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A CASE-STUDY VISION

Detection of relevant information in intrinsic mode function

Detección de información relevante en funciones de modo intrínseco

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ABSTRACT

The empirical mode decomposition (EMD) decomposes a local and adaptive time series into a finite set of intrinsic mode functions (IMF), AM-FM signals that allow to represent a non-linear and non-stationary model with the advantage of not losing the underlying meaning. This study examines time series of sEMG measurements for a case study of healthy individuals with carpal tunnel syndrome. Due to the amount of multiple levels of detail, all around a central frequency and evoked by the number of IMFs obtained through EMD, the informational contribution of each at the intermodal and interindividual level is studied through Shannon entropy to establish a general framework of spectral study given Hilbert Huang's (HHT) transformation to remarkable degrees of information. The results show that the latest IMFs have more disordered states even when they engage in apparently regular behavior, agglomerate more time-frequency information, and in the same way, concentrate more differentiable characteristics for a process of individualization of patterns.

RESUMEN

Este estudio explora la descomposición empírica de modos (EMD), técnica local y adaptativa que descompone una serie de tiempo en un conjunto finito de funciones de modo intrínseco (IMF), señales con amplitud y frecuencia variable que permiten representar un modelo no lineal y no estacionario con la ventaja de no perder el significado físico subyacente. Para el caso se examinan series de tiempo provenientes de mediciones sEMG de un estudio de caso de individuos sanos y con síndrome de túnel del carpo. Debida la cantidad de múltiples niveles de detalle, todos alrededor de una frecuencia central y evocados a la cantidad de IMFs obtenidas a través de la EMD, se estudia el aporte informativo de cada uno a nivel intermodal e interindividual a través de la entropía de Shannon, de manera que se logre establecer un marco general que propicie un enfoque al estudio espectral dada la transformada de Hilbert Huang (HHT) a grados de información destacables. Los resultados permiten evidenciar que sobre las últimas componentes IMF se logran los estados más potenciales al desorden, aun cuando comprometen un comportamiento más regular, aglomeran más información tiempo-frecuencia y del mismo modo, concentran las características más diferenciables para un proceso de individualización de patrones.

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1. Introduction

The dynamics coming from models that conserve information from biological systems under signal optics, are characterized by having non-linear and non-stationary particularities in time. Various methods of signal analysis and processing exist, most of which are restricted to dimensional analysis in an attempt to linearize [1], which biases the information and thus the extraction of study characteristics.

Most of the signal processing methods rely on the use of spectral methods, of which the most popular was the short Fourier transform. Later on, time frequency methods appear differentiated by different distributions, among which we find Wigner-Ville, Kirkwoo-Rihaczek, Levin, exponential, Choi-Williams, Sinc, Born-Jordan [2] and the Wavelets Transform, which depends directly on the selected function, and that leads to a search for components generating a method that is not intuitive but that allows a multiscale study. However, this and in general all the previous ones include the problem that they base their studies on approaches that assume in different ways approximations to linearity and/or stationarity [1–3]. This problem leads to the study of time series with Hilbert Huang's transform (HHT) under the premise of generating a complete, orthogonal, local and adaptive base, with the possibility of performing multi-scale, high-resolution and time-frequency-power spectral analyses [1, 4]. The basis of the HHT is the Empirical Mode Decomposition (EMD), which generates a set of time series, called Intrinsic Mode Functions (IMF), these sums reconstruct the signal being studied, giving the opportunity to have modes without mixed information, i.e. with independent information between them from the optics of frequency, so that orthogonality is established, and each one is an analytical signal that is exposed to the Hilbert's transform to generate the HHT.

Given the current confusion about the correct method of performing EMD, it was established that there is no standard way to apply it, since it depends on the general topology of the study phenomenon. It was also determined that the variant called Çomplete Ensemble Empirical Mode Decomposition with Adaptive Noise"(CEEMDAN), which combines decomposition under multiple realizations of the same time series each one contaminated with WGN, is the most efficient in terms of mode mixing mitigation for forearm sEMG signals [1].

Regarding the use of HHT it is common to find literature where its use to generate spectral studies is exposed given the total assembly of IMFs. Clear examples are [5] and [6] where the HHT is used to identify muscle activation characteristics in myoelectric and speech recognition signals respectively thanks to spectral distributions, [7] to analyze seismic signals from temporal frequency energy, [8] to identify six emotional states through ECG signals, [9] to analyze cardiac variability and [10] to differentiate temporal frequency in ECG signals. The problem of performing a similar practice is that there may be overlap between the spectral forms as a result of the powers of each frequency component in time, this hides information that may be relevant to study since EMD does not ensure that the power of the modes generated by the decomposition corresponds to the instantaneous frequency that they contain [11].

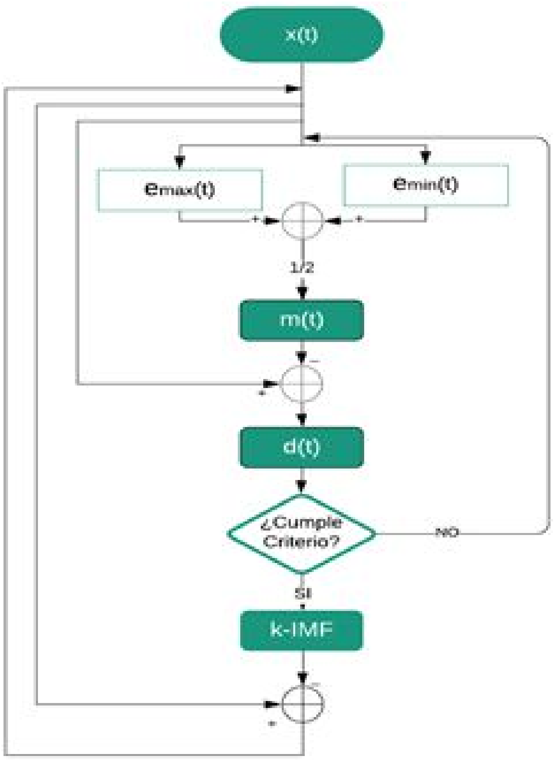
The present work focuses on the uncertainty of selection of relevant information that the HHT provides depending on the scales that conform it for the extraction of characteristics, for which the IMF are studied under the measure of shannon entropy in order to validate the set of components that retain the greatest amount of information. The following article begins with the reference framework, in which the empirical decomposition of modes, CEEMDAN variant, the Hilbert transform and Shannon entropy are discussed. It continues with the application section of the Hilbert Huang transform, where the set of time series is specified, the intrinsic mode functions are found, and the Hilbert spectrum is constructed. Later in the results, the Shannon entropy is used in the IMF to construct the Hilbert Huang's spectrum and finally we have the conclusions.

2. Reference Framework

2.1. *EMD y CEEMDAN*

The empirical mode decomposition [2] considers signal oscillations at a local level, looking at the signal dynamics from two consecutive extremes, in order to find their IMF [1]. An IMF satisfies two conditions, first, it must not be a monotonous signal, that is, it must have frequency information, and second, the value of the local average defined by a lower and upper envelope is zero. The process of decomposition is detailed in Figure 1, in which it can be seen that from an $x(t)$ signal two envelopes are defined, an upper and a lower one, these thanks to a cubic spline that interpolates between the points. Based on the envelopes is the local mean $m(t)$, which is subtracted from the signal to obtain the detail $d(t)$. If it meets the definition of IMF it is included in the set of modes and subtracted from the original signal to form a residual $r(t)$ on which the process is repeated, if not, it is subtracted from the signal again, and it is iterated until $d(t)$ meets the definition of IMF. The process ends when no oscillatory information is available [1, 2]. The method decomposes the signal in such a way that a set N of IMFs is obtained, representing these, from the finest detail to the thickest in frequency, the information contained in the original time series.

Figure 1: EMD process.



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The disadvantage of the EMD method is that the IMFs can contain information that is mixed up with each other, and therefore the HHT is discredited in terms of orthogonality [1, 4, 12]. On the other hand, the method called Çomplete Ensemble Empirical Mode decomposition with adaptive noise.ºr CEEMDAN [4] is an Empirical Mode Decomposition method that uses noise to establish a uniform background in the space-time-frequency to organize the components of the study model and mitigate the mixing of modes [12]. The process finds one mode at a time as an average among several realizations, each one differentiated by the fact that it has been polluted with a different distribution of WGN, so that by averaging all polluted modes, uncorrelated information is eliminated and net information is obtained and in general a set of IMFs in which the mode mix has been mitigated.

2.2. *Hilbert Huang Transform*

The HHT combines Hilbert's spectral analysis, through which the complex envelope of a signal modulated by a real carrier is found, and EMD. The combination of these techniques produces a dynamic characterization of the main oscillatory patterns in the signals. It consists in expanding the time series in IMFs and then applying the Hilbert transform to them and in this way estimating the time-frequency-energy distribution, called Hilbert Huang's spectrum [11, 13, 14] The Hilbert transform of a signal $x(t)$ is defined [2]:

$$y(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(t)}{t - \tau}\, d\tau \tag{1}$$

As shown in equation (2), a complex conjugate pair is obtained that defines an analytical signal $z(t)$, which allows the acquisition of instantaneous frequency information $w(t)$, and instantaneous power $a(t)$.

$$z(t) = x(t) + i * y(t) = a(t)e^{i\theta(t)}$$

$$a(t) = \sqrt{x(t)^2 + y(t)^2} \qquad ; \qquad \theta(t) = \tan^{-1} \frac{y(t)}{x(t)}$$

$$w(t) = \frac{d\theta(t)}{dt} \tag{2}$$

The local and adaptive information exploitation capacity of the HHT implies that the characteristics that it extracts through its individual components and the spectrum it generates, enjoy high resolution, a fact that is evidenced in Figure **2**, through which the robustness of the Wavelets transform is differentiated, which is not intuitive, versus Hilbert's spectrum for an example of the Stokes wave [2].

2.3. *Entropy measurement*

Entropy from various points of view can be understood as the variation of unusable energy in a system, the number of potential states or disorder and chaos in a system, or the expected value or uncertainty of the information, a value that corresponds to the inverse of the probabilities of the events [11, 15]. Given a discrete random variable X, Shannon entropy, H, is determined as the average information of the set of different values that the variable can take, and this is calculated:

$$H = -\sum_{i}^{n} p_i \log_b(p_i) \tag{3}$$

Figure 2: Wavelet spectrum and Hilbert Huang spectrum for Stokes wave. [2]

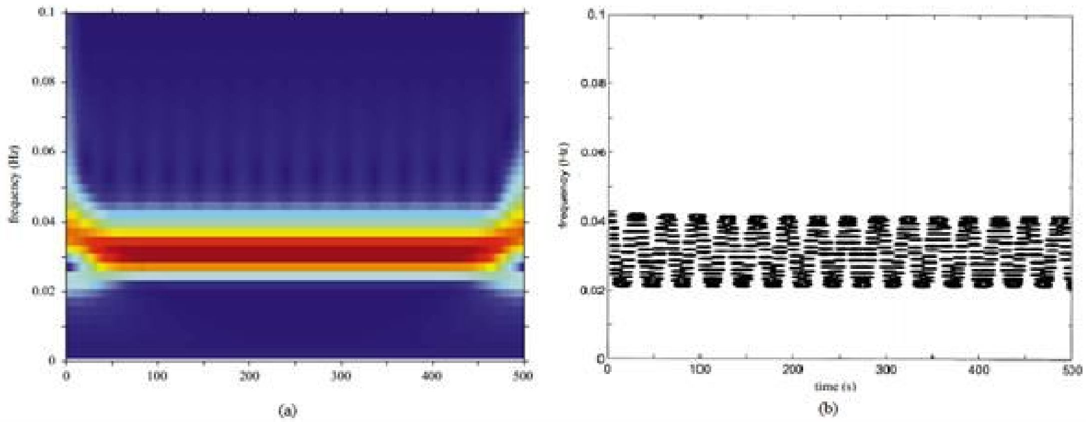
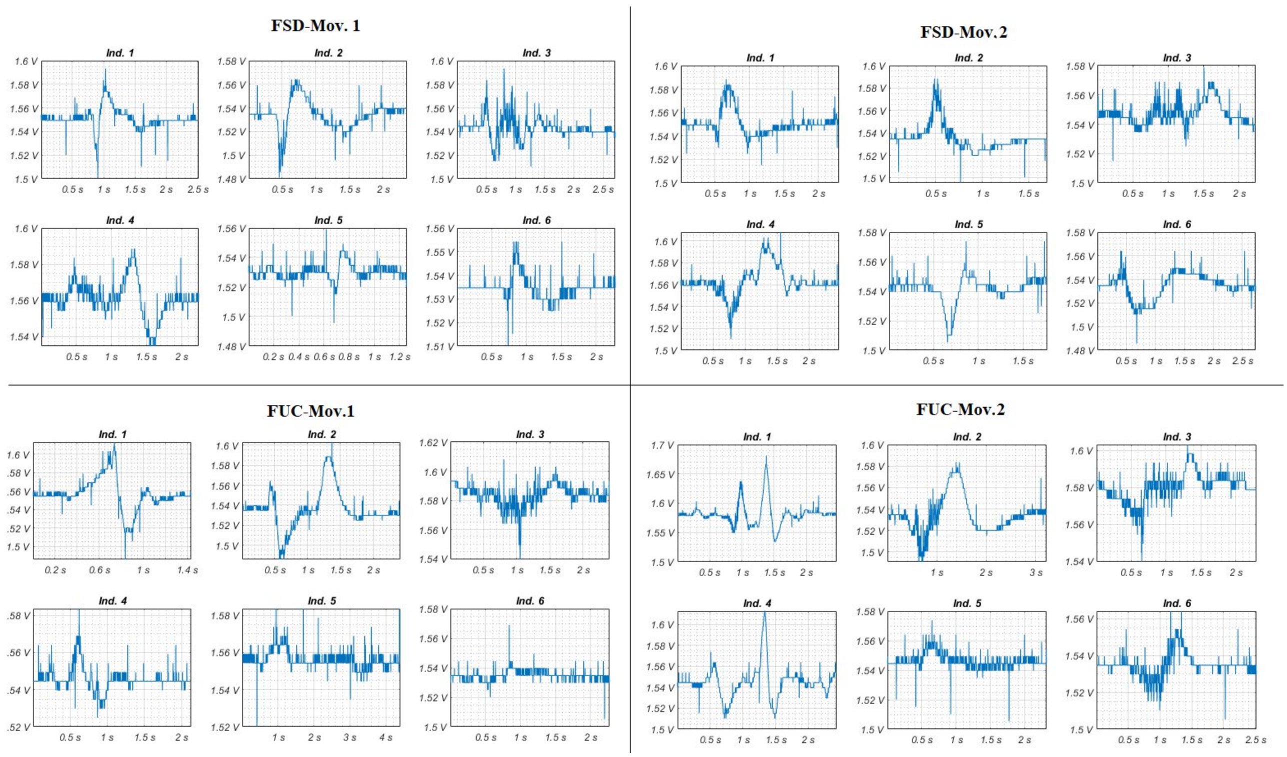


Figure 3: Study time series.



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Knowing that data with lower probability provide more information, under the framework of Shannon entropy, an increasing H value means more uncertainty, and therefore, more average information [14].

3. Use of HHT

The Hilbert Huang transform was used in order to extract analysis characteristics from sEMG signals taken from the forearm, which are time series that, having a biological character, have non-linear and non-stationary dynamics [1, 2].

3.1. Test signals

The set of test signals with surface electromyography is obtained from six subjects, three with carpal tunnel syndrome (Ind. 1-3) and three healthy subjects (Ind.

4-6). This, in order to study differential behaviors. The study pathology is generated by damage to the median nerve, characterized by paralysis of the superficial flexor muscle of the fingers (FMF) due to compression in the wrist area [16, 17], which is usually diagnosed with the sign of Phalen (sustained wrist flexion movement) [18]. Because of this, flexion-extension movements of the fingers (Mov. 1) and flexion of the wrist (Mov. 2) are studied; this from the FMF and ulnar carpal flexor (UCF) muscles, since they are jointly responsible for allowing these dynamics [19, 20]. The movements were measured according to SENIAM standards [21], with transversal measurement to the forearm in the case of FMF muscle measurement, and longitudinal for UCF muscle. Figure 3 shows the 24-time series acquired for the study.

3.2. *Intrinsic mode functions*

The intrinsic mode functions (IMF) were found through the CEEMDAN method of decomposition, establishing 500 noise realizations, each one contaminated with a noise amplitude corresponding to 20 % of the standard deviation of each signal [1], obtaining on average for each signal a computation time t=89.77s and 67410 iterations. The RMSE of reconstruction given the sum of components compared to the original signal for all cases did not exceed 1E-15.

As shown in Figure 4, the decomposition results show the decay in frequency from the first IMF to the last, having a total of 10 for the case of the fourth individual's signal, performing the finger flexion-extension movement measured on the FMF muscle. After the last IMF, a residue is obtained, which, since it does not provide frequency information, is discarded.

From the total of 24 signals, 240 IMF were obtained, 10 for each signal, each one representing different scales of the study phenomenon, so it is simple to find the instantaneous frequency and power with the Hilbert's transform to generate spectrum for each IMF, or some IMFs together.

3.3. Spectres of Hilbert

Applying Hilbert's transform to each obtained IMF and therefore shaping the HHT, a spectral view is generated that is implicitly characterized by local and adaptive exploitation given the empirical mode decomposition, so that it is evident with high resolution the frequency and instantaneous energy in time. Figure 5 shows the potential of the transform making use again of the time series of the individual 4 performing the movement 1 measured on the FMF muscle. There, 10 spectra are contemplated, each one of a IMF that contains different information time- frequency-energy, set that, in assembly composes the study phenomenon.

As shown in the Figure 5, the first components, specifically the first one, contain information of high persistence in time and frequency, which infers the noise content in this level of components. On the other hand, the last IMFs are cleaner, containing more regular information. Otherwise, it is evident that from spectrum one to spectrum ten, the frequencies are lower and lower. Evidenting a general spectrum with all the IMFs together, this frequency drop would not be so visually intuitive, and therefore, the need to establish a general spectrum arises but that limits the information shown so that the most representative is observed, that is, joining only some IMF spectra.

The problem of information content in general, given the HHT, lies in the selection of the most relevant information for the study in question, in order to synthesize the most representative content and distinguish characteristics efficiently. To this end, Shannon entropy is applied to each IMF in each time series. The residues of each case are also included.

4. Results

4.1. *Shannon entropy application*

Equation (3) was applied to obtain the Shannon entropy of the IMF for all-time series. In the following Figures 6 and 7, each point represents an MFI, except the last one which for each case is the residue, and each line represents an individual, the first three healthy, and the last three those with carpal tunnel. Figure 6 shows those that comprise the finger flexion-extension movement. It can be seen that the informational levels for both cases, measured from the FMF and UCF muscle, increase towards the latter IMFs and decrease in the former and in the residue, a fact that confirms the low informational levels and therefore, the favoring of eliminating them. It is important to emphasize that the differential perspective between healthy and sick subjects, the view of the data obtained by the measurements on the UCF muscle allows differentiation by positioning with higher H the healthy subjects in general. In the case of the FMF muscle the same thing happens except for the fourth subject, which is shown with high values towards the end.

Figure 4: IMF of the fourth individual's Mov. 1 signal over the FMF.

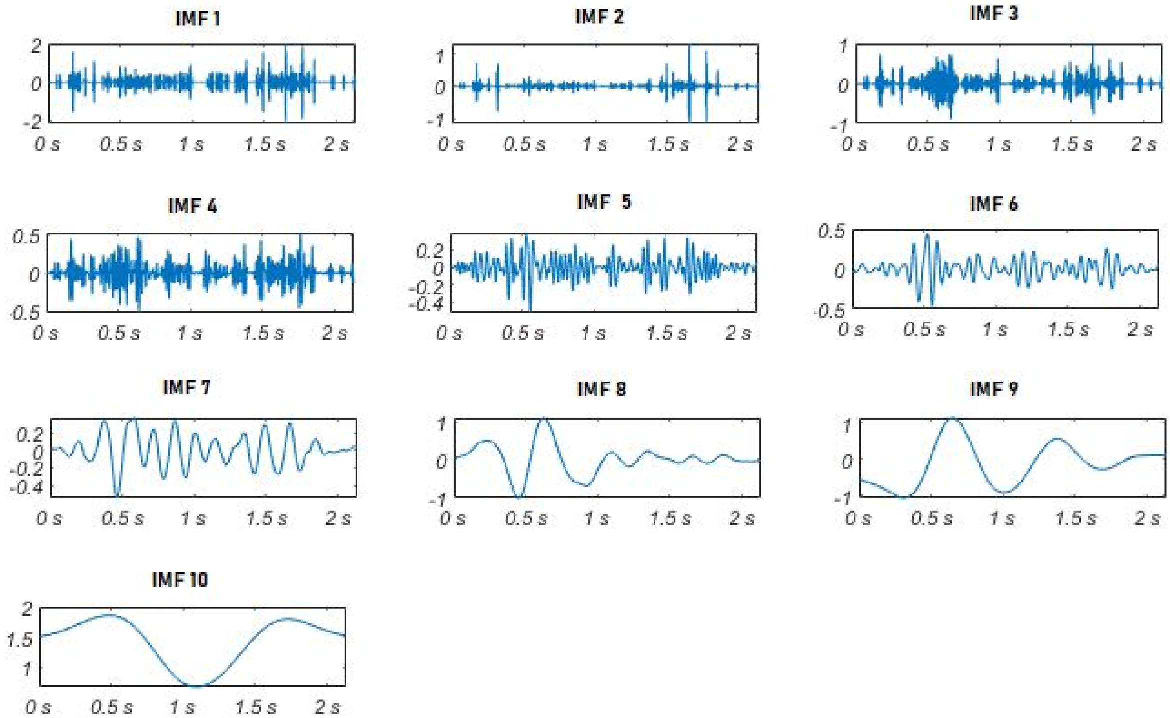

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Figure 5: Hilbert's spectra of the signal of the fourth individual from Mov. 1 on the FMF.

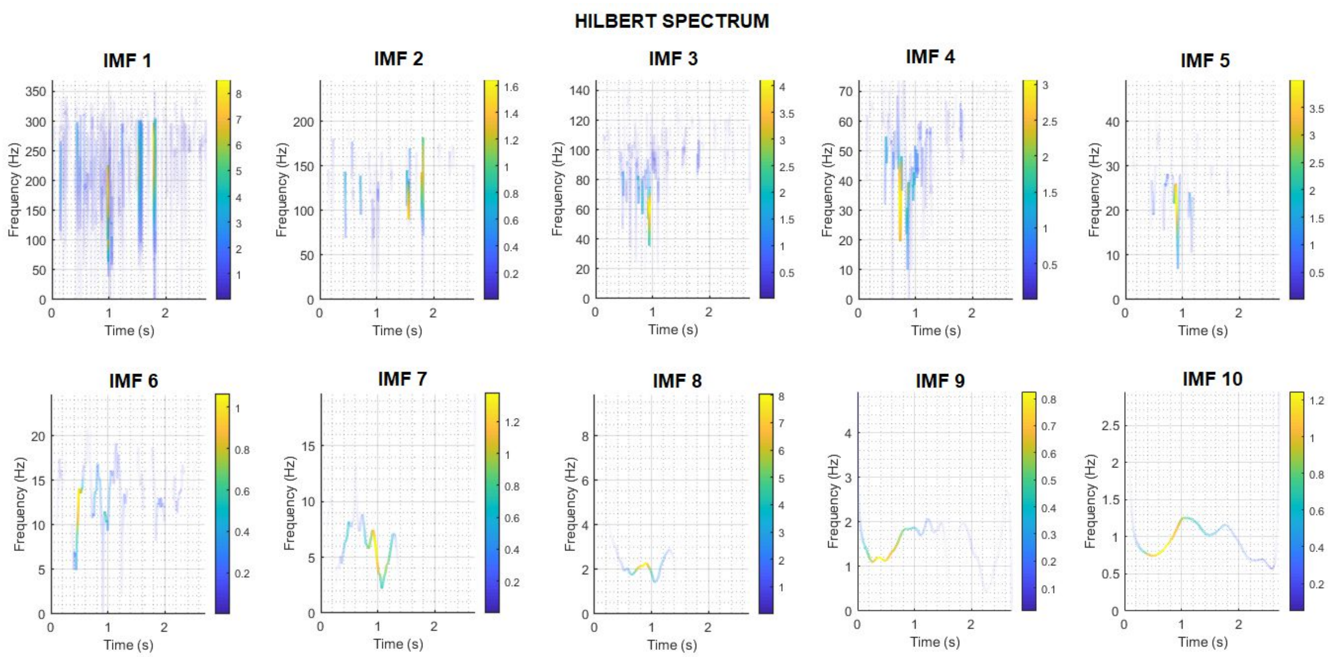

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Figure 6: Shannon's Entropy. Mov 1. Left on FMF, right on UCF.

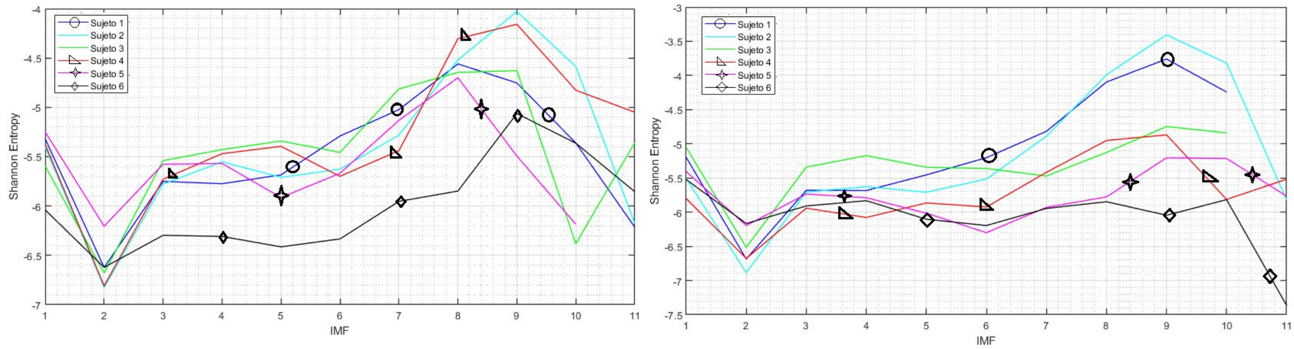

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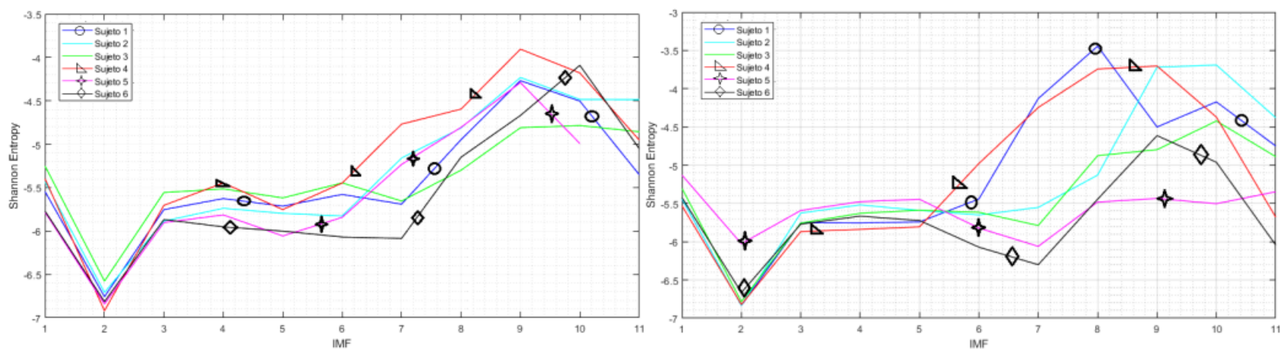
Figure 7: Shannon's Entropy. Mov 2. Left on FMF, right on UCF.



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The results of the wrist flexion movement under the perspectives of measurement of the FMF and UCF muscles are presented in Figure 7. There it is again impetuous the fact of evidencing low levels of information in the first components, with fall in the second IMF for all cases, as well as in the residue, observing in addition a tendency to growth from the seventh and tenth IMF.

With the distributions in Figure 7, more certainty is obtained regarding the differentiation between healthy and sick subjects thanks to entropy. Again subjects 5 and 6 are shown with the lowest levels in general, while subject 4 has high H levels, even higher than those of the three healthy subjects, a fact that becomes clearer towards the latter modes.

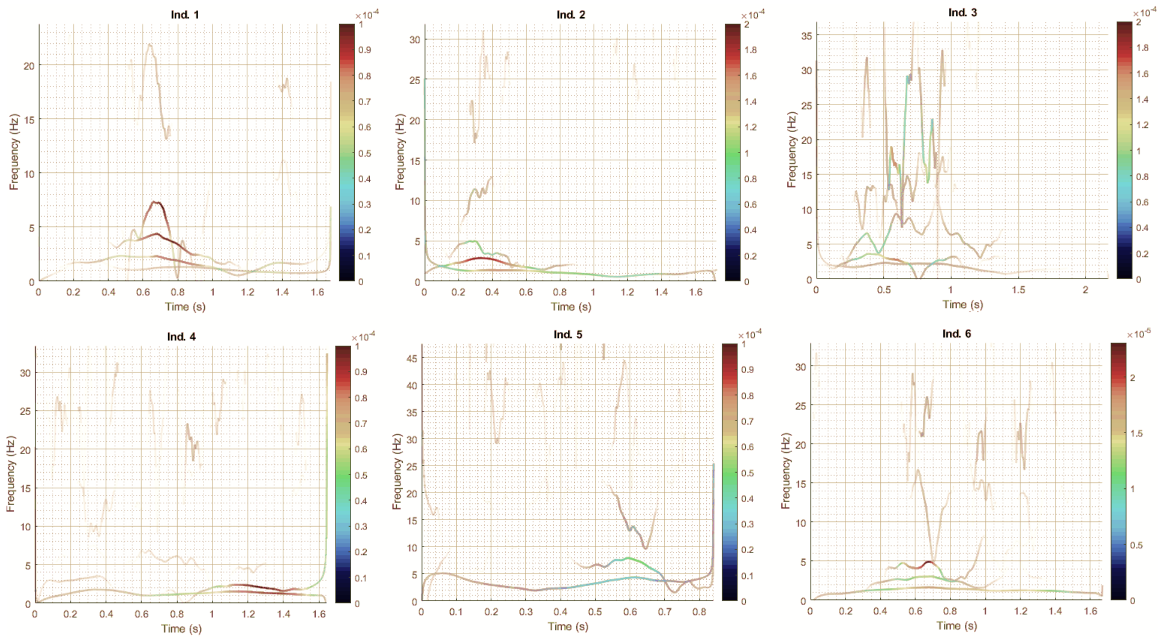
4.2. *Hilbert Huang's Spectrum bounded*

Evidenting the different levels of information input depending on the IMF level of decomposition, it generated a spectral view that included only the highest H modes, i.e., the last four modes. With this, in addition, as observed above, the most relevant information is extracted to generate a differential study. Figure 8 shows the final results obtained with a limited Hilbert spectrum, which contains the fundamental information for the study of time-frequency-energy components. The Figure 8 shows that except for individual 4, subjects 5 and 6 with carpal tunnel, are differentiated from healthy subjects by the absence of high frequency components together with low frequency components with relevant energy levels. On the other hand, subject four presents relevance in low frequency components with persistence in time, however components beyond 10 Hz are not very observable, fact that individualizes this case in general.

5. Conclusion

The shapes presented through the Hilbert-Huang transform given the intrinsic mode functions, concentrate different degrees of information in which the frequency, energy and temporal distribution of these are included. To characterize this behavior, the Shannon entropy measure was used on each of the IMFs. The purpose of this study was not only to look for metrics to extract

Figure 8: Hilbert Huang's spectra bounded, movement 1 over FMF.



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characteristics and therefore patterns, but also to establish a balance of the informative level of components, in order to cross with the information obtained from the frequency-energy representations of each mode to study compact and efficient spectral forms.

It was possible to evidence differential behavior between subjects seen as a group and individually, this being based on the informative level of their IMF. With these, a space was established to search for limited patterns in the spectrum, which is more focused on the last IMF components, in general, from the seventh to the tenth, since they are where more information is condensed. With respect to the high scales discarded, it can be concluded that part of their discarding is caused by the noise content implicit in the signals.

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