A Wearable Technology Revisited for Cardio-Respiratory Functional Exploration: Stroke Volume Estimation From Respiratory Inductive Plethysmography

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ABSTRACT
The objective of the present study is to extract new information from complex signals generated by Respiratory Inductive Plethysmography (RIP). This indirect cardio-respiratory (CR) measure is a well-known wearable solution. We applied time-scale analysis to estimate cardiac activity from thoracic volume variations, witnesses of CR interactions. Calibrated RIP signals gathered from 4 healthy volunteers in resting conditions are processed by Ensemble Empirical Mode Decomposition to extract cardiac volume signals and estimate stroke volumes. Averaged values of these stroke volumes (SV_{RIP}) are compared with averaged values of stroke volumes determined simultaneously by electrical impedance cardiography (SV_{ICG}). There is a satisfactory correlation between SV_{RIP} and SV_{ICG} ($r=0.76$, $p<0.001$) and the limits of agreement between the 2 types of measurements (±23%) satisfies the required criterion (±30%). The observed under-estimation (-58%) is argued. This validates the use of RIP for following stroke volume variations and suggests that one simple transducer can provide a quantitative exploration of both ventilatory and cardiac volumes.

Keywords: Respiratory Inductive Plethysmography, Impedance cardiography, Stroke Volume, Cardio-respiratory interactions, Empirical Mode Decomposition.

INTRODUCTION
Continuous monitoring of vital and behavioral signs is an emerging concept of healthcare. Although wearable technology is more and more implied in such a context (Lymberis & Dittmar, 2011), little attention is paid to its application for functional exploration. Nevertheless, smart shirt technology should provide a new way for non-invasive and yet performing tools in the field of daily medical practice. The classical challenge addressed in the studies dedicated to wearable solutions is the robustness of an indirect measurement devoted to a unique sign. As an example, Lanata *et al.* (2010) have compared the motion susceptibility of different wearable technologies for respiratory rate monitoring. Our challenge here is quite different. The indirect nature of the measurements generates a complexity in the signal due to multiple physiological interactions. Thus we aim to extract new information from these physiological interferences. This extraction will be conducted on a time-scale basis.

In this article, we propose an integrated physiological tool to study cardio-respiratory interactions, which are both of physiological and clinical interest (Bradley *et al.*, 2010; Lalande & Johnson, 2010; Marcora *et al.*, 2008). We investigated Respiratory Inductive Plethysmography (RIP) (Milledge & Stott, 1977) which is a wearable technology already tested for respiratory rate monitoring (Lanata *et al.*, 2010; Grossman *et al.*, 2010) and also used for ventilatory function assessment (Chadha *et al.*, 1982, Tobin *et al.*, 1983., Eberhard *et al.*, 2001). We aim here to assess the estimation of cardiac parameters from the respiratory signal.

The nonlinear local technique, Empirical Mode Decomposition (EMD) has been proposed by Huang et *al.* (1998) for adaptively representing non-stationary signals as sums of zero-mean AM-FM components (Rilling *et al.*, 2003). 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 (Liang et al., 2005; Charleston-Villalobos *et al.*, 2007). 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 (IMF).

In cardio-respiratory EMD applications reported in literature, the extracted modes are speculatively associated with specific physiological aspects of the phenomenon investigated. In (Balocchi *et al.*, 2004), it has been shown that EMD can be useful for estimating R-R interval variations due to respiration. The authors underlined that these variations are the result of many nonlinearly interacting processes; therefore any linear analysis has the potential risk of underestimating a great amount of information content. In (Bu *et al.*, 2007), EMD was used to extract local temporal structures such as the heart beats superimposed on respiration signals in order to monitor respiration and cardiac frequencies during sleep using a flexible piezoelectric film sensor. These studies demonstrate the interest of the EMD in the cardio-respiratory context.

However, from experimental results (Wu & Huang, 2007), it has been shown that one major obstacle to the use of EMD on many signals was mode mixing due to mode intermittency. Therefore, Wu & Huang (2007) have proposed a method called Ensemble Empirical Mode Decomposition (EEMD). In Abdulhay *et al.* (2009), a cardio-respiratory model has been proposed to simulate cardio-respiratory (CR), respiratory and cardiac volume signals; Empirical Mode Decomposition has then been applied on simulated CR signals to extract cardiac activity. It has been shown that EEMD was a promising nonlinear method for efficient cardiogenic oscillations extraction in simulated CR signals.

In this article, we propose then to apply EEMD on real RIP measurements for extraction of cardiogenic oscillations. Validation of the proposed approach is carried out by comparing stroke volume estimations obtained from RIP signals with those simultaneously determined from thoracic electrical impedance (Kubicek *et al.*, 1966; Moshkovitz *et al.*, 2004; Tang & Yong, 2009). In this first study we will not take into account motion artifacts susceptibility, which have to be considered in exercise exploration protocols.

MATERIAL AND METHODS

Subjects and protocol

Four healthy seated volunteers participated in the study. Subjects were asked to make spontaneous calm respiration during 10 min. They were asked not to move during recording in order to avoid any motion artifacts on signals**.** Participants provided informed consent. The study was approved by the relevant ethics committee (CHU Grenoble).

Material

Thorax and abdomen cross sectional area changes were recorded with a computer-assisted RIP vest (Visuresp®, RBI, Meylan, France). During the 2 last minutes of the recording, breathing was recorded simultaneously with a flowmeter (Fleish head no.1) and a differential transducer (163PC01D36, Micro Switch) placed on a face mask. Electrocardiogram (ECG) was also recorded.

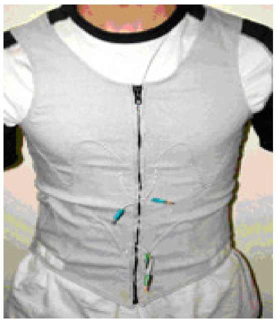

Figure 1. Computer-assisted RIP vest (Visuresp®, RBI, Meylan, France)

Simultaneous measurements were made with a thoracic electrical bioimpedance monitor (PhysioFlow^{TM}, Manatec Biomedical, Paris, France). This device is based on analysis of instant impedance variations using six electrodes: two for ECG measurement (CM5 position) and four for thoracic impedance cardiograph. The PhysioFlow concept has been described in details in Charloux *et al.* (2000). In our study, the six electrodes were taped to the skin under the RIP vest. The stroke volumes values (SV_{ICG}) were continuously estimated from the impedance signal by the PhysioFlow system

Methods

The synchronous acquisition of all signals was realized using a PowerLab data acquisition system and Chart software (ADinstruments). All signals were sampled at 100 Hz.

Starting from the thorax and abdomen cross sectional area changes and the airflow, the method used in Eberhard *et al.* (2001) was applied to obtain a calibrated respiratory inductance plethysmographic volume signal (V_{RIP}). The signal was filtered to eliminate frequencies higher than 10 Hz (200-order FIR).

Empirical Mode Decomposition was then applied on 60 second sequences of V_{RIP} signals. We applied the modified EEMD method, proposed by Yeh *et al.* (2008) and named Complementary EEMD (CEEMD). In EEMD, the intrinsic mode functions are defined as the average over a set of tests; each test is the EMD of original signal added to a white noise, with the intention that we obtain a collection of white noises which cancel each other. Therefore, only the real components can survive and persist in the final average. In CEEMD, two sets of averaged IMFs with positive and negative residues of added white noises are generated. The averaged IMFs without the residue of added white noises are the final result of CEEMD. A set of N=200 white noise signals with an amplitude of 1.6 times the rms of RIP signal was used. This EEMD optimization has also the advantage to reduce the number of tests and therefore, the computation cost.

Figure 2 and Figure 3 show the result of CEEMD application to one 60 second sequence of one V_{RIP} signal. We consider that:

– IMF1 and IMF2 are likely composed of noise
– the cardiac signal is spread over IMF3, IMF4, IMF5 and IMF6
– The remaining IMFs concern respiration and other body movements.

Therefore we define the extracted cardiac signal as the sum of the cardiac IMFs, it is noted V_h and can be observed Figure 4.

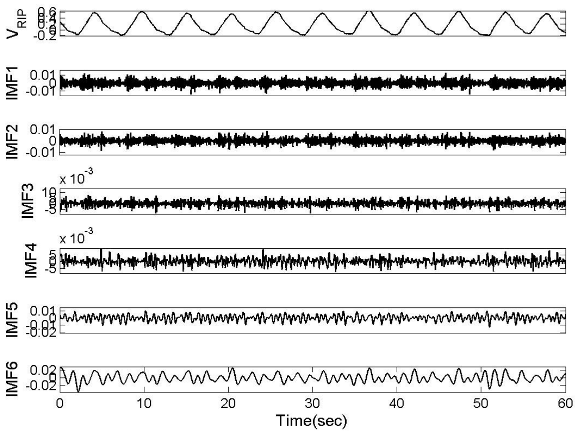

Figure 2. IMF1-6 obtained after the application of CEEMD to one real V_{RIP} signal.

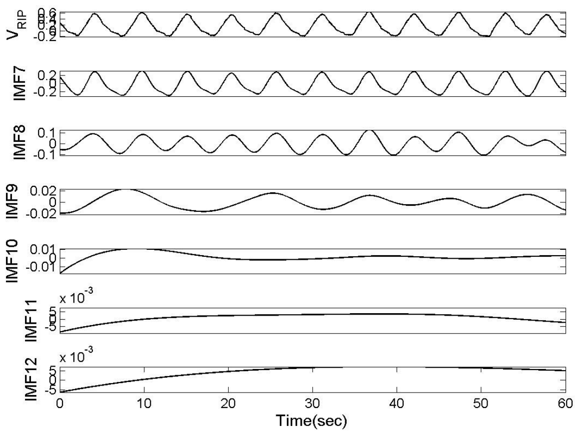

Figure 3. IMF7-12 obtained after the application of CEEMD to one real V_{RIP} signal.

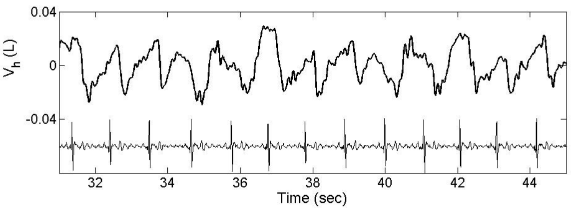

Figure 4. Cardiac signal V_h (bold line) extracted from the previous real V_{RIP} signal: V_h is the sum of IMFs 3 to 6, generated by CEEMD on V_{RIP} and considered as cardiac. ECG signal is shown to indicate each cardiac cycle.

From the extracted cardiac signals V_h, estimations of beat-to-beat stroke volumes, noted SV_{RIP}, are carried out, as the difference between maximum and minimum (Figure 5) of each cardiogenic oscillation (Bloch *et al.*, 1998), detected by the R waves of the ECG.

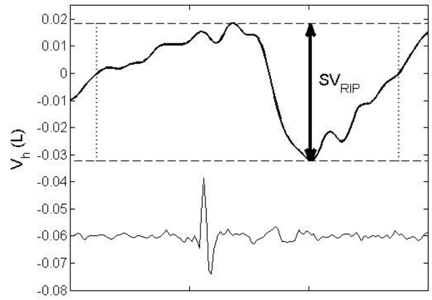

Figure 5. Extracted cardiac volume V_h and ECG signal for one cardiac cycle (defined by the dotted vertical lines). The stroke volume SV_{RIP} is estimated as the difference between the maximum and the minimum of the cardiogenic oscillation.

For preliminary results, we limit our study to sequences where Empirical Mode Decomposition separates efficiently the cardiac and respiratory modes ("no scale mixing") and where there are no ambiguities to decide which IMFs are cardiac. The sequence considered on Figure 2 is a "good" one: IMFs generated by CEEMD are easily attributed to cardiac or respiratory information. On the contrary, CEEMD applied on the signal shown Figure 6 generates some IMFs which present scale mixing. This is the case for IMF6 which is clearly composed of cardiac and respiratory components. In this preliminary study, such a sequence is excluded from the analysis. For all sequences taken into account (for the 4 subjects), beat-to-beat SV_{RIP} values are then continuously estimated, in parallel with those determined by impedance cardiography (SV_{ICG}).

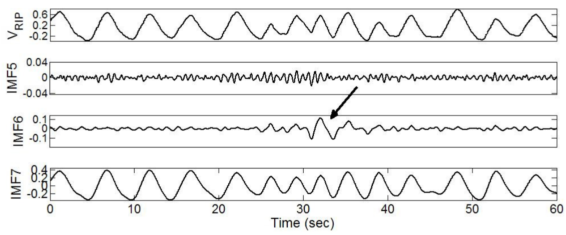

Figure 6. Another sequence of V_{RIP} signal. CEEMD applied on this signal generates IMF6 which shows scale mixing (pointed out by the black arrow).

All subjects taken together, 24 sequences of 5-beats are considered and values of SV are averaged over each sequence. To validate our measurements, we follow a procedure similar to many comparative studies (Charloux *et al.*, 2000; Kemps *et al.*, 2008; Tordi *et al.*, 2004). The relation between these 24 averaged values of SV_{RIP} and SV_{ICG} is first made using linear regression. The statistical test of Bland and Altman (Bland & Altman, 1986) is also used to compare the 2 types of measurements and evaluate whether there is agreement or bias.

RESULTS

A positive correlation is found between SV_{RIP} and SV_{ICG} ($r=0.76$, $p < 0.001$, Figure 7). This coefficient is satisfactory compared to other values reported in the literature (from 0.65 to 0.95 depending on the method used (Warburton *et al.*, 1999)).

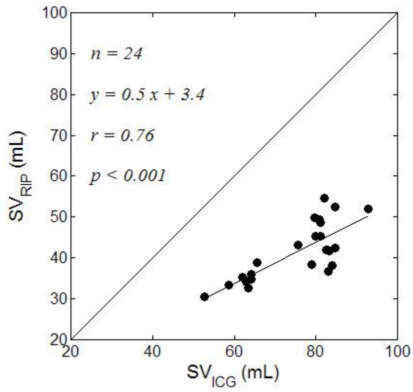

Figure 7. Comparison between the stroke volume values obtained using CEEMD on RIP signals and that obtained using the impedance method. Correlation plot between SV_{RIP} and SV_{ICG} in the same individuals (n=24). The identity line is represented.

Limits of agreement between SV_{RIP} and SV_{ICG} (Figure 8) are ± 23%. These limits of agreement are consistent with the recommendation of Critchley & Critchley (1999) for cardiac output measurements, which says that "acceptance of a new technique should rely on limits of agreement (95% confidence limits) of up to ±30%".

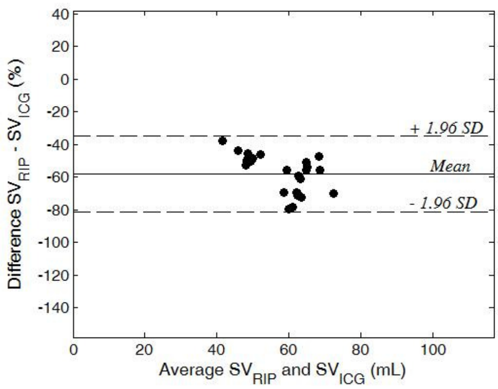

Figure 8. Comparison between the stroke volume values obtained using CEEMD on RIP signals and that obtained using the impedance method. Bland and Altman representation (n=24): graphic representation of the difference between the two measurements (SV_{ICG} -SV_{RIP}) versus the mean of the two measurements ((SV_{ICG} +SV_{RIP})/2) for each measure. The solid line represents the mean difference between the tests, and the dashed lines indicate the 95% confidence intervals of the difference.

The observed bias (-58%) indicates that SV_{RIP} are systematically under-estimated, compared to SV_{ICG} and in accordance with classic physiological data (Guz *et al.*, 1987). This can be explained by the location of the thoracic and abdominal measures during RIP measurements. These locations are not optimal to capture the cardiac thoracic movements. Indeed, thoracocardiography relies on a single loop positioned at transverse level of xiphoid process (Sackner *et al.*, 1991. Moreover, part of the under-estimation has to be attributed to the fact that part of the cardiac contraction is converted into airflow instead of thoracic movements (Abdulhay & Baconnier, 2007).

CONCLUSION

Our results demonstrate that stroke volumes can be estimated from cardiac activity present on Respiratory Inductive Plethysmography signals. This study suggests that RIP can be used as an integrated and non-invasive tool to investigate cardio-respiratory interactions, as it delivers quantitative and synchronized assessment of ventilatory and stroke volumes.
This study is also a proof of the concept that wearable solution can bring multi-dimensional and complex information.

Further steps of validation are considered with more subjects and various recording protocols. We also intend to validate the estimation of the beat-to-beat variation of the stroke volume. In that purpose, improvements in our RIP signals processing are necessary. Even if the EMD solution is well adapted to non-stationary signal analysis, limitations due to scale mixing imposed us to limit our results to sequences where cardiac IMFs identification could be made without ambiguity. Improvements of the algorithm in terms of robustness and definition of an automatic criterion for the IMF choice are our future steps of development.

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