Application of EMD as a novel technique for the study of tremor time series

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***Abstract*— This paper introduces the Hilbert Analysis (HA), which is a novel digital signal processing technique, for the investigation of tremor. The HA is formed by two complementary tools, i.e. the Empirical Mode Decomposition (EMD) and the Hilbert Spectrum (HS). In this work we show that the EMD can automatically detect and isolate tremulous and voluntary movements from experimental signals collected from 31 patients with different conditions. Our results also suggest that the tremor may be described by a new class of mathematical functions defined in the HA framework. In a further study, the HS was employed for visualization of the energy activities of signals. This tool introduces the concept of instantaneous frequency in the field of tremor. In addition, it could provide, in a time-frequency-energy plot, a clear visualization of local activities of tremor energy over the time. The HA demonstrated to be very useful to perform objective measurements of any kind of tremor and can therefore be used to perform functional assessment.**

I. Introduction

Tremor is a rhythmic, involuntary muscular contraction characterized by oscillations of a part of the body [1]. Neurological disorders associated with aging are often accompanied by tremor. It can affect various parts of the body such as hands, head, facial structures, tongue, trunk, and legs. Although the disorder is not life-threatening, it can be responsible for functional disability and social embarrassment [2].

The detection and quantification of tremor are of clinical interest for diagnostic of neurological disorders and objective evaluation of their treatment [3], [4]. Methods based on the Fourier transform (FT) are commonly employed for this purpose, specially because of the similarity between the tremor to a sine wave [2]. For instance, the Weighted Fourier Linear Combiner (WFLC) [5], characterizes the tremor based on its approximation by a sinusoidal waveform. Another example, is the extraction of frequency parameters from the power spectrum (based on the FT) of the tremor for classification purposes [2], [3].

Some inherent drawbacks of techniques based on the FT are pointed out in [6]. First, the signal is *linearly* decomposed as combination of sines and cosines. Secondly, the compromise between time and frequency resolution of methods based on the FT may not highlight the presence of local oscillations in the signal which can have important physical meaning.

Recently, a high-resolution technique that solves most of limitations of the Fourier Analysis has been successfully applied to the investigations of seismological and biological signals [7], [8]. This method, known as Hilbert Analysis (HA) [9], is a tool for investigation of nonlinear and nonstationary time-series. The HA is formed by two complementary tools, i.e. the Empirical Mode Decomposition (EMD) and the Hilbert Spectrum (HS).

In this paper we introduce the HA to the analysis of tremor. First, we show how this technique may be employed in practice for an automatic detection and visualization of tremor from different pathologies. Secondly, we show that other physiological events that normally accompany the tremor, e.g. spasms, may also be identified by the HA. And finally, we suggest that the tremor may be described by a new class of mathematical functions defined in the HA framework.

II. The Hilbert Spectrum

The generation of the Hilbert Spectrum (HS) is performed into two steps. First, the Empirical Mode Decomposition (EMD) decomposes the input time-series into a set of functions designated as Intrinsic Mode Function (IMFs), and secondly those functions are used for generation of a 3-D plot called the Hilbert Spectrum. The following sections provide a description of the constituent steps of the HA.

A. The Empirical mode decomposition

The main aim of the EMD is to decompose a time-series into a set of components or functions, known as IMFs. This class of function was defined in [9]. To be considered an IMF a time-series has to satisfy two conditions: first, in the whole data set, the number of extrema and the number of zero crossings must be either equal or differ at most by one, and secondly, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Note that the decomposition of a time-series into IMFs consists in the identification of the basic units (IMFs) in that time-series. A practical procedure, known as sifting process, is employed for this purpose. Details about it are given in [9]. An important feature of the sifting process is that it, adaptively and based solely on the data, is able to find appropriate time-scales that may reveal important information embedded in the original signal. In fact, single IMFs may have a physical meaning, and an important issue in any practical application is to determine the existence of this meaning.

B. Hibert Spectrum generation

Once IMFs are obtained as result of the sifting process, it is possible to generate the Hilbert Spectrum, or a 3-D plot (time-frequency-energy) that represents the variation of frequency and energy of IMFs over time. The notion of frequency and energy for each IMF is obtained by employing the concept of analytic signals.

An analytic signal is a complex signal with one-sided spectrum that preserves all information contained in the original signal [10]. Note that the representation of a real signal as an analytical signal eliminates redundancy, since the negative half of the signal frequency spectrum containing redundant information with respect to the positive half is eliminated. A very simple way of estimating an analytical signal is by employing the Hilbert Transform [10]. The real part of an analytical signal is the original input time-series, whereas its complex component is the Hilbert Transform of that signal.

Given an analytic signal, $Z(t)$, defined as $Z(t) = X(t) + iY(t) = a(t)e^{j\theta(t)}$, where $X(t)$ is the input time-series and $Y(t)$ the Hilbert Transform of $X(t)$, the following instantaneous attributes of $Z(t)$ can be defined:

$$a(t) = [X(t)^2 + Y(t)^2]^{1/2} \quad (1)$$

$$\theta(t) = \arctan\left(\frac{Y(t)}{X(t)}\right) \quad (2)$$

$$\omega(t) = \frac{d\theta(t)}{dt} \quad (3)$$

where $a(t)$ is the instantaneous amplitude, $\theta(t)$ is the instantaneous phase and $\omega(t)$ is the instantaneous frequency.

With the definition of instantaneous attributes above the Hilbert Spectrum, $H(\omega, t)$, is generated as follows:

1) Estimate intrinsic mode functions from the input signal.
2) Estimate the instantaneous attributes of each IMF.
3) Generate a 3-D plot, $H(\omega, t)$, in which the amplitude is contoured in the time-frequency plane.

In contrast to other time-frequency methods, the HS does not define an explicit equation that maps a 1-D time-series into a 3-D representation that provides information about time, frequency and energy (amplitude).

From the HS it is also possible to estimate the Marginal Hilbert Spectrum (MHS), $h(\omega)$, which is defined in Equation 4. In practice $h(\omega)$ is analogous to the Fourier power spectrum.

$$h(\omega) = \int_0^T H(\omega, t)dt \quad (4)$$

III. The experimental protocol

In order to assess tremor characteristics we studied its behavior in 31 patients suffering from different pathologies. The average age of patients was 52.3 years old (ranging from 23 to 84 years old). All patients provided their written consent for the experiments.

The diagnosis of the condition of patients was given by the neurological staff of the General Hospital of Valencia (GHV, Spain) and the functional state of patients was evaluated by means of the Faher scale. Ethical approval for this research has been granted by the Ethical Committee of the GHV.

A. Sensors

The tremor was detected by a customized sensor [11], which is based on the combination of two independent gyroscopes placed distally and proximally to the joint of interest. The joint angular speed is obtained by subtraction of the angular speed measured by one gyroscope from the angular speed measured by the other one. This system could measure the orthosis joint angle, velocity and acceleration without any external reference. Unlike accelerometers, the measurement of angular velocity is not influenced by gravity and they are in general accurate both in frequency and amplitude. The main advantages of this system is that it is light, cheap and does not cause any discomfort to subjects thus providing a powerful tool to monitor biomechanical variables during physiological tremor movements. Since gyroscope provides absolute angular velocity in its active axis, the combination of two independent gyroscopes was used. Gyroscopes were placed in order to estimate following movements of the upper limb: 1) Elbow flex-extension, 2) Forearm pron-supination, 3) Wrist flex-extension, and 4) Wrist deviation.

B. Tasks

Six different tasks were employed for excitation of tremor: 1) Rest, 2) Reaching for an object, 3) Drawing a spiral, 4) Arm outstretched, 5) Touching nose, and 6) Moving a cup. In all tasks the patient was sitting on a chair. This set of tasks aims to stimulate all different types of tremor.

IV. Data analysis

For estimation of the voluntary movement, VM_{ref}, the cutoff frequencies of this filter was set to 0 - 2 Hz. The cutoff frequencies employed for detection of the tremor, T_{ref}, were 2 - 20 Hz. Previous investigation of this data set showed that the tremor activity was limited between 3 Hz and 8 Hz, [12], and that voluntary movements were always bellow 2Hz for the tasks described above. Note that those digital filters do not introduce phase lag in the filtered signal.

The time-series y was also automatically decomposed via EMD. This decomposition yielded intrinsic mode functions from which it was possible to identify the tremor T_{emd} and voluntary movement VM_{emd}. A comparison between T_{emd} and T_{ref} was performed and resulted in the generation of the estimated square error signal $\hat{e} = \sqrt{(T_{ref} - T_{emd})^2}$. This signal measured the discrepancy between automatic and manual estimates.

An additional investigation showing how the activities of tremor and voluntary movement were perceived in the frequency domain was also performed. For this purpose, the HS and MHS were employed.

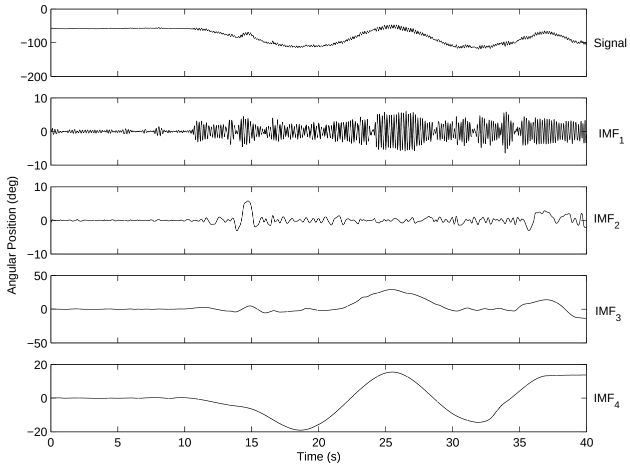

Fig. 1. Decomposition of a movement profile (Signal) detected from an Essential tremor patient provided by EMD. Four intrinsic mode function ($IMF_1, \ldots, IMF_4$) were obtained. IMF_1 was identified as the tremulous movement.

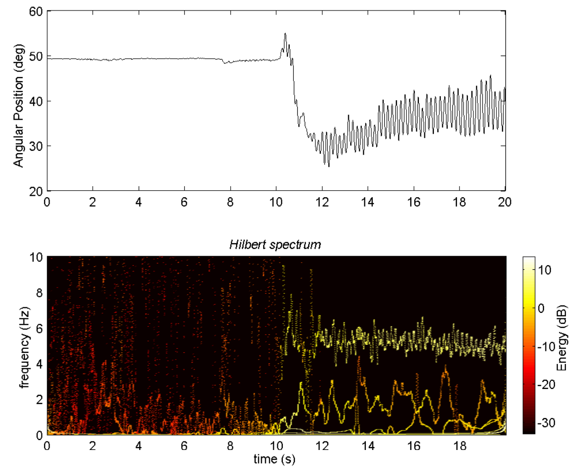

Fig. 2. Hilbert Spectrum of an Essential tremor patient performing the task of Keeping the arms outstretched. Note that the energy is clearly separated from the energy of the voluntary movement. The high levels of energy activities on the HS are perceived when the patient is performing the task.

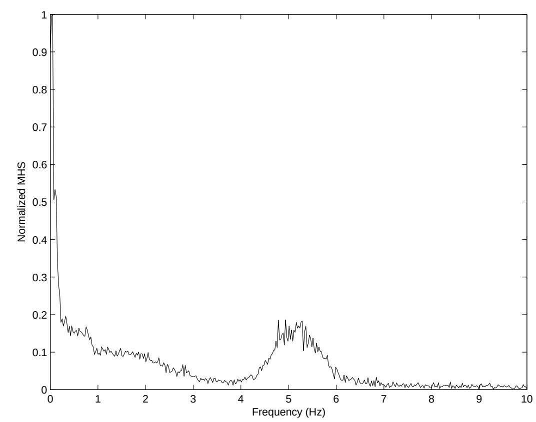

Fig. 3. Marginal Hilbert Spectrum estimated from the signal shown in Figure 2. This energy is bimodal indicating the clear separation between voluntary and tremor in frequency domain.

V. Results

A. Automatic detection of tremor

The signal presented in Figure 1 (top) was detected from a patient with Essential tremor performing the draw spiral test. The signal components, or intrinsic mode functions, obtained by means of the EMD are also shown in this figure. The first component identified as IMF_1 is the finest time-scale component, whereas the last component (IMF_4) is the largest time-scale component. A comparative study between different IMFs and the tremor signal (obtained manually) showed that the IMF_1, which is the component that best represents the high frequencies of the signal, was an accurate estimate of the tremor, i.e. this component had a very strong physical meaning.

The same analysis was carried out for all available data sets. It was also noted that the voluntary movement can be obtained by the summation of all available IMFs but the first one, which represented the tremor. This investigation showed that the first IMF was always a precise estimate of the tremor. This accuracy was quantified by the mean square error signal, $\bar{e} = mean(\hat{e})$. The average and standard deviation of distinct signal errors $\bar{e}$ grouped by patients with different pathologies were estimated. The results indicated that a very small error was obtained.

B. Visualization of tremor on the Hilbert Spectrum

It has been shown that a particular intrinsic function is physically related to the tremor. Besides the representation of embedded components in the signal those functions may also be employed for a time-frequency analysis of time-series. This is obtained via the Hilbert Spectrum. In practice it was observed that the Hilbert Spectrum could describe the variation of the energy and frequency of tremor and voluntary movement activities distinctly. That is, the energy of tremor and voluntary movement was very well localized in time and frequency. This is illustrated in Figure 2 for a patient with essential tremor. The oscillations around 5 Hz are related to tremor activities whereas the others are related to other components of the global movement.

C. Analysis of the power based on the MHS

The integration of the HS over the time results in the MHS. The MHS describes how the signal energy varies as function of the frequency. Figure 3 shows the MHS for a patient with essential tremor performing the task of touching the nose. Note that the distribution provided by the MHS is bimodal and that its first peak is related to the voluntary movement, whereas the second is the energy of tremor activity.

VI. Discussion

In this section, an analysis of the results of the above proposed methodology is reported. We mainly focus on the application of Empirical Mode Decomposition as a new tool for the study of tremor time series. EMD has been identified as a very useful tool for an automatic decomposition of the signal into tremor and voluntary signal. The results presented in this paper showed that the first IMF could accurately estimate the tremor. This was observed in the whole data set, which had more than 2000 samples of signals with tremor activity, collected from 31 patients performing 6 different tasks.

Currently, there is no available technique that can accurately model the tremor [3]. Most of methodologies are based on the assumption that the tremor is stationary or is similar to sine wave. The fact that the tremor time series could be described by an intrinsic mode function states that the tremor signal, for all patients considered in this study, satisfies two conditions [9]: 1) in the whole data set, the number of extrema and the number of zero crossings must be either equal or differ at most by one; 2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. These observations suggest that any investigation concerning the modelling of tremor should take into account those properties.

Having obtained the intrinsic mode function components, the Hilbert transform can be applied to each component and the instantaneous frequency can be computed, according to equations (1), (2) and (3). The Hilbert Spectrum enables the representation of the amplitude and the instantaneous frequency of the input signal as function of time in which the amplitude could be contoured on the time-frequency plane. Since the tremulous movements is well described by the first IMF, this method is a very useful tool for visualization of energy activity of tremor.

Due to its oscillatory characteristic, tremor is well suited to spectral analysis such as the Fourier Transform, which is the most popular method of tremor quantification [3]. FFT-based spectral methods model the input signal as stationary periodic signal. Yet tremor amplitude and frequency are time-varying [3], and therefore it is desirable to develop quantitative methods which do not assume stationarity. The Marginal Hilbert Spectrum offers a measure of the total amplitude (or energy) contribution from each frequency value over the entire data span being able to precisely detect the energy activities of tremor and voluntary movements. In the Fourier representation, the existence of energy at a frequency, ω, means a component of a sine or a cosine wave persisted through the time span of the data. Here, the existence of energy at a frequency, ω, means only that, in the whole time span of data, there is a greater likelihood for such wave to have appeared locally.

VII. Conclusion

This paper introduced Empirical Mode Decomposition as a novel tool for analysis of tremor time series. The main advantage of this technique it that it allows an automatic estimate of the tremulous movement in the different pathologies considered in this paper. Additional investigation should be pursued in order to validate the performance of this technique in the estimation of tremulous movements from others pathologies.

The authors believe that there is an evidence that EMD could identify other types of involuntary movements besides tremor, such as spasms. Nevertheless, this hypothesis should be validated by means of future investigation correlating involuntary movement activity and EMG signals from the muscles involved in generating these movements. The technique presented is a high-resolution technique that solves most of limitations of the Fourier Analysis (the standard technique to the study of tremor time series). This technique provides, in a time-frequency-energy plot, a clear visualization of local activities of tremor energy over the time.

The application of this technique introduces new attributes to the tremorous signal such as instantaneous amplitude, instantaneous phase and instantaneous frequency. This attributes opens the research field in the tremor field. Future work will be focused on the use of these parameters as parameters for the diagnosis of tremor pathologies.

References

[1] A. Anouti and W. Koller, “Tremor disorders: diagnosis and management,” *The Western Journal of Medicine*, vol. 162, no. 6, pp. 523–530, 1998.

[2] R. Elble, “The pathophysiology of tremor,” in *Movement Disorders: Neurologic Principles and Practice*, R. Watts and W. Koller, Eds. New York: McGraw-Hill, 1997, pp. 405–417.

[3] E. Rocon, J. Belda-Lois, J. Sanchez-Lacuesta, and J.L.Pons, “Pathological tremor management: Modelling,compensatory technology and evaluation,” *Technology and Disability*, vol. 16, pp. 3–18, 2004.

[4] J. Timmer, C. Gantert, G. Deuschl, and J. Honerkamp, “Characteristics of hand tremor time series,” *Biological Cybernetics*, vol. 70, pp. 75–80, 1993.

[5] C. Riviere, “Adaptive suppression of tremor for improved human-machine control,” Ph.D. dissertation, Johns Hopkins University, 1981.

[6] M. Akay, *Detection and estimation methods for biomedical signals.* San Diego - California - USA: Academic Press, 1999.

[7] A. D. O. Andrade, P. J. Kyberd, and S. D. Taffler, “A novel spectral representation of electromyographic signals,” in *Engineering in Medicine and Biology Society - 25th Annual International Conference*, R. S. Leder, Ed., vol. 1. Cancun, Mexico: IEEE, 2003, pp. 2598–2601.

[8] N. E. Huang, C. C. Chern, K. Huang, L. W. Salvino, S. R. Long, and K. L. Fan, “A new spectral representation of earthquake data: Hilbert spectral analysis of station TCU129, Chi-Chi, Taiwan, 21 September 1999,” *Bulletin of the Seismological Society of America*, vol. 91, no. 5, pp. 1310–1338, 2001.

[9] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N.-C. Yen, C. C. Tung, and H. H. Liu, “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis,” *Proceedings of Royal Society of London*, vol. 454, pp. 903–995, 1998.

[10] J. Lawrence Marple, S, “Computing the discrete-time ”analytic” signal via fft,” *IEEE Transactions on signal processing*, vol. 47, no. 9, pp. 2600–2603, 1999.

[11] E. Rocon, A. Ruiz, and J. Pons, “On the use of rate gyroscopes for tremor sensing in the human upper limb,” in *Proceedings of the International Conference Eurosensors XIX*, 2005, p. MP30.

[12] J. M. Belda-Lois, J. Sanchez-Lacuesta, M. J. Vivas-Broseta, E. Rocon, L. Bueno, and J. Pons, “Tremor movement analysis techniques: an approach towards ambulatory systems,” *Asistive Technology - Shaping the future*, pp. 827–831, 2003.