (5) shows that the HVD algorithm gets executed in only 2.54 sec, whereas the VMD algorithm takes 16.84 seconds to be executed. As already mentioned in [27], in our study we found that the VMD is robust to noise and performs better than HVD only in noisy condition whereas HVD is superior than VMD when there is less noise and time is a constraint.

### C. Clinical validation and Kappa Score

As the results are validated once by objective quantification like MSE and correlation coefficient, the separated heart sound is then validated by a panel

of two independent clinicians. As there are a total number of 120 separated heart sound signals which are obtained from 120 HLS signals, that belongs to three groups as already mentioned. We have provided each of them with 30 samples (10 from each group). They were requested to fill their observation in a provided form. On the basis of their observations, the kappa coefficients (k) [23] for two different cases were obtained. Table (6) shows the data layout by emphasizing the important points which are very crucial in obtaining kappa coefficient. The concurrence among the two observers is shown by A and D whereas B and C shows no concurrence among the observers. In case of full concurrence, the value of B and C will be zero and thus the value of observed concurrence (P0) will be 1, or 100%. In case of no concurrence among the observers, the value of A and D will be zero and hence the value of P0 will be 0. Table (7) lists the interpretations for different values of kappa coefficient (k) and table (8) gives insight in the interpretation of concurrences. Table (9) and table (10) contains the observations of the clinicians in matrix form for the heart sound presence and medical significance respectively.

TABLE V. DATA LAYOUT [23]

| O1 \ O2 | Yes            | No             | Total          |
|---------|----------------|----------------|----------------|
| Yes     | A              | B              | M <sub>1</sub> |
| No      | C              | D              | M <sub>0</sub> |
| Total   | N <sub>1</sub> | N <sub>0</sub> | n              |

TABLE VI. EXPLANATION OF KAPPA SCORE [23]

| Poor | Mino<br>r | Fair | Reasonab<br>le | Considerab<br>le | Almost<br>Perfect |
|------|-----------|------|----------------|------------------|-------------------|
| 0.0  | 0.20      | 0.40 | 0.60           | 0.80             | 1.0               |

# Journal of Coastal Life Medicine

**TABLE VII.** EXPLANATION OF LEVEL OF CONCURRENCE OF KAPPA SCORE [23]

| Kappa Score  | Concurrence                  |
|--------------|------------------------------|
| Less than 0  | Less than chance concurrence |
| 0.01 to 0.20 | Minor concurrence            |
| 0.21 to 0.40 | Fair concurrence             |
| 0.41 to 0.60 | Reasonable concurrence       |
| 0.61 to 0.80 | Considerable concurrence     |
| 0.81 to 0.99 | Almost perfect concurrence   |

For table (9), the value of  $P_0$  is obtained as zero and the value of  $P_e$  is 0.7688. By using the formula for  $k$ , given in (13), we get  $k=1$ , that shows there is 100% concurrence among the observers regarding the presence of heart sounds in the samples which means that the observers are in almost perfect concurrence. Also, in table (10), the value of  $P_0$  is 0.9667 and the value of  $P_e$  is 0.5667. By using the formula once again,

we get  $k=0.9231$ , that shows there is almost perfect concurrence among the observers about the clinical significance of the purposed work. Both of the clinicians agree that 26 out of 30 separated HS are audible and 21 out of those 26 can be used for medical analysis. These outcomes show that the performance of the purposed method for the HS extraction from HLS signal by suppressing the lung sounds is precise.

**TABLE VIII.** OBSERVATION OF CLINICIANS ON THE PRESENCE OF HEART SOUND IN THE SAMPLES

| O1 \ O2 | Yes | No | Total |
|---------|-----|----|-------|
| Yes     | 26  | 0  | 26    |
| No      | 0   | 4  | 4     |
| Total   | 26  | 4  | 30    |

| O1 \ O2 | Yes | No | Total |
|---------|-----|----|-------|
| Yes     | 20  | 0  | 20    |
| No      | 1   | 9  | 10    |
| Total   | 21  | 9  | 30    |

**TABLE IX.** OBSERVATION OF CLINICIANS ON THE SIGNIFICANCE OF HEART SOUND FOR MEDICAL PURPOSE

## 6. Conclusion

The segregation of HS and LS is a challenging task. The spectral overlap of these two signals make it even harder, as the critical information extraction is very crucial in order to analyze a subject. As number of deaths are higher because of CVDs, having more and accurate information regarding the heart sounds is appreciable. The segregation of HS by suppressing the LS using the HVD method is proposed in this study. The outcomes show that the noise in the HS signal is minimized to a greater extent. It also evident from the results that the HVD algorithm works better in less noisy condition. The segregated HS has also been verified by both the subjective as well as quantitative

investigation. For the subjective investigation, the physicians were made to listen to the outcomes and give their feedback on random sample. The quantitative investigation is done by obtaining the correlation coefficient and MSE between the original HS signal and the segregated HS signal. The results of both, correlation coefficient and MSE shows that the HVD technique is superior to VMD in less noisy condition. Therefore, the segregated HS signals that we get after segregation of HLS signal by HVD technique can be used for further analysis.

# Journal of Coastal Life Medicine

## 7. Acknowledgement

The authors would like to offer their gratitude to Dr. Deepak Pandey and Shashi Pandey from Shri Krishna Medical College and Hospital, Muzaffarpur, India and Darbhanga Medical College and Hospital, Darbhanga, India respectively for the clinical validation.

## References

- [1] "Cardiovascular diseases," [https://www.who.int/cardiovascular\\_diseases/world-heart-day/en/](https://www.who.int/cardiovascular_diseases/world-heart-day/en/).
- [2] Robert A Malkin, "Technologies for clinically relevant physiological measurements in developing countries, *Physiological Measurement*, vol.28, pp.8,2007.
- [3] D. Papadaniil and L. J. Hadjileontiadis, "Efficient heart sound segmentation and extraction using ensemble empirical mode decomposition and kurtosis features, *IEEE J. Biomed. Health Inform*, vol. 18, no. 4, pp. 1138-1152, July 2014.
- [4] M. Mishra, S. Banerjee, D. C. Thomas, S. Dutta and A. Mukherjee," Detection of Third Heart Sound Using Variational Mode Decomposition," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 7, pp. 1713-1721, July 2018
- [5] Delgado-Trejo, A. F. Quiceno-Manrique, J. I. Godino Llorente, M. Blanco-Velasco and G. Castellanos-Dominguez auscultation analysis for heart murmur detection. *Annals of Biomed. Eng.*, 37(2): 337-353, 2009.
- [6] J. Gnitecki and Z. M. K. Moussavi, "Separating heart sounds from lung sounds - accurate diagnosis of respiratory disease depends on understanding noises," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 26, no. 1, pp. 20 -29, Jan. 2007.
- [7] Guyton, Hall. "Heart Muscle; The Heart as a pump and Function of the Heart Valves." *Textbook of Medical Physiology*, edited by Schmitt et. al., eleventh edition, Elsevier Inc., 2006, pp. 103-114.
- [8] V. K. Iyer, P. A. Ramamoorthy, H. Fan, and Y. Ploysongsang, "Reduction of heart sounds from lung sounds by adaptive filtering," *IEEE Trans. Biomed. Eng.*, vol. BME-33, no. 12, pp. 1141-1148, Dec. 1986.
- [9] M. Kompis and E. Russi, "Adaptive heart-noise reduction of lung sounds recorded by a single microphone," in *Proc. 14th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 2, Oct./Nov. 1992, pp. 691-692.
- A. Mondal, P. Bhattacharya, and G. Saha, "Reduction of heart sound interference from lung sound signals using empirical mode decomposition technique," *J. Med. Eng. Technol.*, vol. 35, nos. 6-7, pp. 344-353, 2011.
- B. Lin, W. A. Tanumihardja, and H. Shih, "Lung-heart sound separation using noise assisted multivariate empirical mode decomposition," in *Proc. Int. Symp. Intell. Signal Process. Commun. Syst.*, 2013, pp. 726-730.
- [10] L. Sun et al., "A method for estimating the instantaneous frequency of non-stationary heart sound signals," in *Proc. IEEE Int. Conf. Neural Netw. Signal Process.*, Nanjing, China, Dec. 2003, pp. 798-801.
- [11] Vakman, "New high precision frequency measurement," *Meas. Sci. Technol.*, vol. 11, no. 10, pp. 1493-1497, Feb. 2000.
- [12] E. Vakman, *Signals Oscillations Waves: A Modern Approach*. Boston, MA, USA: Artech House, 1998.
- [13] M. Caciotta et al., "Detection of short transients and interruptions using the Hilbert transform," in *Proc. World Congr. Fundam. Appl. Metrol.*, Lisbon, Portugal, Sep. 2009, pp. 913-916.
- [14] Hermanowicz et al., "On an instantaneous frequency estimator with FIR filters having maximally flat frequency response error

# Journal of Coastal Life Medicine

- magnitude,” *Signal Process.*, vol. 81, no. 7, pp. 1491–1501, Jul. 2001.
- [15] Minge, “Design of equiripple linear-phase FIR filters using MATLAB,” in *Proc. IEEE Int. Conf. Control Autom. Syst. Eng.*, Singapore, Jul. 2011, pp. 1–4.
- [16] M. Feldman, “Theoretical analysis and comparison of the Hilbert transform decomposition methods,” *Mech. Syst. Signal Process.*, vol. 22, no. 3, pp. 509–519, Apr. 2008.
- [17] M. Feldman, “Time-varying vibration decomposition and analysis based on the Hilbert transform,” *J. Sound Vibration*, vol. 295, no. 3, pp. 518–530, Aug. 2006.
- [18] S. Barma, B. W. Chen, W. Ji, S. Rho, C. H. Chou, and J. F. Wang, “Detection of the third heart sound based on nonlinear signal decomposition and time–frequency localization,” *IEEE Trans. Biomed. Eng.*, vol. 63, no. 8, pp. 1718–1727, Aug. 2016.
- [19] Bakeman, R.; Quera, V.; McArthur, D.; Robinson, B. F. (1997). "Detecting sequential patterns and determining their reliability with fallible observers". *Psychological Methods*. 2 (4): 357–370.
- [20] "The Kappa Statistic in Reliability Studies: Use, Interpretation, and Sample Size Requirements". *Physical Therapy*. 2005.
- A. J. Viera and J. M. Garrett, “Understanding interobserver concurrence: The kappa statistic,” *Family Med.*, vol. 37, no. 5, pp. 360–363, 2005.
- [21] Demonstrations: Heart Sounds & Murmurs. Accessed: Oct. 2016. [Online]. Available: <https://depts.washington.edu/physdx/heart/demo.html>
- [22] 50 Heart and Lung Sounds Library. Accessed: Oct. 2016. [Online]. Available: [http://solutions.3mae.ae/wps/portal/3M/en\\_AE/3M-Littmann-EMEA/stethoscope/littmann-learning-institute/heart-lungsounds/heart-lung-sound-library/](http://solutions.3mae.ae/wps/portal/3M/en_AE/3M-Littmann-EMEA/stethoscope/littmann-learning-institute/heart-lungsounds/heart-lung-sound-library/)
- [23] Heart Sound & Murmur Library. Accessed: Nov. 2016. [Online]. Available: [http://www.med.umich.edu/lrc/psb\\_open/html/repo/primer\\_heartsound/primer\\_heartsound.html](http://www.med.umich.edu/lrc/psb_open/html/repo/primer_heartsound/primer_heartsound.html)
- [24] K. Dragomiretskiy and D. Zosso, “Variational mode decomposition, *IEEE Trans. Signal Process.*, vol. 62, no. 3, pp. 531-544, 2014.
- [25] Sangita Das, Saurabh Pal, Madhuchhanda Mitra, Supervised model for Cochleagram feature based fundamental heart sound identification, *Biomedical Signal Processing and Control*, Volume 52, 2019, Pages 32-40.
- [26] V. Mondéjar-Guerra, J. Novo, J. Rouco, M.G. Penedo, M. Ortega, Heartbeat classification fusing temporal and morphological information of ECGs via ensemble of classifiers, *Biomedical Signal Processing and Control*, Volume 47, 2019, Pages 41-48.
- [27] Alex Paul Kamson, L.N. Sharma, S. Dandapat, Multi-centroid diastolic duration distribution based HSMM for heart sound segmentation, *Biomedical Signal Processing and Control*, Volume 48, 2019, Pages 265-272.
- [28] Adriana Leal, Diogo Nunes, Ricardo Couceiro, Jorge Henriques, Paulo Carvalho, Isabel Quintal, César Teixeira, Noise detection in phonocardiograms by exploring similarities in spectral features, *Biomedical Signal Processing and Control*, Volume 44, 2018, Pages 154-167.
- [29] Shahid Ismail Malik, Muhammad Usman Akram, Imran Siddiqi, Localization and classification of heartbeats using robust adaptive algorithm, *Biomedical Signal Processing and Control*, Volume 49, 2019, Pages 57-77.
- [30] Shanti R. Thiyagaraja, Ram Dantu, Pradhuma L. Shrestha, Anurag Chitnis, Mark A. Thompson, Pruthvi T. Anumandla,

# Journal of Coastal Life Medicine

Tom Sarma, Siva Dantu, A novel heart-mobile interface for detection and classification of heart sounds, Biomedical

Signal Processing and Control, Volume 45, 2018, Pages 313-324.