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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 signals 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 empirical mode decomposition (EMD) to simulated cardio-respiratory signals demonstrates that the mode mixing phenomenon affects the extraction performance and hence also the 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 the bedside presence of an experienced examiner or may 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 a 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, because their accuracy under clinical conditions has been questioned [1]. Another non-invasive method, called thoraco-cardiography (TCG), has been proposed [2]. It is based on the principles of respiratory inductive plethysmography (RIP), a method widely applied for quantitative recording of breathing patterns. The output of an inductive plethysmograph is a measure of 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 aims to non-invasively monitor left ventricular stroke volume by ECG-triggered ensemble averaging and digital band-pass filtering [0.7*(cardiac frequency) 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 depend on the heart rate estimation. This solution is not adapted to strong non-stationary conditions.

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 method for extraction of cardiogenic oscillations 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 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].

By contrast with decomposition methods based on wavelets, the 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 number of small undesired spikes over the whole frequency range of time consuming continuous wavelet transform ([12], [8]). In addition, although wavelet decomposition has good time resolution in the high-frequency region, it often cannot separate events separated by a small time interval. Thus, EMD operation is not time consuming, can deal with large nonlinear non-stationary signals [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

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useful to extract local temporal structures such as the heart beat superimposed on respiration signals in order to monitor respiration and cardiac frequencies during sleep using a flexible piezoelectric film sensor (pressure fluctuations). NB.: cardiac stroke volume (SV) of the extracted cardiac signal was not studied here.

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 defining requirements of an IMF, the sifting process for extracting IMFs from a given signal *x(t)*, *t*= 1… 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 the 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 one obtains a monotonic residual, or a single maximum or minimum-residual satisfying some stopping criterion [5].

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

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

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 orthogonal to each other and all have zero means [16].

III. Mode Mixing and Ensemble Empirical Mode Decomposition

It is worth noting 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 mode intermittency are the major obstacles to the use of EMD on many signals, including cardio-respiratory signals like the ones measured using a flexible piezoelectric film sensor, as in the above-mentioned reference [14]. Mode mixing indicates that oscillations of different time scales coexist in a given IMF, or that oscillations with the same time scale have been assigned to different IMFs. Hence, this leads to a misunderstanding of the real process.

Reference [17] summarizes EMD behavior for the case of the sum of two sinusoidal signals as well as for the case of the sum of two non-linear signals. The authors show that when studying mode mixing the 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). This method defines the true IMF as the average over a set of tests; each test is the EMD of the original signal with added white noise, in order to obtain a collection of white noise signals which cancel each other. Therefore, only the real components can survive and persist in the final average. The amplitude of white noise signals must force the ensemble to find 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. Cardio-respiratory Model

In this paper, we use an improved version of our cardio-respiratory (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 the respiratory pattern, alveolar volume, pleural pressure, and 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 the fact that LV stroke volume lies within [0.08 0.2] * Tidal Volume. Ranges of physiological respiratory-to-cardiac frequency ratios are respected (3Fr<Fc<8Fr) and are held constant in the simulations.

Our previous model [18] aiming to simulate apnea did not take into consideration CR interactions during respiration. It consisted of three interconnected elements: rib cage, heart, and lung. The relationship between rib cage, alveolar, and intra-thoracic blood volumes (respectively, *Vth*, *VA* and *Vlv*) is given by the equation:

$$Vth = Vlv + VA \tag{2}$$

Cardiac mechanical activity is represented by the periodic (cardiac frequency, Fc) changes of intra-thoracic 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 Tc =1/Fc), there are two phases: filling until the onset of ejection (Tej; we arbitrarily chose Tej = Tc*3/4) and ejection. Between *t*=0 and Tej, the simulated intra-thoracic blood volume (*Vlv*) increases linearly with time from 0 to stroke volume (*Vstr*). Between Tej and Tc, simulated intra-thoracic blood volume decreases linearly with time from *Vstr* to 0. The shape of the generated cardiac wave is then triangular, similar to cardiogenic oscillations observed during apnea [18].

In the previous model, *Vstr* was held constant along the simulated period, and the chest wall was purely elastic (elastance Ecw) such that

$$Ppl = \mathrm{Ecw} * Vth \tag{3}$$

where *Ppl* is pleural pressure, considered as intra-thoracic pressure.

The lung was simulated by an elastic compartment (elastance El, volume *VA*) submitted to pleural pressure and connected to the atmosphere by a resistive tube (resistance Raw). The behavior of this compartment obeys the following equation:

$$\frac{d(VA)}{dt} = \frac{-(Ppl + \mathrm{El} * VA)}{\mathrm{Raw}} \tag{4}$$

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 (5), where C is a parameter (equal to 0.03 L^2).

$$Vstr = \frac{\mathrm{C}}{VA}, \text{ limited to 0.15 L.} \tag{5}$$

Respiratory pattern generator behavior is described by [19]:

$$\frac{d}{dt}(y) = \alpha . x \tag{6}$$

$$\frac{d}{dt}(x) = \alpha . \left((\mathrm{a}.y^2 + \mathrm{b}.y).(x+y) + \mathrm{HB}.\frac{d(VA)}{dt} \right) \tag{7}$$

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

$$\alpha = \frac{\mathrm{Fr}}{12.7} \tag{8}$$

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 (*Pmus*) leading to the reduction or rise in the pleural pressure (*Ppl*). This leads to replacement of equation (3) by (9):

$$Ppl = Pmus + (Vth - \mathrm{Vth0}) * \mathrm{Ecw} \tag{9}$$

where *Pmus* is defined as follows:

$$\frac{d}{dt}(Pmus) = \lambda . y + \mu \tag{10}$$

where μ and λ are parameters (1.1 and 1.03 respectively) and Vth0 represents the non-stressed rib cage volume (2 L).

Simulated stationary *Vth* is decomposed by the EMD (2000 sifting iterations) and the EEMD methods (a set of 5000 white noise signals with an amplitude of 1.6 times the r.m.s of RIP signal). For EEMD, the number of sifting iterations is limited to 10 in order to avoid over-sifting [6]. 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.

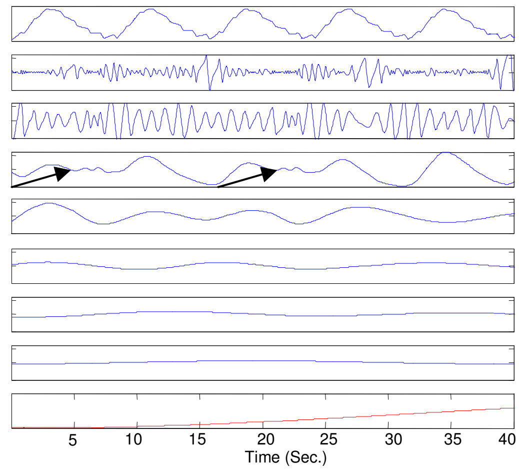

Fig. 1. Curves represent (from top to bottom) simulated *Vth (L)*, IMFs and residual. IMF1 and IMF2 scale (A.U) is [-0,0448 0,056], other IMFs and residual scale (A.U) is [-0,4481 0,5601]. The method used is classical EMD. Mode mixing is indicated by arrows.

Figure 2 shows simulated *Vlv* and extracted *Vlv* (the sum of the first two IMFs) superimposed. As mentioned previously, the 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 the Teager-Kaiser energy calculated for every IMF[20]. Figure 3 shows simulated *Vlv* and extracted *Vlv* (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. The Bland & Altman test for stroke volume comparison between extracted and simulated cardiac activity shown in the figure gives limits of agreement (95% confidence interval) between -18% and 21%, indicating that EEMD gives satisfactory results.

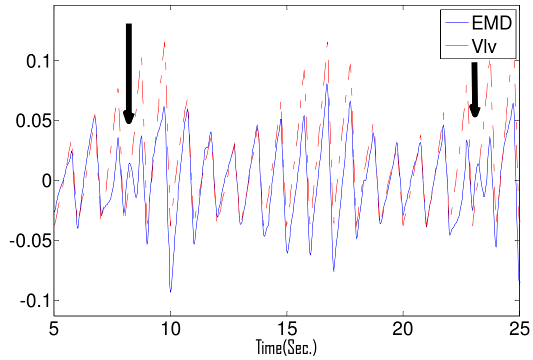

Fig. 2. Curves represent simulated *Vlv* (dashed) and symmetric extracted volume by EMD (as the sum of the first two IMFs). All beats are found. Amplitude scale is in A.U. Mode mixing is indicated by arrows.

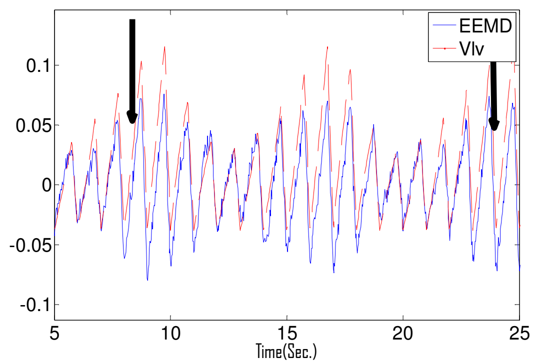

Fig. 3. Curves represent simulated Vlv (dashed) and symmetric extracted volume by EEMD (as the sum of IMFs 2:5). All beats are found. Amplitude scale is in A.U. There is no mode mixing at the previously observed positions indicated by arrows.

VI. Conclusion

In this paper, we apply EMD and EEMD to a simulated stationary cardio-respiratory signal in order to extract cardiac activity. These preliminary results show that the EMD method 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. Nevertheless, EEMD may lead to scale mixing. Scale mixing [6] is caused by the limitation of sifting iterations number, and is represented by IMF containing the sum of two consecutive modes. The solution of ''post-processing'' is proposed in [6]. One of our perspectives is to study the presence of scale mixing in cardio respiratory decomposition. More precisely, we will study EEMD efficiency when applied to non-stationary simulated and real signals.

REFERENCES

[1] D. R. Spahn et al., *Noninvasive versus invasive assessement of cardiac output after cardiac surgery: clinical validation.* Journal of cardiothoracic anesthesia. (1990), 4, 1, pp. 46-59.

[2] M. A. Sackner et al., *Thoracocardiography part 1: non-invasive measurement of changes in stroke volume; comparisons to thermodilution,* Chest. (1991), 99, 3, pp. 613- 622.

[3] G. B. Bucklar et al., *Signal processing technique for noninvasive real-time estimation of cardiac output by inductance cardiography (thoracocardiography),* Medical & biological engineering & computing. (2003), 41, 3, pp. 302-309.

[4] N. E. Huang et al., *The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis,* Proceedings - Royal Society. Mathematical, physical and engineering sciences. (1998), 454, 1971, pp. 903-995.

[5] G. Rilling et al., *On empirical mode decomposition and its algorithms,* IEEE-EURASIP Workshop on Nonlinear Signal and Image proc., (2003), NSIP-03, Grado (I).

[6] W. Zhaohua et al. *Ensemble Empirical Mode Decom-position: A Noise Assisted Data Analysis Method.* Advances in Adaptive Data Analysis, (2009), 1, pp. 1-41.

[7] H. Liang et al., *Empirical mode decomposition: A method for analyzing neural data.* Neurocomputing, (June 2005), 65-66, pp: 801-807.

[8] S. Charleston-Villalobos et al., *Crackle sounds analysis by empirical mode decomposition.* Engineering in Medicine and Biology Magazine, IEEE. (Jan.-Feb. 2007), 26, 1, pp 40-47

[9] R. Blocchi et al., *Deriving the respiratory sinus arrythmia from the heart beat time series using empirical mode decomposition,* Chaos, Solitons and Fractals (2004), 20, 1,pp.171-177.

[10] W. Huang et al., *Engineering analysis of biological variables: An example of blood pressure over 1 day,* Proc Natl Acad Sci U S A. (April 1998), 95, 9, pp. 4816–4821.

[11] S. Mallat, et al., *Singularity detection and processing with wavelets.* Infor-mation Theory, IEEE Transactions (Mar 1992), 38, 2, Part 2, pp 617-643.

[12] Z. Peng et al., *Vibration signal analysis and feature extraction based on reassigned wavelet scalogram,* Sound and Vibration. (20 June 2002), 253, 5, pp. 1087-1100

[13] R.X. Gao et al., *Non-stationary signal processing for bearing health monitoring,* International Journal of Manufacturing Research. (2006), 1, 1, pp. 18 – 40.

[14] B. Nan et al., *Monitoring of Respiration and heart beat during sleep using a flexible piezoelectric film sensor and empirical mode decomposition,* 29th Annual International Conference of the IEEE. (2007), pp. 1362 - 1366.

[15] R. Deering, et al., *The use of a masking signal to improve empirical mode decomposition.* Acoustics, Speech, and Signal Processing (18-23 March 2005), 4, 4, pp iv/485- iv/488.

[16] H. Liang, et al., *Application of the empirical mode decom-position to the analysis of esophageal manometric data in gastro-esophageal reflux disease,* IEEE EMBS (2004).

[17] G. Rilling et al., *One or Two Frequencies? The Empirical Mode Decomposition Answers,* IEEE Trans. on Signal Processing (2008), 56, 1, pp. 85-95.

[18] E. Abdulhay et al., *Stroke volume estimation by Thoraco-cardiography is better when glottis is closed,* IEEE EMBC, (2007).

[19] L. Forest et al., *Lienard systems and potential-Hamiltonian decomposition – III Applications,* C. R. Acad. Sci. Biologies, (2007), 330, pp. 97-106.

[20] C. Yunchao et al., *Analysis and solution to the mode mixing phenomenon in EMD,* Congress on Image and signal processing (2008).