SIGNAL PROCESSING OF HEART RATE VARIABILITY USING WAVELET TRANSFORM FOR MENTAL STRESS MEASUREMENT

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ABSTRACT

This paper presents the evaluation of mental stress measurement using heart rate variability. The heart rate signals are processed first using Fourier transform, and then it is applied to wavelet transform. The activity of the autonomic nervous system is noninvasive studied by means of autoregressive (AR) frequency analysis of the heart-rate variability (HRV) signal. Some methods of noise rejection and robustness for AR recursive identification are presented that make on-line frequency analysis of the heart-rate variability signal more reliable. The goodness of the algorithms is first tested through simulations, and then results obtained on real data during ischemic episodes are presented. Spectral decomposition of the Heart Rate Variability during whole night recordings was obtained, in order to assess the characteristic fluctuations in the heart rate and their spectral parameters during REM and NREM sleep stages. Mental stress is accompanied by dynamic changes in autonomic nervous system (ANS) activity. Heart rate variability (HRV) analysis is a popular tool for assessing the activities of autonomic nervous system. This paper presents a novel method of HRV analysis for mental stress assessment using fuzzy clustering and robust identification techniques. The approach consists of 1) online monitoring of heart rate signals, 2) signal processing (e.g., using the continuous wavelet transform to extract the local features of HRV in time-frequency domain),

Keywords —*Heart rate variability (HRV), Electrocardiogram (ECG) wavelet transforms, Autonomic Nervous System.*

I. INTRODUCTION

Assessment Of mental stress under different workload conditions is a recurrent issue in many engineering and medicine fields. Although mental stress cannot be measured directly, the physiological response of an operator can be interpreted to assess the level of mental stress. Several physiological parameters (like electroencephalograph, blood pressure, heart rate, heart rate variability (HRV), electro dermal activity (EDA), event-related potentials, and electromyography) have been found sensitive toward any changes occurring in the mental stress level of an operator. Cardiac activity is the most common physiological measure for the assessment of mental workload [1]. An electrocardiogram (ECG) is a cardiac measure that shows sensitivity towards variations in workload [2]. Heart rate variability (a measure of electrocardiography activity) has been widely accepted in the literature for the assessment of mental workload (see, e.g., [2]– [8]).

Previous studies have shown that heart rate presents a diminution during sleep phase as compared with wakefulness. This change attains typical fluctuations at the different sleep stages. During REM (Rapid Eye Movement) and NREM (Non Rapid Eye Movement) sleep stages the heart rate is lower than during relaxing wakefulness, and higher in REM when compared with NREM sleep stages. These variations in heart rate fluctuations have been explained as a depression or decreasing in the activation of the sympathetic activity during NREM and by instability and increasing in REM [1]. Spectral analysis, in the study of the cardiovascular signals, has demonstrated to be a fine non invasive tool for evaluating the state of the Autonomic Nervous System (ANS), and it has been used in order to assess the Heart Rate Variability (HRV) changes during sleep [2-5]. These variations exhibit characteristic oscillations which corresponds to variations of parasympathetic and sympathetic branches of the ANS. Wide band of the spectral components of HRV ranges from 0.003 Hz until 0.5 Hz, where the range between 0.003–0.04 Hz (Very Low Frequency component VLF) takes account of long-term regulation mechanisms, 0.04–0.15 Hz (Low Frequency Component LF) represents sympathetic activation, and finally the range between 0.15–0.5 Hz (High Frequency Component HF) corresponds to tone and it is highly influenced by respiration [6-7].

Spectral decomposition technique has shown consistent results: a vagal increase during NREM sleep stage measured by the HF component and increase of sympathetic activity measure by the LF and LF/HF ratio during REM sleep stage [5]. HRV signal is stationary in constant conditions, its first and second statistic moments through a time window of a few minutes do not change, and application of Fourier Transform or Autoregressive Batch analysis are adequate spectral decomposition techniques [8]. However, when it is necessary to analyze sequences where transitory changes in the signal could happen, such as variations during Valsalva maneuver, tilt test or Obstructive Sleep Apnea events, these approaches don't result to be the most suitable for the analysis, because the signal acquires non-stationary characteristics. To overcome this inconvenient there are two possible ways. On one hand, techniques such as Short Time Fourier Transform, Discrete Wavelet Analysis, Time- Frequency Distributions and Time-Varying Analysis could be used. On other hand, it could be taken a short data sequences where fast changes are not present as some studies proposed, in different sleep stages [2-5]. However, time-varying autoregressive models allow to assess, on a beat to beat basis, the spectral parameters of HRV signal in a fast and efficient way independently on the transitory events found through the whole night recording (provoked by arousals, body movements, changes on sleep stages or apneas).

The aim of this work is to assess the spectral parameters by time-varying autoregressive spectral analysis of the HRV during whole night recordings, in a beat to beat basis. The study focus on the temporal evolution of LF, HF spectral powers and on the module and phase of a representative pole of the autoregressive model in HF band during REM and NREM sleep stages

II. METHODOLOGY

The autonomic nervous system (ANS), which controls cardiac muscle, is of interest for stress detection. ANS is concerned with the regulation of heart rate, blood pressure, breathing rate, body temperature, and other visceral activities. The ANS activity is divided into two branches: sympathetic and parasympathetic, which influence the sinus node of the heart, thereby modulating heart rate. The sympathetic activity is primarily related to the preparation of body for stressful situations by *boosting of energy*. On the other hand, parasympathetic activity (most active under restful situations) counterbalances the effects of the sympathetic activity and restores the body to a resting state. Under normal situations, there is a balance between these two activities. However, during stress this balance will be altered and an analysis of heart rate signals could be potentially used to detect this alteration in system balance [9]–[10]. HRV is a measure of the variability in heart rate, i.e., variability in inter beat interval (IBI), which is defined as the time in milliseconds between consecutive R waves of an electrocardiogram. The IBI series (R-R intervals) can be analyzed using some mathematical theories (e.g., fast Fourier transform, wavelet theories, chaos) to assess ANS activities. The analysis of HRV provides a theoretical framework for ANS assessment by identifying the sympathetic and parasympathetic activities. The analysis of HRV in frequency domain could provide various information about cardiovascular control [5], [6]. Overall spectra of human HRV can be divided into three main frequency zones: below 0.04 Hz is very low frequency (VLF), between 0.04 and 0.15 Hz is low frequency (LF), and between 0.15 and 0.5 Hz is high frequency (HF). The LF is affected by both the sympathetic and parasympathetic activities, and the HF is found to be dominated by the parasympathetic activity [7]. The VLF is related to factors like temperature, hormones, etc. [8]. The ratio of the LF to HF power has been associated with the sympathovagal balance [8]. An emerging body of literature seems to suggest that HRV analysis can be potentially used to measure mental stress. However, a practical problem, which is so far not well addressed in the literature, is to derive some form of mathematical (quantitative) relations between parameters of

ANS activity and mental stress. The problem can be formally stated as follows.

Given a 3-min IBI series (R-R intervals), estimate the level of mental stress on a scale ranging from 0 to 100 by monitoring the functioning of autonomic nervous system using HRV analysis. The solution of above problem not only would provide a physiological interpretation of a so-called *mental stress* but also has the direct applications in engineering fields like adaptive automation and man–machine interface design. The major difficulties in solving Problem 1 are the following. 1) HRV signal is non stationary, i.e., it is characterized by time variations in its frequency components. 2) The alterations in HRV signal due to a change in the level of mental stress (these alterations would be used to detect the corresponding change) are subjective to individuals. The changes, which result in the HRV pattern of individuals due to a change in stress level, are different among individuals. This difference in behavior among the individuals may arise due to different body conditions, gender, age, physical fitness, emotional states, and so on. To overcome the first difficulty, spectral components of HRV can be determined in the time-frequency domain using a wavelet transform [9]. Moreover, the logarithmic resolution of the wavelet transform enables the finer estimation of very low frequencies components. To resolve the second difficulty, some of the approaches coming from the area of neural network have been used [2] and references therein. This is done by combining HRV analysis with a neural network such that individual variations are learnt by a neural network. However, neural network–based approaches are like a "black box," since these do not provide a human-understandable insight into relationships between ANS activities and level of mental stress.

III. SIGNAL PROCESSING USING WINDOWS

Signal processing is performed using windows technique and wavelet transform. The output obtained for signal processing using window functions are given. Used windows are Hanning, Hamming and Triangular. The signal in time domain and its frequency response is given below. The triangular window function is first used to find its frequency response. The variation in the frequency response is obtained through Hamming and Hanning windows. Fig.1 shows the time domain and frequency response of the given signal.

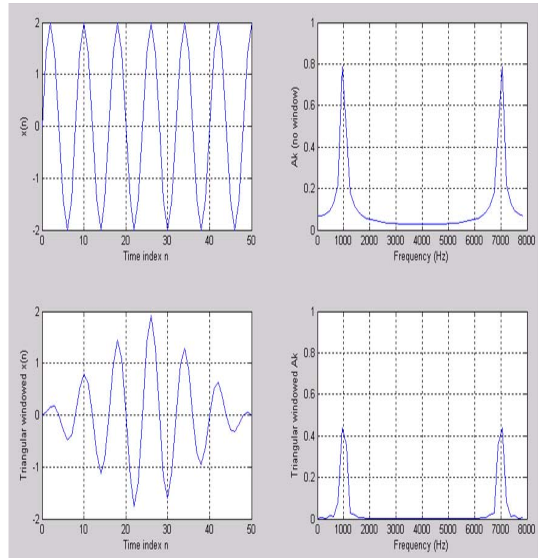

Fig.1.Triangular window frequency response

Fig.2 describes the time domain and frequency response obtained for Hamming window.

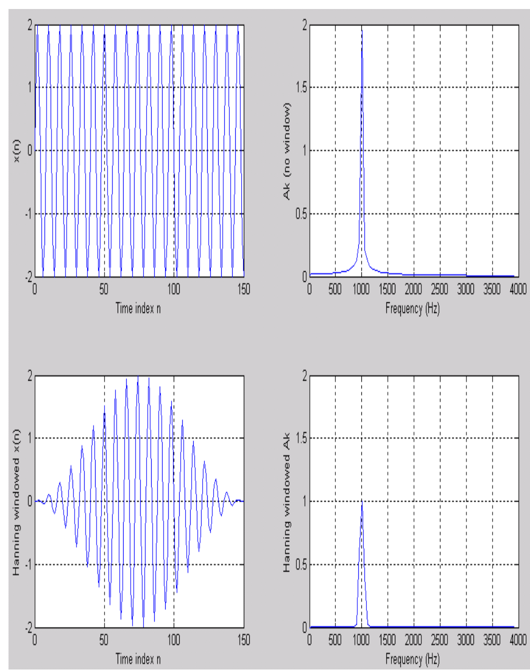

Fig.2. Hamming window frequency response

Fig.3 describes the time domain and frequency response obtained for Hanning window.

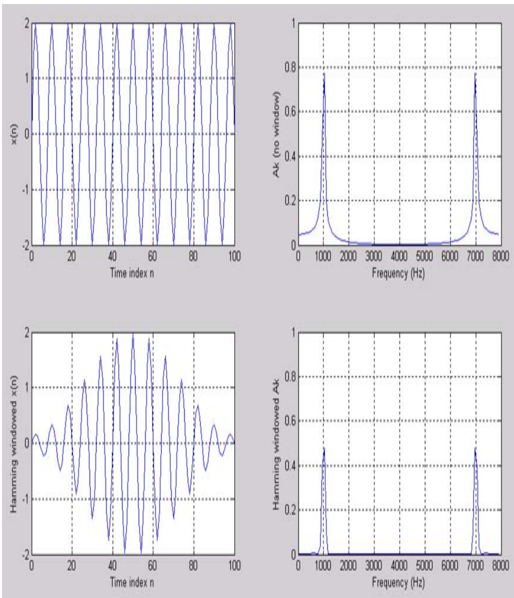

Fig.3. Hanning window frequency response

IV. ECG SIGNAL PROCESSING USING WAVELET TRANSFORM

Fourier analysis, using the Fourier transform, is a powerful tool for analyzing the components of a stationary signal (a stationary signal is a signal that repeats). For example, the Fourier transform is a powerful tool for processing signals that are composed of some combination of sine and cosine signals.

The Fourier transform is less useful in analyzing non-stationary data, where there is no repetition within the region sampled. Wavelet transforms (of which there are, at least formally, an infinite number) allow the components of a non-stationary signal to be analyzed. Wavelets also allow filters to be constructed for stationary and non-stationary signals.

Although Haar wavelets date back to the beginning of the twentieth century, wavelets as they are thought of today are new. Wavelet mathematics is less than a quarter of a century old. Some techniques, like the wavelet packet transform are barely ten years old. This makes wavelet mathematics a new tool which is slowly moving from the realm of mathematics into engineering. For example, the JPEG 2000 standard is based on the wavelet lifting scheme.

The Fourier transform shows up in a remarkable number of areas outside of classic signal processing. Even taking this into account, I think that it is safe to say that the mathematics of wavelets is much larger than that of the Fourier transform. In fact, the mathematics of wavelets encompasses the Fourier transform. The size of wavelet theory is matched by the size of the application area. Initial wavelet applications involved signal processing and filtering. However, wavelets have been applied in many other areas including non-linear regression and compression. An offshoot of wavelet compression allows the amount of determinism in a time series to be estimated.

A wavelet is simply a small wave which has energy concentrated in time to give a tool for the analysis of transient, non stationary or time-varying henomena such as a wave shown in figure 4. A signal as the function of f(t) shown in Fig. 4 can often be better analyzed and expressed as a linear decomposition of the sums: products of the coefficient and function. In the Fourier series, one uses sine and cosine functions as orthogonal basis functions. But in the wavelet expansion, the two-parameter system is constructed such that one has a double sum and the coefficients with two indices.

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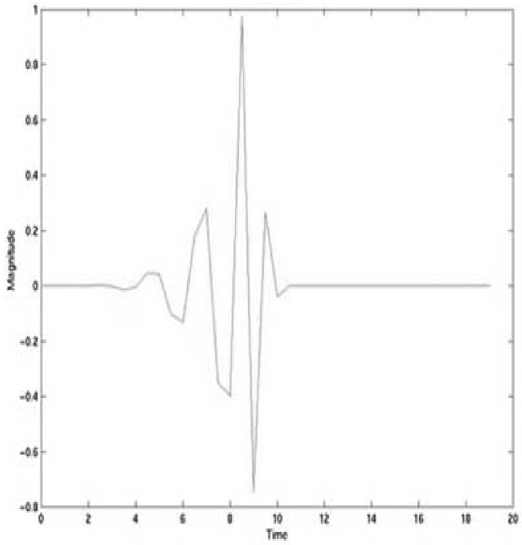

Fig.4.Wavelet function

Consider a 3-min IBI series extracted from the ECG. The R-R intervals were used to produce an HR signal in beats per minute, i.e., HR (R-R interval). Fig. 5 shows the analysis using the above defined complex wavelet function by plotting frequency response.
The frequency response of the original ECG with noise provides less information.

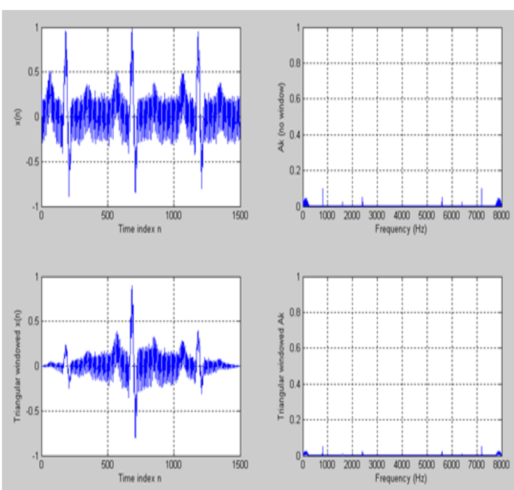

Fig.5. frequency response of noisy ECG

Thresholding approaches resorting to term-by-term modification on the wavelets coefficients attempt to balance variance and bias contribution to the mean squared error in the estimation of the underlying signal. However, it has been proven that such balance is not optimal. Term-by-term thresholding end sup removing to many terms leading to estimation prone to bias and with a slower convergence rate due to the number of operations involved.

A useful resource to improve the quality of the aforementioned balanced is by using information of the set of data associated to a particular wavelet coefficient. In order to do so, a block strategy for threshold is proposed. The main idea consists in isolating a block of wavelet coefficients and based upon the information collected about the entire set make a decision about decreasing or even entirely discards the group. This procedure will allow faster manipulation of the information and accelerated convergence rates. The processed ECG signal using wavelet decomposition is given in Fig.6

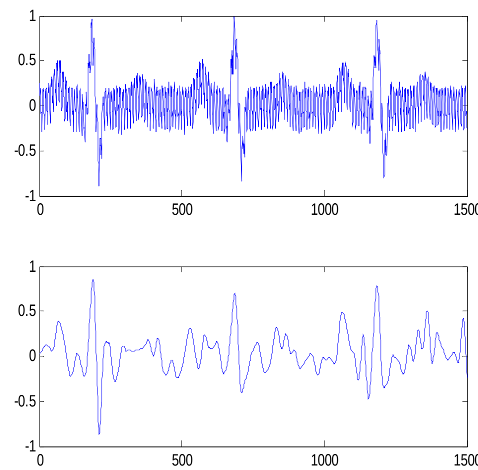

Fig.6. Recorded ECG and processed
ECG using wavelet

V. CONCLUSION

The stastical signal processing is usually performed using window functions and Fourier transform. The wavelet transform allows processing non stationary signals such as ECG signal. This is possible by using the multi resolution decomposing into sub signals. This assists greatly to remove the noise in the certain pass band of frequency. The presented method shows a new experimental threshold of wavelet transform coefficients. This threshold value is accomplished experimentally after using a loop of calculating a minimum error between the de noised wavelet sub signals and the original free of noise sub signals.

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