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Assessment of Empirical Mode Decomposition Implementation in Cardiovascular Signals

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***Abstract*-**Biomedical signals are relentlessly superimposed with interferences and noise. The nonlinear processes which generate the signals, and the interferences, regularly exclude or limit the usage of classical linear techniques, and even wavelet transforms, to decompose the signal.
Empirical Mode Decomposition (EMD) is a recently proposed method for analyzing signals from a nonlinear viewpoint. EMD is not defined by a formal mathematical analysis, instead the decomposition is obtained by following an algorithm, requiring experimental investigation, thus being a fully data-driven technique.
Hence, this work evaluates the impact of EMD implementation in the processing of biomedical signals, namely on electrocardiogram, impedance and photoplethysmogram, and ballistocardiogram. All these signals are very sensible to motion artefacts, and therefore mode decomposition is important to separate the representative component from the pure noise. EMD was never applied to most of these signals, which are very physiologically meaningful, so the implementation's impact is assessed.

I. Introduction

Monitoring the cardiovascular activity recurring to electrophysiological signals is the most appropriate way of non-invasively assessing the cardiovascular activity. From cardiovascular signals, the foremost is recognizably the electrocardiogram (ECG), while the photoplethysmogram (PPG) has earned some popularity, due to its implementation in pulse oximeters. Two other signals which have gained some attention lately due to the possibility of being acquired without the patient's awareness are the impedance plethysmogram (IPG) and the ballistocardiogram (BCG). The devices acquiring and processing these signals are becoming smaller and more common [1–6], but all face similar problems: motion artefacts, baseline wandering, and other signal-specific issues, as power line frequency interference.
The cardiovascular signals referred exhibit nonlinear and non-stationary behaviour, even if the devices are completely immune to artefacts, because of the unrepeatability of the stimuli provided by a living subject's cardiopulmonary system. The classical frequency domain techniques have harsh limitations to deal with nonlinear, non-stationary signals, which are however the majority of real world signals, namely those of physiological origin [7].To overcome this obstacle, analysis techniques based on time-frequency properties of the signals have been developed, and, have proven to be appropriate for a wide range of such nonlinear and non-stationary problems, including signals enclosing localized artefacts, from spikes and bursts, to discontinuities, or are subject to a monotonic trend [8]. Time-frequency methods are of two types, the ones where a predefined basis is used, case of Continuous Wavelet or the Short Time Fourier Transform, and other techniques, such as the Wigner-Ville distribution [9]. Within strictly data-based techniques, the recently introduced Empirical Mode Decomposition (EMD) may be considered [10].
EMD, also known as Hilbert-Huang Transform, is a method for decomposing nonlinear, multi-component signals, into Intrinsic Mode Functions (IMFs). Each IMF admits an unambiguous definition of instantaneous frequency and amplitude through the Hilbert transform, and the higher the IMF order, the lower frequency component it represents. However, our understanding of EMD comes from experimental algorithm application rather than analytical results [11]. EMD has become an attractive tool, and has been used is various engineering areas [12], including biomedical engineering, for automated detection of venous gas bubbles, classification of EEG, and ECG denoising [13–15].
As the ECG is the sole electrophysiological signal to have been subject to EMD, the purpose of this work is to assess the potential of EMD implementation in a wider number of cardiovascular signals, with the addition of BCG, PPG, IPG acquired with high frequency systems with published results [1–2]. All these signals have large benefits to extract from mode decoupling, especially in baseline removal. The following sections describe EMD application to this set of signals, and the assessment of such

implementation, regarding both time performance and representation efficiency.

II. Implementation

A. Cardiovascular signals

ECG is the well-known signal produced by the electrical activity of the heart, while the BCG records the vibrations produced in the body during the cardiac cycle [2]. Plethysmography is a measurement of the volumetric changes of an organ, to measure PPG the patient's skin is illuminated in some spot, usually the finger [16], being measured the variations on the amount of light transmitted or reflected into a light sensing device. The IPG measures the electrical resistance changes, due to blood passage, of a body tissue of interest. Fig. 1 presents a depiction of the four signals, recorded from a healthy subject, using proper acquisition circuitry.

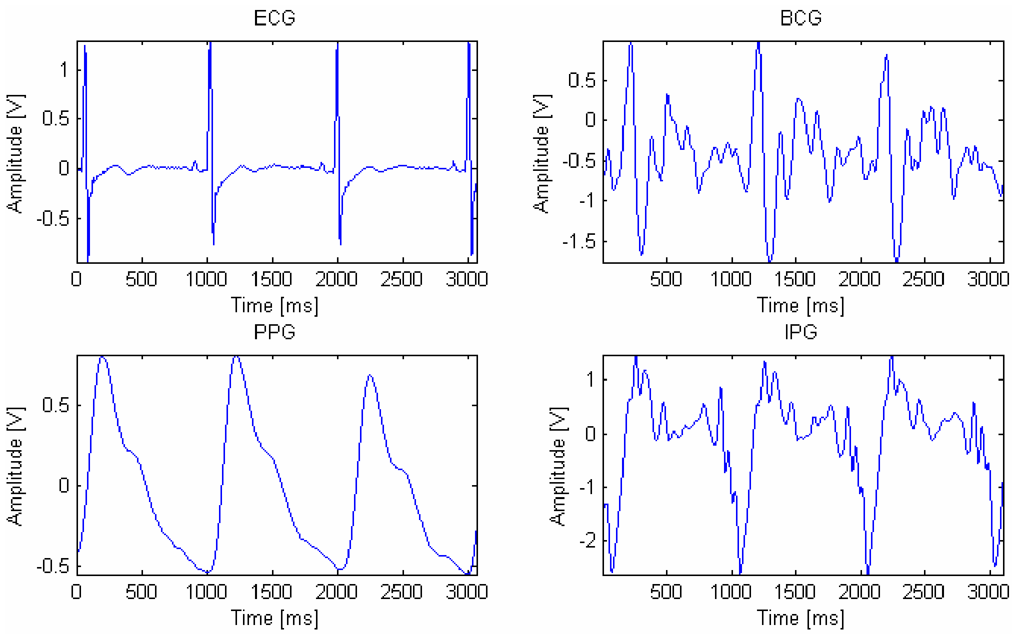

Figure 1. Set of 3 second segments of the cardiovascular signals to analyse: ECG, BCG, PPG, and IPG

To acquire the BCG a piezoelectric film sensor was embedded in the backrest of a normal office chair, the voltage BCG signal was obtained by connecting the sensor output to an high input impedance charge amplifier. The ECG was recorded using three chest leads, followed of filtering and amplification stages built using high input impedance operational amplifiers. The PPG curves were gathered by means of controlled red light emission, and transduction of the amount of absorption of the radiation in the subject's index finger. IPG sensing circuitry was embedded in the seat of the office chair, composed of a tetrapolar arrangement of plane electrodes, two injecting current and two measuring the resulting voltage, again high input impedance operational amplifiers were required. All the signals were sampled at 1 kHz, a frequency used for cardiac analysis of high precision [2], using a 16-bit data acquisition board.

B. Empirical Mode Decomposition

EMD is a signal processing technique which empirically extracts the oscillatory tones embedded in a signal, without requiring any *a priori* knowledge about the data, thus being fully data-driven. This procedure aims at decomposing a time series into components with well-defined frequency, the IMFs, by empirically discovering the time scales intrinsic to the data, which is perceived as the distance between successive extrema [10,11]. An Intrinsic Mode Function ends-up being a well-behaved function, to which the Hilbert Transform may be applied, and satisfying two conditions, to guarantee unambiguous definition of instantaneous amplitude and frequency [10]:

a) the number of local extrema and the number of zero crossings may differ by no more than one
b) the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero

The procedure taken in order to separate the signal in its IMFs is called sifting process (steps 1-4), and it consists in removing the information on lower frequencies until only the highest frequency remains (details). The algorithm for a given signal $x(t)$, of the EMD can be summarized as follows [10]:

1. Identify all local extrema of $x(t)$
2. Obtain the maxima and minima envelope $e^{max}(t)$ and $e_{min}(t)$, by spline interpolation
3. Compute the mean of the envelopes $m(t)=(e^{max}(t) + e_{min}(t))/2$
4. Extract the detail $d(t)= x(t) - m(t)$
5. Iterate steps 1-4 on the detail signal $d(t)$ until it can be considered an IMF
6. Iterate on the residual, $m(t)$.

The stopping criterion determines the number of sifting steps to produce an IMF, and it is related with property *b*, so the IMF is obtained when the detail is considered as zero-mean, comparing the amplitude of the mode with the mean value and defining a threshold [10]. A further development on this was the implementation of two thresholds, to guarantee globally small fluctuations in the mean, while taking into account locally large excursions [11]. The decrease on the number of extrema, when going from one residual to the next, guarantees that the decomposition has a finite number of modes, and $x(t)$ may be recovered by linear superposition.

III. Assessment Tests

A. Decomposition

The algorithm described in the previous section was implemented in a Matlab script, and it was successfully applied to the various signals gathered. A result obtained from the decomposition of a 30s IPG signal is exemplified in Fig. 2.

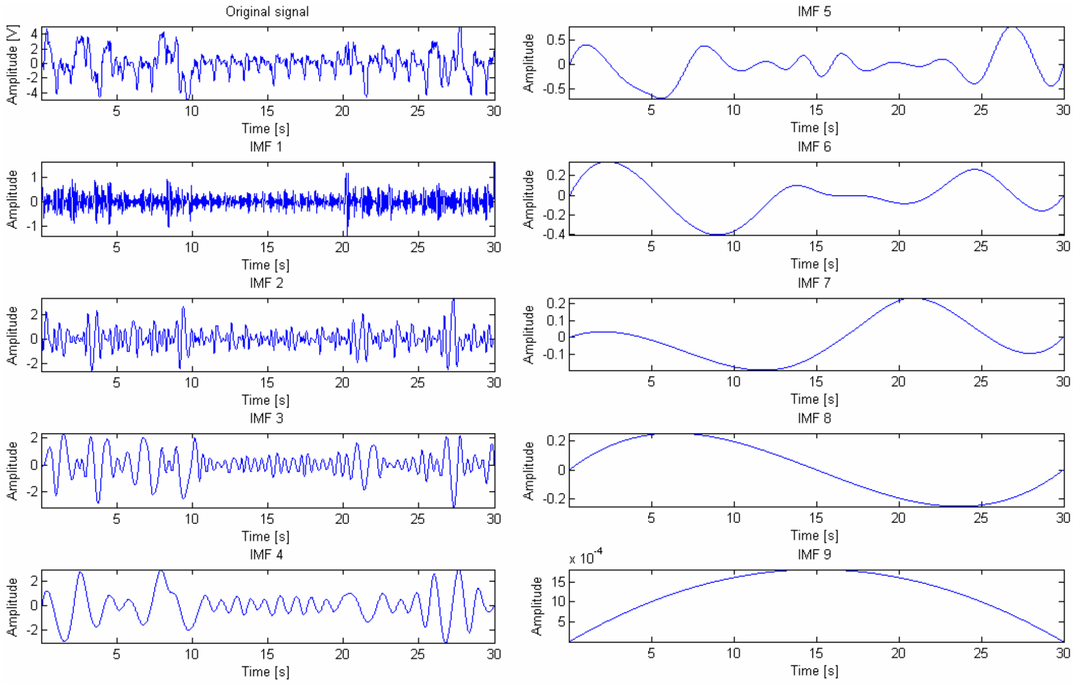

Figure 2. Set of IMFs generated by the application of the decomposition in empirical modes to 30 seconds of IPG signal affected by movement artefacts

This example focus on the most unstable signal gathered, and it can be seen that there are some movement artefacts both in the beginning and in the end of the example IPG considered. As reported previously, it is visible the reduction in the number of maxima and minima of the IMFs, as the order increases. Moreover, the two columns reinforce the separation of the baseline-related IMFs, from the detail-related IMFs, so, even for this signal very sensitive to movement, approximately three IMFs are enough to represent the signal without baseline. Even regarding the baseline, the 9th IMF is of no interest, as its amplitude is negligible, thus 8 IMFs are enough to decompose 30 seconds of IPG data with plenty

of movement noise.
Table 1 presents the total number of IMFs resulting from the algorithm implementation for different lengths of the signals.

Table 1. Number of IMFs generated, for different lengths of cardiovascular data sampled at 1 kHz

Total IMFs	Length = 10 s	Length = 20 s	Length = 30 s	Length = 60 s
IPG	8	9	9	11
BCG	8	9	10	10
ECG	8	9	9	9
PPG	6	7	8	10

The previous results show that, relatively stable signals (ECG and PPG) and for highly unstable signals (IPG and BCG), a small number of intrinsic mode functions can represent the data without significant baseline wandering. The PPG is the signal generally demanding less IMFs, which may be explained by its reduced number of waves and high-frequency components. The remaining signals have small variations on the number of IMFs generated.

B. Computational Overhead

Given the specific necessity of the implementation, for instance, high-frequency filtering or baseline removal, the expected number, and position of IMFs to compute will be different, and may be hinted previously, thus the algorithms may experience an important increase of performance. The time taken in the calculations to present the previous figure, employing 30000 samples of IPG signal, was 536 ms, when running the EMD algorithm in an Intel Core 2 Duo E6600 Dual-Core 2.4 GHz Processor, with 2 GB RAM, equipped with Windows XP and MATLAB R2009a. Therefore, these first results show, for PC-based acquisition systems, a convincingly fast performance. Following Table 2 presents, for the hardware specified, for different lengths of IPG signal, the overhead introduced by EMD, in terms of average ± standard deviation, for 100 repetitions of the calculations

Table 2. Overhead of EMD computation, for different lengths of cardiovascular data sampled at 1 kHz

Signal Overhead [ms]	Length = 10 s	Length = 20 s	Length = 30 s	Length = 60 s
IPG	162±0.6	249±1.7	595±27	3068±113
BCG	167±2.9	323±12.3	962±66	2815±104
ECG	133±1.5	249±1.9	543±3	7524±14
PPG	194±3.1	5021±45.6	9159±233	49009±1070

The computational overhead of the decompositions may vary substantially if prolonged artefacts are gathered. This happens because the number of peaks and valleys of the signals will increase significantly, thus obliging to the calculation of a larger number of IMFs. Nevertheless, the results in the previous table show that the IPG and the BCG, who suffer similarly with motion artefacts, have a resembling behaviour regarding computational overhead. It is also visible that the ECG is quite similar to these two except if the length considered is 60 seconds. The PPG had an uncharacteristic, and much significant, overhead, about one order of magnitude above the other signals, thus making it unable to be subject to this technique, for sets above 10 kS, if real-time performance is mandatory.

C. Recomposition

Following Table 3 presents the number of IMFs necessary to represent the cardiovascular signals, with different lengths, without the baseline, and the total number of IMFs generated.

Table 3. Number of IMFs generated, for different lengths of cardiovascular data sampled at 1 kHz

Signal/Total IMFs	Length = 10 s	Length = 20 s	Length = 30 s	Length = 60 s
IPG	3 / 8	3 / 9	3 / 9	4 / 11
BCG	3 / 8	3 / 9	3 / 10	3 / 10
ECG	3 / 8	4 / 9	4 / 9	4 / 9
PPG	5 / 6	3 / 7	4 / 8	4 / 10

The previous results show that, relatively stable signals (ECG and PPG) and for highly unstable signals (IPG and BCG), a small number of intrinsic mode functions can represent the signal. A single exception is the 10 second PPG, where a long artefact misleads the algorithm. An additional property of EMD is the rejection of baseline movement, including diverse pure DC components, slow-motion, and fast artefacts. Fig. 3 illustrates these properties, where it may be seen that the BCG and the PPG are changed to zero-mean, the ECG is practically unaltered, and the IPG movement artefacts are considerably reduced.

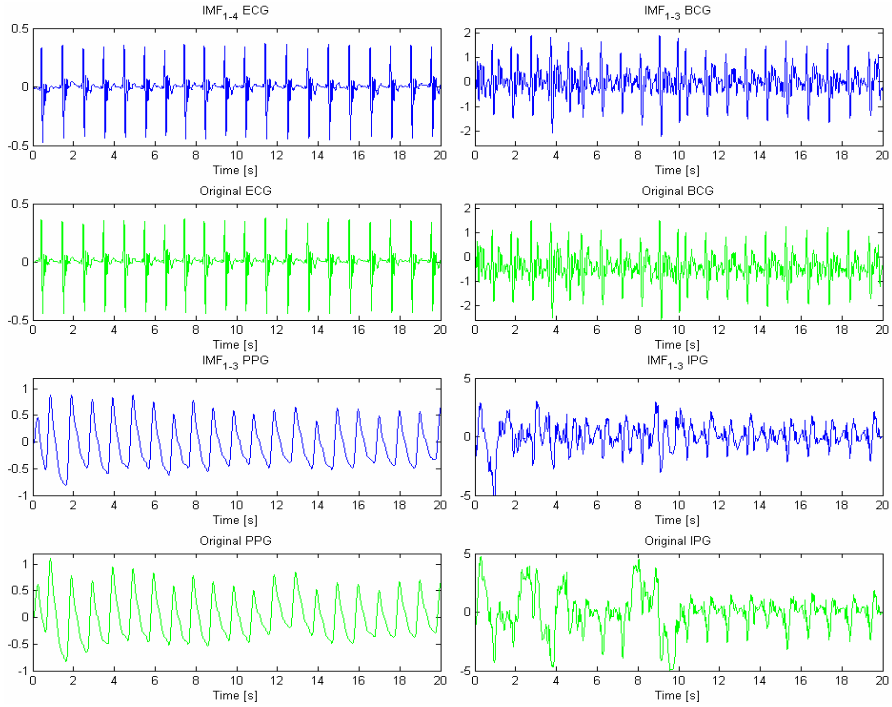

Figure 3. 20 seconds of cardiovascular signals recomposed with few IMFs after EMD application. ECG is unchanged, BCG and PPG are centred on zero, and IPG artefacts are reduced.

A set of 30 seconds of BCG data was used to obtain the following Fig. 4. This figure depicts the recomposition of a signal with wavering baseline, but without major artefacts. It were obtained 10 IMFs, the first three were responsible by the signal, and after the 3rd it were responsible by baseline wandering. The residual, the difference between the original signal and the sum of the IMFs, is insignificant. Reconstructing the IMFs according with the preceding judgment shows this division, and demonstrates that EMD application is most helpful to remove unstable baselines in sets without major motion artefacts, but without zero-average and with wavering issues.

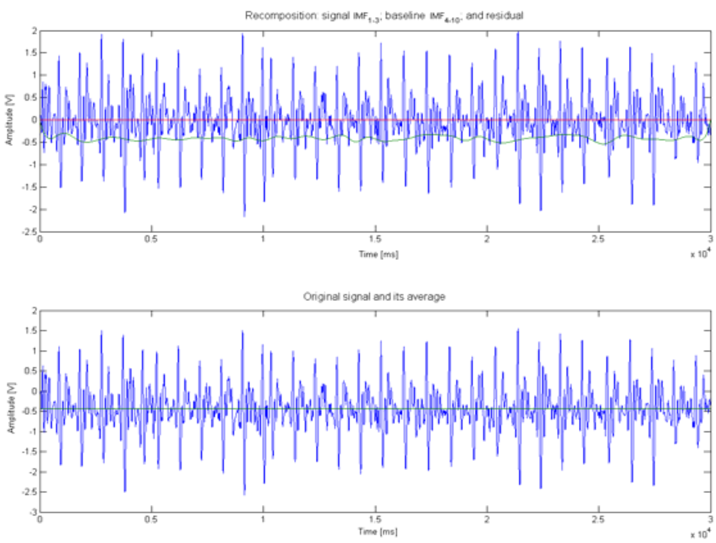

Figure 4. Recomposition (top) of the IMFs gerenated by the application of EMD to 30 seconds of BCG signal (bottom), with non-zero average and affected by baseline wandering. The first three IMFs construct the BCG, and the remaining IMFs the baseline

IV. Conclusions

The Empirical Mode Decomposition technique was applied to a set of, very physiologically meaningful, cardiovascular signals. Comprehensive discussion was provided to clarify the interpretation of the assessment tests, being confirmed that this technique is useful in separating the different components of a signal, especially data from baseline noise. This capability was verified in a number of different scenarios, obtained from recordings of six healthy subjects.
EMD has been shown to deal equally well with high-amplitude artefacts, slow baseline wandering, baseline wavering, and non-zero mean, common difficulties on the processing of biomedical signals, which lead to the fail of several other approaches. Therefore EMD is a method which presents adequate characteristics for processing of cardiovascular signals, at the same time as it generally improves the signal-to-noise ratio.

Acknowledgments

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