Comparison of Heart Rate Variability Analysis with Empirical Mode Decomposition and Fourier Transform

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Abstract. The heart rate variability (HRV) analysis allows the study of the regulation mechanisms of the cardiovascular system, in both normal and pathological conditions, and the power spectral density analysis of the short-term HRV was adopted as a tool for the evaluation of the autonomic function. The Ensemble Empirical Mode Decomposition (EEMD) is an adaptive method generally used to analyze non-stationary signals from non-linear systems. In this work, the performance of the EEMD in the decomposition of the HRV signal in the main spectral components is studied, in a first instance to a synthesized series to calibrate the method and achieve confidence and then to a real HRV database. In conclusion, the results of this work propose the EEMD as useful method for analysis HRV data. The ability of decomposes the main spectral bands and the capability to deal with non-linear and non-stationary behaviors makes the EEMD a powerful method for tracking frequency changes and amplitude modulations in HRV signals generated by autonomic regulation.

Keywords: Heart rate variability · Comparison of methods · EEMD · Fourier analysis · Spectrum decomposition

1 Introduction

The HRV analysis allows the study of the regulation mechanisms of the cardiovascular system, not only under normal conditions, but also when these are altered to produce pathological conditions, for example high blood pressure, heart failure and diabetes among others [1,2].

It is feasible to involve the autonomic control mechanisms in cardiac function, these influence the short-term fluctuations of the time interval between consecutive heart beats (RR) [3,4]. Indeed, the power spectral density analysis of the short-term HRV was adopted as a tool for the evaluation of the autonomic

H. Florez and M. F. Pollo-Cattaneo (Eds.): ICAI 2021, CCIS 1455, pp. 278–289, 2021.
https://doi.org/10.1007/978-3-030-89654-6_20

function [3,4]. Three main spectral components can be highlighted, very low frequency component (VLF), from 0.003 Hz to 0.04 Hz; low frequency component (LF), from 0.04 Hz to 0.15 Hz; and high frequency component (HF), from 0.15 Hz to 0.4 Hz [3,5].

Numerous techniques have been applied in the frequency domain, among the most important measures, some linear models that generate comparable results can be included. Nonparametric models, such as windowed fast Fourier transform (FFT) and Blackman-Tukey spectral estimation, and parametric models, such as autoregressive (AR) and moving average autoregressive (ARMA). After calculating the spectrum with any of the above methods, the energies within each band can be calculated [1,2].

These linear methods must assume stationary conditions that are difficult to achieve, even in short-term records under controlled conditions. To correctly attribute spectral components to specific physiological conditions, the heart rate modulation mechanisms must not make any changes during the measurement process [3]. Due to the nature of HRV signals, non-linear techniques appears as attractive methods for their analysis in order to solve the difficulty of achieving the conditions of strict stationarity and correctly reflecting the non-linear content of the data.

The Empirical Mode Decomposition (EMD) is an adaptive method generally used to analyze non-stationary signals from non-linear systems [6]. The algorithm produces a decomposition of the time series into a finite quantity of oscillating functions and a residue. These zero local mean functions are modulated amplitude / frequency signals called intrinsic mode functions (IMF).

In the EMD process a problem called mode mixing occurs, oscillations with very different scales can exist in one mode. To reduce this effect, a new method called ensemble empirical mode decomposition [7] was proposed. The decomposition is performed from a set of noisy copies of the original signal, obtaining the final results by averaging whereas the noise converges to zero. These decomposition methods have proven their competence in different applications, for heart rate variability analysis [8], assessment of cardiovascular autonomic control [9], automated identification of congestive heart failure[10], classification of ECG heartbeats [11], early detection of sudden cardiac death [12].

In this work, the performance of the EEMD in the decomposition of the HRV signal in the main spectral components is studied, in a first instance to a synthesized series to calibrate the method and achieve confidence and then to a real HRV database. Looking to generate a stationary behavior for the measurement, we used 5 min short-term recordings of 14 subjects before and during the application of a pharmacological autonomic blockade in combination with posture changes during controlled breathing [13]. The energy of the three main spectral bands acquired by the windowed FFT method and the energy of each IMF obtained using the EEMD was calculated to obtain their correlation. The objetive was to validate the correlation between them and verify the effectiveness of the EEMD method applied to HRV signals.

2 Materials and Methods

2.1 Simulated Signal

A typical 5-minutes short-term HRV segment with zero mean was produced to evaluate the performance of the EEMD. As shown in the Fig. 1, the synthesized HRV series $s(t)$ is composed of $s_1(t)$,$s_2(t)$ and $s_3(t)$, three sinusoidal signals whose oscillation frequency was located in the center of each main spectral band [3].

The s_1 component recreates the HF with an angular frequency $\omega_{HF} = 2\pi(0.275)t$, s_2 represents the LF with an angular frequency $\omega_{LF} = 2\pi(0.095)t$, and s_3 simulate the VLF with an angular frequency $\omega_{VLF} = 2\pi(0.0215)t$. The signal was divided into 3 different segments in order to recreate a non-stationary environment, amplitude changes of the LF and HF components were made every 100 s. For the sampling frequency a rate of 7 hz was used [14]. The resultant series $s(t) = s_1(t) + s_2(t) + s_3(t)$ can be described as follows:

$$s(t) = \begin{cases} 30sin(\omega_{VLF}) + 15sin(\omega_{LF}) + 5sin(\omega_{HF}) & 0 \leq t < 100 \\ 30sin(\omega_{VLF}) + 20sin(\omega_{LF}) + 2sin(\omega_{HF}) & 100 \leq t < 200 \\ 30sin(\omega_{VLF}) + 10sin(\omega_{LF}) + 10sin(\omega_{HF}) & 200 \leq t \leq 300 \end{cases} \quad (1)$$

2.2 Dataset

We used recordings from a database developed by Harvard Medical School (HMS, Children's Hospital), Massachusetts Institute of Technology (MIT), and the Favaloro Foundation School of Medicine (FFMS). The HMS-MIT-FFMS database was designed to perform training and comparison of a variety of methodologies used to analyze the cardiac function. A total of 82 segments of 5-minute short-term recordings of 14 subjects were used [13].

The signal measurement process begins with each subject in a supine position where they perform a breathing protocol, then they move to the standing position and after 5 min for hemodynamic balance they repeat the breathing protocol. After that, the subject is then returned to the supine position and atropine (0.03 mg/kg, n = 7) or propranolol (0.2 mg/kg, n = 7) is administered, after 10 min, it is performed the breathing protocol with the subject in the supine position and then standing. Finally, the subject is placed back in the supine position to administer the other autonomous blocking agent, and the measurement process is repeated for the supine and standing positions. The doses chosen for complete parasympathetic blockade (atropine) and complete P-adrenergic blockade (propranolol) were based on previous studies [15]. Instances of pure sympathetic or parasympathetic modulation before and during the application of a pharmacological autonomic block in combination with posture changes during controlled breathing were generated. The RR interval signal were acquired from an ECG using a peak detection program, where time series of HR smoothed 3 Hz [16].

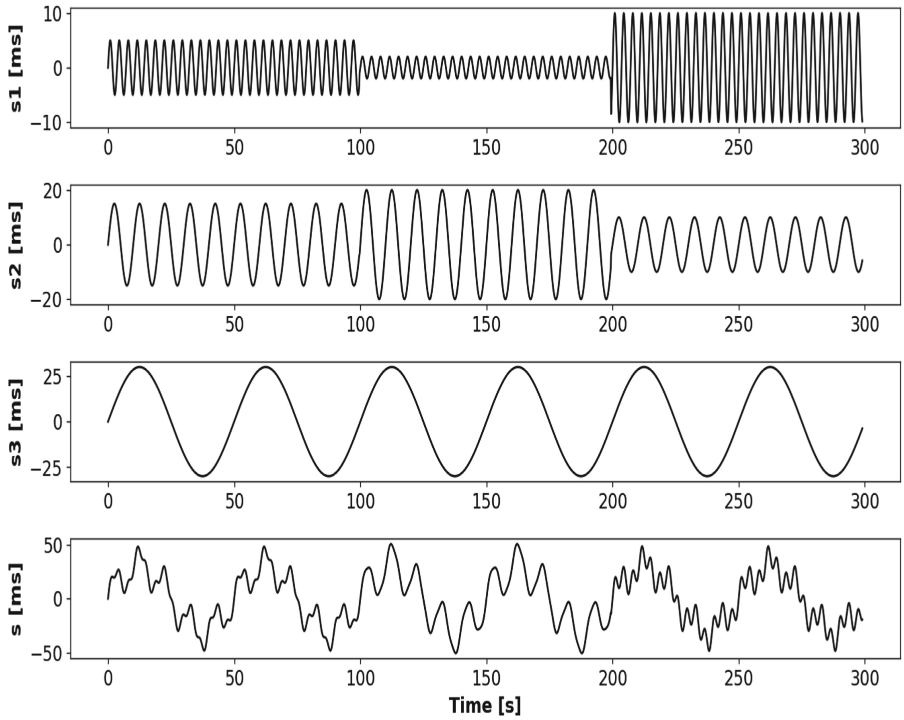


Fig. 1. Composition of the synthesized typical HRV 5-min segment. $s_1(t)$ represents the HF, $s_2(t)$ the LF and $s_3(t)$ the VLF. The resultant segment can be described as: $s(t) = s_1(t) + s_2(t) + s_3(t)$.

2.3 Resampling

It is necessary to convert the signal with an interpolation step, HRV data has an uneven sampling nature, whereas most feature extraction methods require uniform sampling [17]. Among the many resampling methods already defined in the literature, the Cubic Spline method is possibly the most widely used due to the minimal interference it has on frequency domain measurements [18]. The upper frequency of HRV data is 0.5 Hz [3] and a rate of 1 10 Hz is normally used for interpolation [14]. In this case, we applied the Cubic Spline resampling method with a sampling rate 7 Hz to HRV data.

2.4 HRV Signal Analysis

As suggested by HRV guidelines [19], standard frequency domain features for short-term HRV were extracted from 5-minute segments. In addition, an EEMD was applied in these HRV segments to analyze them based on a non-linear model [20].

Frequency Domain Analysis. The standard spectral analysis, in the frequency domain, can distinguish three main spectral components in a spectrum calculated from short-term HRV signals [5], the developed energy in each of them can be linked to physiological events [3]. The VLF, from 0.003 Hz to 0.04 Hz, represents different physiological influences, hormonal activity, chemoreflexes, thermoregulation and also parasympathetic modulations of heart rate.

The LF, from 0.04 Hz to 0.15 Hz, reflects sympathetic and parasympathetic modulations of HR. The HF, from 0.15 Hz to 0.4 Hz, can be associated with vagal modulation by the parasympathetic system. In this study, we calculated the energy of each main spectral band by using the windowed FFT method [1,2].

Empirical Mode Decomposition. The EMD [6] is an adaptive method generally used to analyze non-stationary signals from non-linear systems. The algorithm, empirically, produces a decomposition of the time series into a finite quantity of oscillating functions and a residue.

These functions are modulated amplitude/frequency signals called intrinsic mode functions (IMF). An IMF is a zero local mean function with an unique extreme between zero crossings. The EMD decomposes the signal into IMFs by a sifting process that can be described as follows:

Use a signal $x(t)$, identify the local maximum and minimum and produce the upper and lower envelops by a cubic spline line. Considering the mean of these envelops as m_1, the first component f_1 can be represented as:

$$f_1 = x(t) - m_1 \tag{2}$$

Take f_1 as the original signal and replicate the sifting process considering m_{11} as the mean of its upper and lower envelopes. Then, get f_{11} as:

$$f_{11} = f_1 - m_{11} \tag{3}$$

Repeat k times the sifting process until f_{1k} becomes itself to an IMF

$$f_{1(k-1)} - m_{1k} = f_{1k} \tag{4}$$

Then, obtain the first IMF component from the data:

$$IMF_1 = f_{1k} \tag{5}$$

The IMF_1 must contain the fastest, or the highest frequency, components of the signal. Once determined, get the residue r_1 separating this IMF_1 from the rest of the data

$$r_1 = x(t) - IMF_1 \tag{6}$$

Take the residue r_1 as a new signal, repeat the sifting process steps performed previously and obtain the second IMF component IMF_2. This procedure can be repeated resulting in:

$$r_1 - IMF_2 = r_2, ..., r_{n-1} - IMF_n = r_n \tag{7}$$

The stop process criteria are two: when the IMF_n or the r_n becomes less than a predetermined value or when the r_n becomes a monotonic function. Finally, the signal $x(t)$ can then be represented as a sum of the IMFs and a residue:

$$x(t) = \sum_{i=1}^{n} IMF_i + r_n \tag{8}$$

In the EMD process a problem called mode mixing occurs, oscillations with very different scales can exist in one mode. To reduce this effect, the new method EEMD [7] was proposed. The decomposition is performed from a set of noisy copies of the original signal, obtaining the final results by averaging whereas the noise converges to zero.

The addition of Gaussian white noise reduces the mixing of modes by populating the entire time-frequency space, taking advantage of the behavior of the EMD's dyadic filter bank [21] and obtaining more regular modes. Therefore, EMD mode mixing problem is solved effectively by using EEMD [20]. The EEMD algorithm can be computed as follows:

1. Add to the original signal $x(t)$, J different series of Gaussian white noise with a defined standard deviation n^j $(j = 1, ..., J)$. Then, return the observations:

$$x^j_{(t)} = x(t) + n^j_{(t)} \tag{9}$$

2. Decompose each $x^j_{(t)}$ into IMFs by the EMD process, obtaining a J sets of IMFs per observation IMF^j_i.
3. Compute the ensemble mean of each IMF as the final i^{th} IMF:

$$\overline{IMF_i} = \frac{1}{J} \sum_{j=1}^{J} IMF^j_i \tag{10}$$

2.5 Software Tools

In this experiment, the Python language was used to developed all the scripts and they were run in a JupyterLab notebook as integrated development environment. Pandas 1.0.3, Numpy 1.19.4, Scipy 1.5.4 and emd 0.4.0 packages were used.

3 Results

The EEMD analysis on a synthesized signal as shown in Fig. 3 produces the decomposition in five IMF, therefore is possible to see that the IMF_1 is mainly composed of the remaining noise used to average the assembly, the IMF_2 and IMF_3 are identified as the HF component of the signal, the IMF_4 is associated with the LF component and the IMF_5 with the VLF component.

Also, it can be observed that the amplitude modulations carried out in the LF and VLF components during the simulation are correctly represented by each corresponding IMF.

As suggested [7], a noise ratio of 0.2 of the signal standard deviation and a ensemble number of 100 was used. With this configuration, a set of 5 IMFs of each HRV segment was obtained both in the simulated case and with the real signals as shown in Fig. 2 and Fig. 3 respectively.

In the case of real RR signals, as shown in Fig. 3, the EEMD also produces the decomposition of five IMFs. A total of 410 IMFs from 82 short-term HRV segment were obtained, the correlation between their energies with the energies of the main spectral bands was calculated in order to validate their link.

In the Fig. 4 it can be observed a 0.96 correlation between the HF energy (Ehf) with the energy of the IMF_1 ($Eimf_1$), a correlation of 0.98 and 0.97 between the LF energy (Elf) with the energies of IMF_2 and IMF_3 respectively ($Eimf_2, Eimf_3$) and a correlation of 0.93 and 0.88 between the VLF energy ($Evlf$) with the energies of IMF_4 and IMF_5 ($Eimf_4, Eimf_5$). It is also possible to see that exist a correlation of 0.94 between the energies of IMF_2 and IMF_3 ($Eimf_2, Eimf_3$), and a 0.91 correlation with the energies of IMF_4 and IMF_5 ($Eimf_4, Eimf_5$).

4 Discussion

In this paper, the EEMD is presented as an adaptive method suitable for the non-linear and non-stationary behavior of HRV signals. This multi-resolution decomposition technique can evaluate the intrinsic characteristics of signals even with non-stationary components [14]. In the study of the congestive heart failure was used to improve the accuracy of an automated identification system [10], and to produce new features and indices that could serve as a new way of evaluating [22]. Also has been used to extract the feto-maternal heart rate from the abdominal ECG signal where they obtained a mean accuracy of approximately 95% in the quantification [23] and to classify ECG heartbeats with a mean accuracy greater than 95% [11]. The EEMD has been demonstrated that is a very useful technique for tracking frequency changes and amplitude modulations generated by autonomic regulation [8].

Autonomic function, through the sympathetic and parasympathetic nervous systems, controls the functioning of vital organs [24]. The autonomic control mechanisms are involved in cardiac function influencing short-term fluctuations of the RR time interval [3,4]. Indeed, the power spectral density analysis of the short-term HRV was adopted as an evaluator of the autonomic function [3,4]

The EEMD has the issue of decomposing the series analyzed in a set of IMFs according to the nature of the signal analyzed [25]. In this experiment, the numbers of the modes obtained by analyzing the synthesized signal do not coincide with those obtained in the real data set, a problem that requires prior knowledge of the data to correctly attribute the information to an IMF.

The method has shown that it can decompose HRV signals into four functions associated with four frequency bands, functions even validated by Hilbert-Huang transform [26]. It seems that, using the IMFs obtained through the EEMD in real short-term HRV series, it is possible to reconstruct separately the main spectral

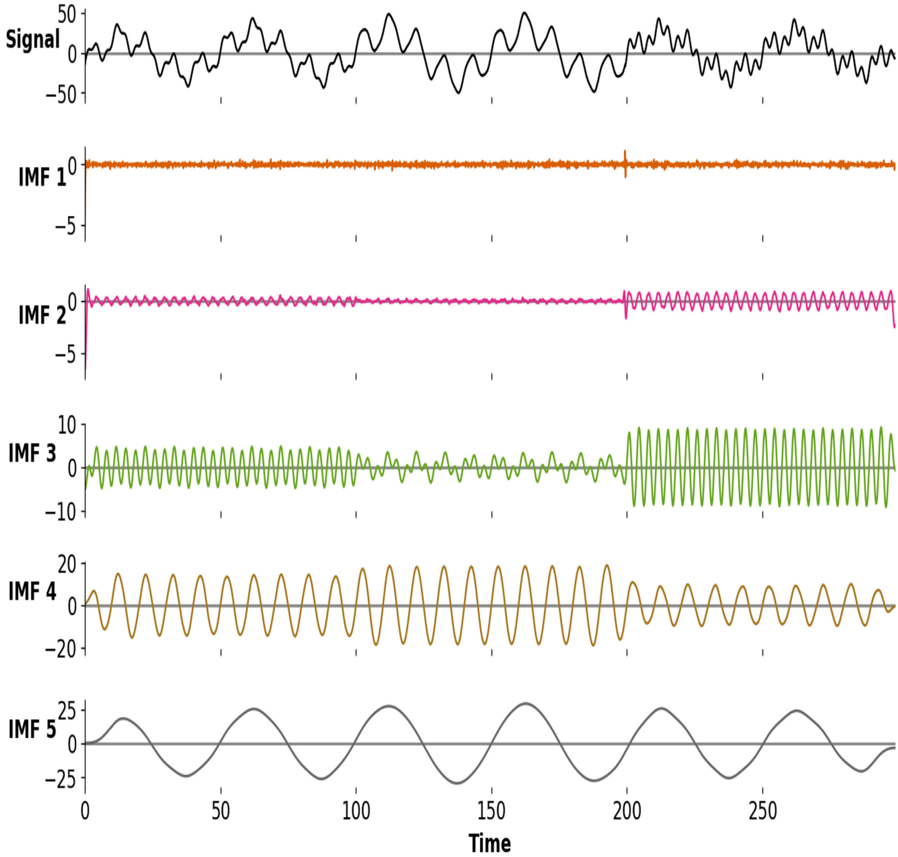
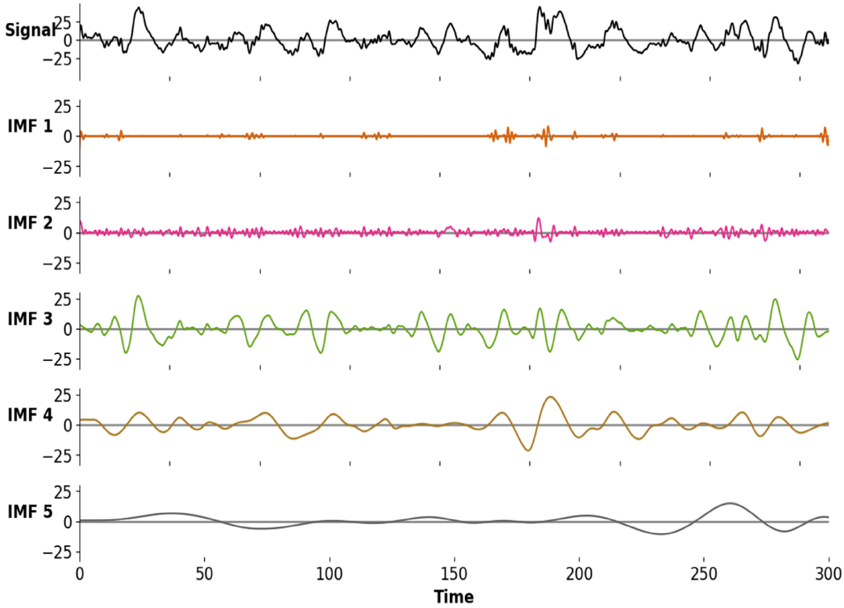


Fig. 2. Results of EEMD on synthesized typical HRV 5-minutes segment s(t).

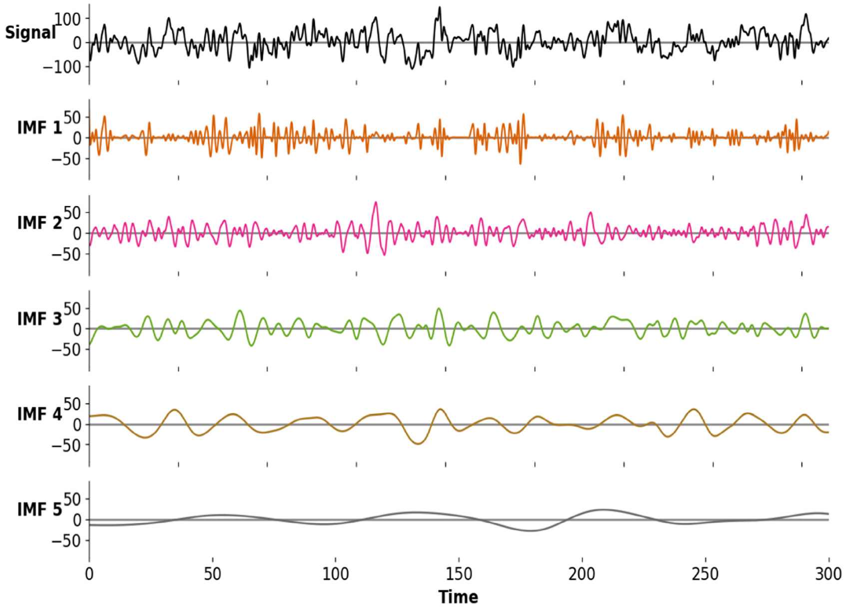
bands avoiding their interference and allowing to analyze each one of them in particular. In the results it can be observed a 0.96 correlation between the $IMF1$ and the HF band and correlations of 0.98 and 0.97 between the $IMF2$ and the $IMF3$ with the LF band achieving a correct discrimination without using any type of fixed filtering. If this correlation is sufficient to validate the link between the IMFs with the autonomic function, it is possible to say that IMFs describe their temporal activity.

In future works, with the objective to analyze the mode mixing level that exists in the different IMFs, will be to use a spectral or time-frequency method, as the Hilbert-Huang transform [6], in order to validate the correspondence of the IMFs with the main spectral bands. Also, to confirm the correlation between the IMFs with the autonomic function, we will construct a classification system where the IMFs will be evaluated as classification features.

One of the most significant limitations is the computational cost attributed by its iterative nature that slows down the method [27], it can be solved by



(a)



(b)

Fig. 3. Results of EEMD on two real HRV segments: (a) Subject in a pure sympathetic modulation state, (b) another subject in a pure parasympathetic modulation state.

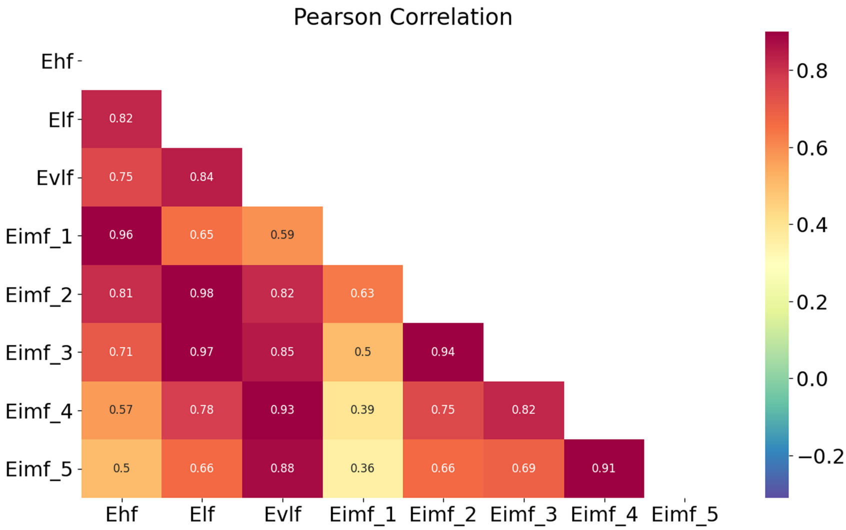


Fig. 4. Correlation between the energies of the HRV main spectral bands with the energies of the 5 IMFs obtained with the EEMD.

computing the EEMD in parallel processing threads, making real-time implementation possible. Another limitation was that we have used only data from 14 subjects, the analysis must be applied to a larger dataset to validate the results. Finally, we can mention that although the FFT is taken as the goal standard measurement, it is based on a linear method that requires stationarity for its correct operation.

4.1 Conclusions

In this work we have presented the EEMD as an algorithm that can solve the problem of analyzing non-linear and non-stationary signals such as the HRV series. The method was successfully tested on artificial and real signals. It is possible to say that the EEMD solves the mode mixing phenomenon by adding white noise to the original signal, the synthetized signal shows the capability to decompose the signal into IMFs.

Regarding the performance using the real data set, it can be observed a 0.96 correlation between the $IMF1$ and the HF band and correlations of 0.98 and 0.97 between the $IMF2$ and the $IMF3$ with the LF band, we can achieve a correct discrimination without using any type of fixed filtering.

In conclusion, the results of this work propose the EEMD as useful method for analysis HRV data. The ability of decompose the main spectral bands and the capability to deal with non-linear and non-stationary behaviors makes the EEMD a powerful method for tracking frequency changes and amplitude modulations in HRV signals generated by autonomic regulation.

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