

# Cardiogenic Oscillations extraction in inductive plethysmography: Ensemble empirical mode decomposition

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**Abstract**— The purpose of this study is to investigate the potential of the ensemble empirical mode decomposition (EEMD) to extract cardiogenic oscillations from inductive plethysmography signal in order to measure cardiac stroke volume. First, a simple cardio-respiratory model is used to simulate cardiac, respiratory and cardio-respiratory signals. Second, application of classical empirical mode decomposition (EMD) to simulated cardiorespiratory signals demonstrates that mode mixing phenomenon affects the extraction performance and hence cardiac stroke volume measurement. Stroke volume is measured as the amplitude of extracted cardiogenic oscillations and it is compared to the stroke volume of simulated cardiac activity. Finally, we show that the EEMD leads to mode mixing removal.

## I. INTRODUCTION

Monitoring of cardiac mechanical activity is of great medical interest. Some of the recent measurements of ventricular volumes and cardiac output involve insertion of intra-vascular invasive catheters, or exposure to radiation. Some may also require bedside presence of experienced examiner or depend on holding a transducer in the hand, which makes them less applicable for continuous monitoring. To avoid the risks associated with the insertion and indwelling of pulmonary artery catheter, non-invasive techniques such as trans-thoracic electrical bio-impedance and non-invasive echocardiography have been developed. However, they are not generally accepted for routine use since their accuracy under clinical conditions has been questioned [1]. Another non-invasive method, called thoracocardiography (TCG), has been proposed [2]. It is based on the principles of respiratory inductive plethysmography, a method widely applied for quantitative recording of breathing patterns. The output of an inductive plethysmograph represents the sum of all changes in the volume enclosed by the transducer. According to chest TCG, respiratory movements during natural breathing account for approximately 95% and left heart ventricle activity (cardiogenic oscillations) for 5% of the amplitude of the waveform recorded at the level of the xiphoid process [2]. TCG pretends to non-invasively monitor left ventricular stroke volume by ECG triggered ensemble averaging and digital band-pass filtering  $[0.7*(\text{cardiac frequency}) \text{ Hz} - 10$

Hz] [3] of this waveform in order to suppress low frequency harmonics, related to respiration and other body movements, as well as high frequency electrical noise. TCG shows a good accuracy of stroke volume and cardiac output measurements. However, the filter parameters used in TCG, first, depend on the current measured heart rate and require an ECG channel reference. Second, TCG is not adapted to strong non-stationary conditions as the heart rate estimation needs a windowed procedure.

The nonlinear technique, *Empirical Mode Decomposition (EMD)* has been proposed by N.E. Huang et al. for adaptively representing non-stationary signals as sums of zero-mean AM-FM components ([4], [5]). In this work, we use a simple cardio-respiratory (CR) model to test the performance of the EMD for cardiogenic oscillations extraction in inductive plethysmography. We also use the model to analyze the performance of a method based on EMD and named ensemble empirical mode decomposition (EEMD) [6].

## II. EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition is a signal processing technique proposed to extract all the oscillatory modes embedded in a signal without any requirement of stationarity or linearity of the data ([7], [8]). The extracted modes, with well-defined instantaneous frequencies, are speculatively associated with specific physical or physiological aspects of the phenomenon investigated [9]. Hence, EMD has found immediate applications in biomedical engineering [10].

Different from the decomposition methods based on wavelets, EMD method is data driven; hence when applying EMD we neither need to define a mother wavelet beforehand for singularity detection or wavelet decomposition [11], nor face the inevitable interference terms and energy leakage that generate a lot of small undesired spikes all over the frequency scales of time consuming continuous wavelet transform ([12], [8]). In addition, although wavelet decomposition has good time resolution in high-frequency region, it often cannot separate events with too small time interval between them. Briefly, EMD operation is not time consuming, can deal with large size nonlinear non-stationary signals and does not involve frequency and time resolution (in contrast to Wavelet decomposition and short time Fourier transform) [13].

With the EMD technique, any complicated signal can be decomposed into a definite number of high frequency and low frequency components, which are called intrinsic mode functions (IMFs). In [14], it has been shown that EMD can

be useful to extract local temporal structures like heart beat superimposed on respiration signals in order to monitor respiration and cardiac frequencies during sleep using a flexible piezoelectric film sensor (pressure fluctuations). It must be noticed here that cardiac stroke volume (SV) of extracted cardiac signal was not studied.

By definition an Intrinsic Mode Function satisfies two conditions

1. The number of extrema and the number of zero crossings may differ by no more than one, and
2. The local average is zero. It is defined by the average of the maximum and minimum envelopes.

These properties of IMFs allow for instantaneous frequency and amplitude to be defined unambiguously [15].

Given these two definitive requirements of an IMF, the sifting process for extracting IMFs from a given signal  $x(t)$ ,  $t = 1 \dots T$  is described as follows [16]:

1. Identify all the maxima and minima of  $x(t)$ .
2. Generate its upper and lower envelopes,  $x_{up}(t)$  and  $x_{low}(t)$ , with cubic spline interpolation.
3. Calculate the point-by-point mean from upper and lower envelopes,  $m(t) = (x_{up}(t) + x_{low}(t))/2$ .
4. Extract the detail,  $d(t) = x(t) - m(t)$ .
5. Check the properties of  $d(t)$ :
  - If  $d(t)$  meets the above-defined two conditions, an IMF is derived. Replace  $x(t)$  with the residual  $r(t) = x(t) - d(t)$ ;
  - If  $d(t)$  is not an IMF, replace  $x(t)$  with  $d(t)$ .
6. Repeat Steps 1)-5) until obtaining a monotonic residual, or a one maximum or minimum-residual satisfying some stopping criterion [5].

At the end of this process, the signal  $x(t)$  can be expressed as follows:

$$x(t) = \sum_{j=1}^N c_j(t) + r_N(t) \quad (1)$$

where  $N$  is the number of IMFs and  $r_N(t)$  denotes the final residue which can be interpreted as the DC component of the signal.  $c_j(t)$  are the IMFs and are nearly orthogonal to each other and all have nearly zero means [16].

### III. MODE MIXING AND ENSEMBLE EMPIRICAL MODE DECOMPOSITION

It is worthy of note that EMD is defined by the algorithm and has no analytical formulation; hence our understanding of EMD comes from experimental rather than analytical results [5]. From experimental results, it has been shown that mode mixing and modes intermittency are the major obstacles to the use of EMD on many signals including cardio-respiratory signals like the ones measured by flexible piezoelectric film sensor as in the beforementioned reference [14]. Mode mixing indicates that oscillations of different time scales coexist in a same IMF, or that oscillations with same time scale have been assigned to different IMFs. Hence, this leads to misunderstanding of the real process.

[17] summarizes EMD behaviors for the case of the sum of two sinusoidal signals as well as for the case of the sum of two non-linear signals. It shows that, when studying mode mixing, amplitude and frequency ratios between the components of the signal should be taken into account.

To overcome mode mixing, a new method using added noise has been proposed: EEMD [6] (ensemble empirical mode decomposition). It defines the true IMF as the average over a set of tests; each test is the EMD of the original signal added to a white noise, in order to obtain a collection of white noises which cancel each other. Therefore, only the real components can survive and persist in the final average. The amplitude of white noises must force the ensemble to get all possible solutions: the noise makes the various components reside in the corresponding IMF dictated by the EMD filter banks and the significant physical sense of IMF. The number of tests must be sufficiently high which leads to a time consuming procedure.

### IV. CARDIORESPIRATORY MODEL

We use in this paper an improved version of our cardiorespiratory (CR) model [18] to simulate CR, respiratory and cardiac volume signals. The model consists of a respiratory module added to a simple cardiac wave generator to simulate respiratory pattern, alveolar volume, pleural pressure, cardiac activity as well as chest wall mechanics and volume variations (simulated inductive plethysmography signal). We develop here an improved model taking into account left ventricle (LV) stroke volume modulation during respiration and that LV stroke volume lies within  $[0.08 \ 0.2] * \text{Tidal Volume}$ . Ranges of physiological respiratory-to-cardiac frequency ratios are respected ( $3Fr < Fc < 8Fr$ ) and held constant in the simulations.

Our previous model [18] intended to simulate apnea did not take CR interactions during respiration into consideration. It consists in three interconnected elements: rib cage, heart and lung. The relationship between rib cage, alveolar and intra-thoracic blood volumes (respectively  $V_{th}$ ,  $V_A$  and  $V_h$ ) is given by the equation:

$$V_{th} = V_h + V_A \quad (2)$$

Cardiac mechanical activity is represented by the periodic (cardiac frequency,  $F_c$ ) changes of intrathoracic blood volume. In every cardiac cycle, intra-thoracic blood volume varies with amplitude equal to the stroke volume [18]. In a heart cycle (cardiac period  $T_c = 1/F_c$ ) there are two phases: filling till ejection onset ( $T_{ej}$ ; we arbitrarily chose  $T_{ej} = T_c * 3/4$ ) and ejection. Between 0 and  $T_{ej}$ , simulated intra-thoracic blood volume ( $V_h$ ) increases linearly with time from 0 to stroke volume ( $V_{str}$ ). Between  $T_{ej}$  and  $T_c$ , simulated intra-thoracic blood volume decreases linearly with time from  $V_{str}$  to 0. The shape of cardiac wave generated is then quasi-triangular, similar to cardiogenic oscillations observed during apnea [18].

In the previous model,  $V_{str}$  was held constant along the simulated period, and the chest wall was purely elastic (elastance  $E_{cw}$ ) such that

$$Ppl = E_{cw} * Vth \quad (3)$$

where  $Ppl$  is pleural pressure, considered as intrathoracic pressure.

The lung is simulated by an elastic compartment (elastance  $EI$ , volume  $VA$ ) submitted to pleural pressure and connected to the atmosphere by a resistive tube (resistance  $R_{aw}$ ). The behaviour of this compartment obeys the following equation:

$$\frac{d(VA)}{dt} = \frac{-(Ppl + EI * VA)}{R_{aw}} \quad (4)$$

The improved model has been developed to include mechanical CR interactions during respiration. Stroke volume modulation due to respiration (decrease during inspiration and increase during expiration) is simulated by equation (4), where  $C$  is a parameter (equal to  $0.03 \text{ L}^2$ ).

$$V_{str} = \frac{C}{VA}, \text{ limited to } 0.15 \text{ L.} \quad (5)$$

Respiratory pattern generator behavior is described by [19]:

$$\frac{d}{dt}(y) = \alpha * x \quad (6)$$

$$\frac{d}{dt}(x) = \alpha * \left( (a * y^2 + b * y)(x + y) + \text{HB} * \frac{d(Valv)}{dt} \right) \quad (7)$$

where  $a$ ,  $b$  and  $\text{HB}$  are  $-0.8$ ,  $-3$  and  $1$  respectively, and  $y$  represents the respiratory centers activity. This dynamical system takes into account the observed reflex effect of changes in lung volume on the respiratory centers. The parameter  $\alpha$  that we added to the initial respiratory oscillator [19] allows to simulate various respiratory frequencies ( $\text{Fr}$ ) observed among individuals.

$$\alpha = \frac{\text{Fr}}{12.7} \quad (8)$$

The value  $12.7$  cycles/min is the respiratory frequency of the initial respiratory oscillator.

Respiration occurs as a result of nonzero respiratory muscles activity ( $P_{mus}$ ) leading to the reduction or rise in the pleural pressure ( $Ppl$ ). This leads to replace (3) by (9):

$$Ppl = P_{mus} + (Vth - Vth0) * E_{cw} \quad (9)$$

where  $P_{mus}$  is defined as follows:

$$\frac{d}{dt}(P_{mus}) = \lambda * y + \mu \quad (10)$$

where  $\mu$  and  $\lambda$  are parameters ( $1.1$  and  $1.03$  respectively) and  $Vth0$  represents the non-stressed rib cage volume ( $2 \text{ L}$ ).

Simulated stationary  $Vth$  is decomposed by the EMD (2000 iterations) and the EEMD methods (a set of 5000 white noises of a  $1.6$  standard deviation ratio) to extract cardiac activity. Left ventricle volume signal ( $Vlv$ ) is used as the reference cardiac activity. Stroke volumes and periods of stationary extracted cardiac activity are compared with  $SV$  and periods of simulated cardiac mechanical activity.

## V. RESULTS ON SIMULATED DATA

Figure 1 shows simulated  $Vth$  and the result of its decomposition by classical EMD. In IMF 3, we clearly

notice mode mixing between respiratory and cardiac components.

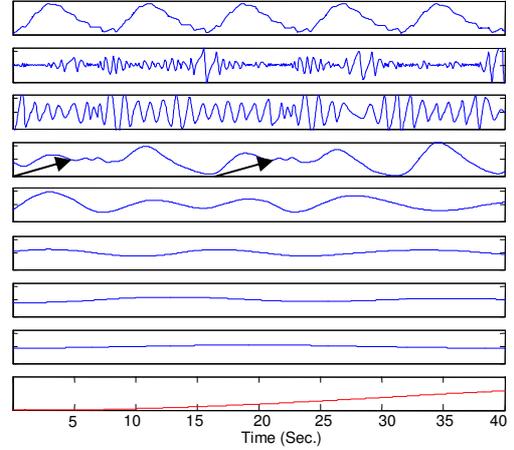


Fig. 1. Curves represent (from top to bottom) simulated  $Vth$  ( $L$ ), IMFs and residual. IMF1 and IMF2 scale (A.U) is  $[-0.0448 \quad 0.056]$ , other IMFs and residual scale (A.U) is  $[-0.4481 \quad 0.5601]$ . The method used is classical EMD. Mode mixing is indicated by arrows.

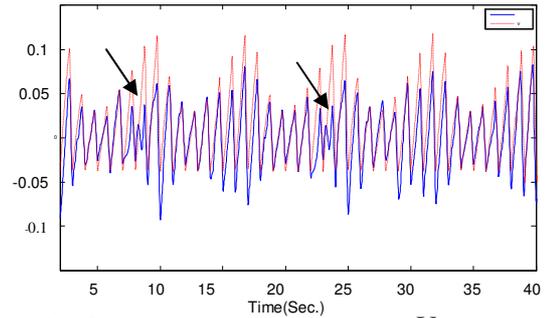


Fig. 2. Curves represent simulated  $Vlv$  (dashed) and symmetric extracted volume by EMD (as the sum of the first two IMFs). All beats are found. Amplitude scale is in A.U. Mode mixing is indicated by arrows.

Figure 2 shows simulated  $Vlv$  and extracted  $Vlv$  (the sum of the first two IMFs) superimposed. As mentioned previously, EMD algorithm results in locally symmetric IMFs [5]. For this reason, we can see that the sum of the first two IMFs in figure 2 does not fit the asymmetric simulated cardiac reference. Besides, mode mixing between cardiac and respiratory components leads to the fact that there are some components missing in the extracted cardiac activity. Bland & Altman test for stroke volume comparison between extracted and simulated cardiac activity gives limits of agreement (95% confidence interval) between  $-20\%$  and  $40\%$  whereas TCG gives limits of agreement between  $-20\%$  and  $20\%$  according to TCG results in [2]. This means that classical EMD should be further optimized to get better results.

When we apply EEMD, no mode mixing is found as indicated by Teager-Kaiser energy calculated for every IMF[20]. Figure 3 shows simulated  $V_{lv}$  and extracted  $V_{lv}$  (the sum of IMFs 2:5) superimposed. We do not take the first IMF as one of the cardiac modes because it is considered as white noise.

Bland & Altman test for stroke volume comparison between extracted and simulated cardiac activity gives limits of agreement (95% confidence interval) between -18% and 21%. This means that EEMD gives satisfying results.

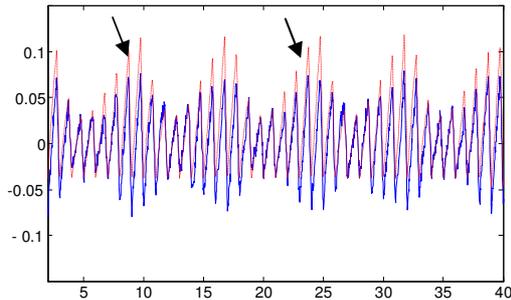


Fig. 3. Curves represent simulated  $V_{lv}$  (dashed) and symmetric extracted volume by EEMD (as the sum of IMFs 2:5). All beats are found. Amplitude scale is in A.U. There is no mode mixing at the previously observed positions indicated by arrows.

## VI. CONCLUSION

In this paper, we apply EMD and EEMD to a simulated stationary cardiorespiratory signal in order to extract cardiac activity. These preliminary results show that the EMD suffers from mode mixing problems which can be solved by EEMD.

EEMD is a promising nonlinear method for efficient cardiogenic oscillations extraction in inductive plethysmography signal.

In future works, we will study EEMD efficiency when applied to non-stationary simulated and real signals.

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