Feature extraction by wavelet transforms to analyze the heart rate variability during two meditation technique

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Abstract: - In this study we present the analysis of HRV signals by wavelet transform. HRV, described by the extraction of the physiological rhythms embedded within its signal, is the tool through which adaptations of activity of the ANS have been widely studied. The assessment of wavelet transform (WT) as a feature extraction method was used in representing the electrophysiological signals. The purpose of all this is to study the ANS system of subjects who are doing some meditation exercises such as the Chi and Yoga. The computed detail wavelet coefficients of the HRV signals were used as the feature vectors representing the signals. These parameters characterize the behavior of the ANS. In order to reduce the dimensionality of the data under study, the following statistical parameters were computed.

Key-Words: - HRV, wavelet, feature extraction, ANOVA, meditation.

1 Introduction

Within different countries, many people died because of cardiac diseases. A great number of exams, containing so much data of diversified nature, make subjects' visual evaluation harder. Added to that, the visual fatigue is the main cause leading to an error-prone task in making the manual analysis. Hence, the suitability to develop the automatic systems to process the electrocardiogram (ECG) signal. In order to allow an early diagnosis and an efficient treatment, the recognition of patterns of cardiac diseases can be improved through automatic feature extraction [1], [2], [3]. An electrocardiogram (ECG) can be defined as an electrical signal that represents the heart's cardiac activity. In general, this signal is recorded by means of certain number of electrodes which are pasted on the body. The most important waves responsible for the formation of a typical ECG are generally the P, QRS and T waves. The P wave corresponds to the atrium's depolarization. The QRS complex results from the ventricular depolarization. The T wave corresponds to the polarization of the ventricle.

In general, the signal, which corresponds to the atrium polarization, is merged with the QRS one. What is noticed here is that the ECG beat's shape can dynamically change. It's also highly correlated with the pathology type. The R-wave that manifests the depolarization process of the ventricle is the largest amplitude of a single cycle of the normal ECG [2], [4].

RR intervals the time between successive R-waves and RR tachogram is the series of RR intervals. Thus, in this time series, variability has been largely used as a heart function's measure. Through this we can identify risky patients who are subject to cardiovascular accidents or death. In fact, in this time series, variations' analysis is known as Heart Rate Variability (HRV) analysis [5], [6]. The parameter used in assessing Autonomous Nervous System (ANS) activity is defined as Heart Rate Variability. HRV, described by the extraction of the physiological rhythms embedded within its signal, is the tool through which adaptations of activity of the ANS have been widely studied. The HRV's non-stability presents a challenge to the technical aspects of its measurement, especially in the dynamic conditions of functional testing [7].

There have been various mathematical methods used to analyze HRV. The most common one is the Fourier Transform but, it is limited to stationary signals. The most important thing to do, while calculating a signal expansion is to localize a given basis function in time and in frequency. For instance, in Fourier Transform, while analyzing the functions used are infinitely sharp in their frequency localization. They exist at one exact frequency but have no time localization due to their infinite extends [8].

In order to define a particular basis function's localization, we can find different ways but they are linked to the expansion of the function in time and frequency. In fact, to overcome this very limitation, we applied the Wavelet Transform (WT). Wavelet analysis is one among the options available that may help to quantify HRV in non-stationary conditions [7].

Wavelet Transform (WT) represents a mathematical way used to study non-stationary signals. Therefore, its usefulness has been increasingly adapted over the last 10 years. It was employed in different fields such as communication technology, geophysics and image processing.

2 Methods

The RR interval variations present during resting conditions represent a fine tuning of beat-to-beat control mechanisms. Because it helps to evaluate the equilibrium between the sympathetic and parasympathetic influences on heart rhythm, HRV signals analysis is very important and crucial for the study of the Autonomic Nervous System (ANS). The nervous system's sympathetic branch increases the heart rhythm resulting in shorter beat intervals whereas the parasympathetic branch decelerates the heart rhythm leading to longer beat intervals. The spectral analysis of the HRV has led to the identification of two fairly distinct peaks: high (0.15-0.5 hz) and low (0.05-0.15 hz) frequency bands. Fluctuations in the heart rate, occuring at the spectral frequency band of 0.15- 0.5 hz, known as high frequency (HF) band, reflect parasympathetic (vagal) activity, while fluctuations in the spectral band 0.05-0.15 hz, known as low frequency (LF) band are linked to the sympathetic modulation, but includes some parasympathetic influence (sympathetio-vagal influences) [6]. It is now established that the level of physical activity is clearly indicated in the HRV power spectrum. For example, when a healthy subject stands up there is an increase of HRV in the LF spectral band, which is considered to be an estimate of the sympathetic influence on the heart. Consequently, the LF/HF ratio is considered to mirror sympathovagal balance or to reflect sympathetic modulations [9], [10], [8].

In this very research, we are looking for an effective way to analyze the HRV with advanced technique of signal processing. The purpose of all this is to study the ANS system of subjects who are doing some meditation exercises such as the Chi and Yoga.

2.1 Justification and purpose of the study

The purpose of this study is the separation of the two bands of frequency: HF an LF of HRV signal through the multiresolution decomposition by discrete wavelet transform. After the access to these components, which inform us about the function of ANS system, we can demonstrate that the WT analysis can be an effective clinical tool in examining the heart rhythm.

This proposition will be applied on a data base drown from physioBank [11] entitled "Exaggerated Heart Rate oscillations during two meditation techniques" contains a data of heart rate time series of two groups of healthy subject experiencing two series of records, one as pre-meditation and other record during the period of meditation (during specific traditional forms of Chinese Chi and Kundalini Yoga meditations). We have used another control signal for sane subjects in normal respiration (Table 1).

This data was used by [9] who applied both spectral analysis and analytic technique based on the Hilbert transform to quantify the heart rate. This method proved to be not very effective compared to the wavelet method. The ability of this latter technique to give simultaneous time and frequency resolution and separation of sympathetic and parasympathetic bands makes it an ideal tool for studying HRV.

TABLE 1
database

Exercise	Notation
Chi Meditation	C1,C2,… C8 (before and during)
Yoga Meditation	Y1, ….Y4 (before and during)
Normal Respiration	N1,N2,…….,N11

2.2 Feature extraction

By means of wavelet analysis, a matrix of data is obtained, where time and frequency domain information is present. A mother waveform is ''compressed'' or ''stretched'' to obtain wavelets of different scales that are used along time comparing them with the original signal. Low scale levels correspond to rapidly changing details or high frequency, whereas high scale levels correspond to slow changing details or low frequency. For every scale level and time a correlation coefficient was obtained, representing the correspondence between the analysis wavelet and the original signal. For example, a high correlation coefficient between the original signal and a low scale wavelet at the beginning of the record means that high frequency components are present at that time. Thus, this coefficient provides information about the moment that the RR interval is changing (time domain) and about the frequencies that are involved in these changes (frequency domain). In short-term recordings, high frequency (HF) components (0.15–0.40 Hz) reflect vagal activity, while low frequency (LF) components (0.04–0.15 Hz) are considered to be under the influence of both sympathetic and parasympathetic tone. Thus an increased LF/HF ratio may indicate either increased sympathetic activity or decreased vagal tone [13], [14].

Tests are often carried out using different types of wavelets and the most effective one is chosen for the particular application. We can detect changes of the HRV signals by means of the smoothing feature of Daubechies wavelet of ordre (db4). This wavelet (db4) is used by most researchers ([7], [8], [9], [10], [13], [14]) to analyze the HRV. Therefore, the wavelet coefficients were computed using the db4 in the present study. The wavelet coefficients were computed using the MATLAB software package.

Selection of appropriate wavelet and the number of decomposition levels is very important in analysis of signals using the WT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In order to determine the appropriate number of decomposition levels, different experiments were performed. In the present study, the number of decomposition levels was chosen to be 6. As the HRV signal was resample at 4 Hz. Thus scale 1 corresponds to 2-1 Hz, and scale 2 to 1-0.5 Hz. Scales 3 and 4 correspond approximately to HF (0.125–0.5 Hz), and scales 5 and 6 to LF (0.03125–0.125 Hz).

TABLE 2
Localization of the two bands LF and HF after decomposition by DWT

HRV composante	Scales	Frequency bands (Hz)
	D1	1-2
	D2	0.5-1
HF	D3	0.25-0.5
	D4	0.125-0.25
LF	D5	0.0625-0.125
	D6	0.03125-0.0625

The computed detail wavelet coefficients of the HRV signals were used as the feature vectors representing the signals. These parameters characterize the behavior of the ANS. In order to reduce the dimensionality of the data under study, the following statistical parameters were computed:

- STDLF and STDHF: Standard deviation of the wavelet coefficients in each subband.
- %LF and %HF : LF and HF powers of wavelet coefficients in each subband measured in normalized units:

%LF=LF/(LF+HF)×100; %HF=HF/ (LF+HF)×100.

- R: ratio R=LF/HF

2.3 statistics analysis

The ANOVA test takes into account not only changes in mean values and standard deviation, but also changes occurring in each subject in different exercise of meditation. This test is considered significant when $p < 0.05$, where p is the probability that the data recorded from the same subject in the two state before and during the meditation.

3 Results and discussion

Fig. 1 shows the parameters taken from the wavelet coefficients of the HRV signals of three subjects: two during meditation exercises and the third subject in normal respiration state who is referred to as control in the histogram.

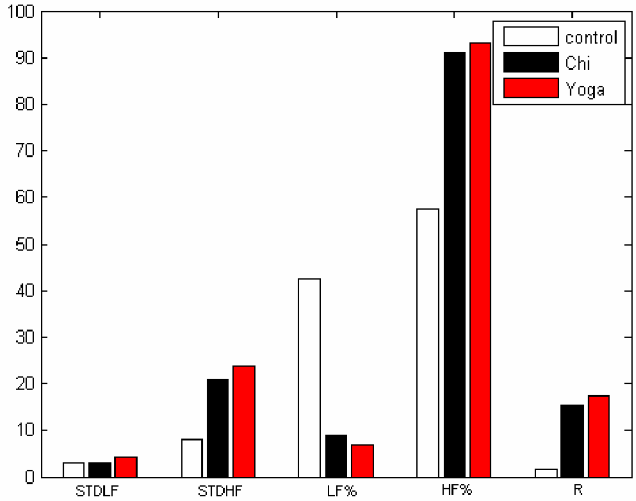

Fig. 1 parameters extracted from HRV before and during Chi an Yoga meditation and control group

We notice that the ANS behavior is characterized by a decrease of the concentrated power in the LF band and an increase at the HF band level.
During the tests, the pursuit of these changes is clear in the LF and HF powers of wavelet coefficient in each subband measured in normalized units (LF% and HF%).

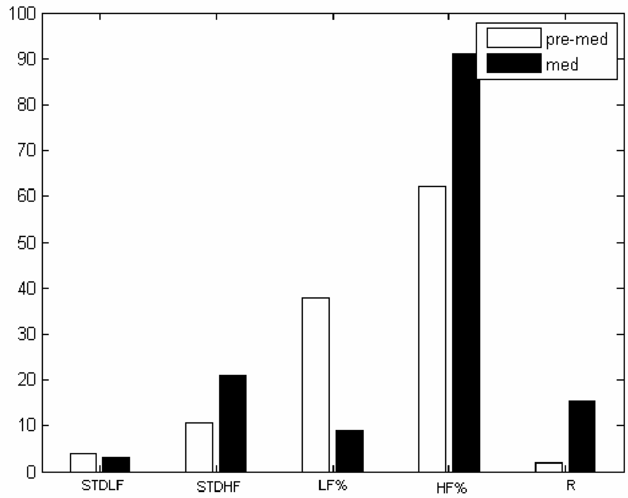

Fig. 2 parameters extracted from HRV before and during Chi meditation

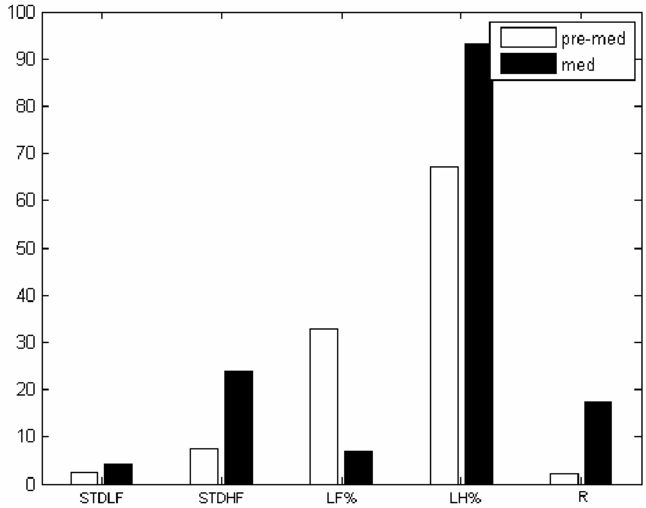

Fig. 3 parameters extracted from HRV before and during Yoga meditation

The results depicted in Fig. 2 and Fig. 3 demonstrate that the percentage of HF during the meditation is greater than the percentage of that in the premeditation, which indicates that the sympathetic nerves are more active during meditation and this situation causes the heart rate of the subjects to be quicker than the ordinary situation.

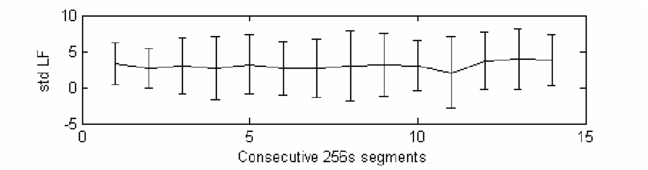

Fig. 4 variation of standard deviation of wavelet coefficients in LF band over each consecutive drive segment

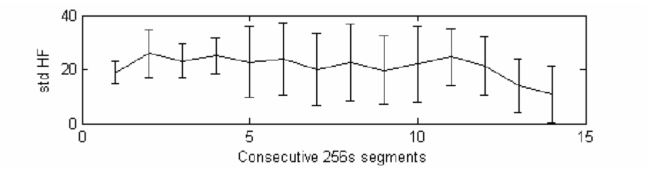

Fig. 5 variation of standard deviation of wavelet coefficients in HF band over each consecutive drive segment

Studying the different segments of 256s, we can notice the peak of the high variation indexed on the Fig.4 and Fig.5 (error bars) present a relative stability on standard deviation of LF. Moreover, the peak that represents the acceleration of respiration rhythm is localized on the variation of standard deviation HF.

TABLE 2
p-value: statisticts test

parameters	Chi	Yoga
STDLF	p<0.0007	p<0.0072
STDHF	p<8.1154e-008	p<0.0003
%LF and %HF	p<5.6301e-007	p<7.5352e-006
R	p<1.1877e-006	p<0.0287

The statistical test ANOVA on the subject before and during the meditation is always significant (p<0.05). However, when we increase the data base, we move to non significant values of the balance of LF/HF.

4 Conclusion

Using wavelet transforms, we managed to separate the two essential components (LF and HF) of HRV signal. The analysis of the two bands LF et HF is described by wavelet coefficients informs us about the behavior of ANS. The response of ANS during the exercise of meditation Chi and Yoga was studied well in time-frequency domain by calculating of statistical parameters and the localization of energy concentration reflect as a result of amplitude variation that is to say the acceleration and the refraining of sympathetic and parasympathetic systems.
Thus we can deal with the approaches of classification with guarantee of ample feasibility of anomalies of cardiac insufficiency.

References:

[1] P.V. Madeiro, Paulo C. Cortez, Francisco I. Oliveira, Robson S. Siqueira, *A new approach to QRS segmentation based on wavelet bases and adaptive threshold technique*, Medical Engineering & Physics 29, 26–37, 2007.

[2] L. El Khansa, A. Naït-Ali, *Parametrical modelling of a premature ventricular contraction ECG beat: Comparison with the normal case,* Computers in Biology and Medicine 37, 1–7, 2007.

[3] M. Engin, *Spectral and wavelet based assessment of congestive heart failure patients*, Computers in Biology and Medicine, 2006

[4] M. C.K. Khoo, T. Kim and R. B. Berry , *Spectral Indices of Cardiac Autonomic Function in Obstructive Sleep Apnea,* SLEEP, Vol. 22, No. 4, 1999.

[5] O. Faust, R. Acharya, SM. Krishnan and L. C. Min, *Analysis of cardiac signals using spatial filling index and time-frequency domain*, BioMedical Engineering OnLine, 2004

[6] N. Jafarnia-Dabanlooa, D.C. McLernona, H. Zhangb, A. Ayatollahic, V. Johari-Majd, *A modified Zeeman model for producing HRV signals and its application to ECG signal generation*, Journal of Theoretical Biology 244, 180–189, 2007.

[7] V. Pichot, J.M. Gaspoz, S. Molliex, A. Antoniadis, T. Busso, F. Roche, F. Costes, L. Quintin, J.R. Lacor, J. Barthelemy, *Wavelet transform to quantify heart rate variability and to assess its instantaneous changes*, J. Appl. Physiol. 86, 1081–1091, 1999.

[8] N. Y. Belova , S. V. Mihaylov, Boriana G. Piryova, *Wavelet transform: A better approach for the evaluation of instantaneous changes in heart rate variability*, Autonomic Neuroscience: Basic and Clinical 131, 107–122, 2007.

[9] Jou-Wei Lin, Juey-Jen Hwang, Liang-Yu Lin, Jiunn-Lee Lin, *Measuring Heart Rate Variability with Wavelet Thresholds and Energy Components in Healthy Subjects and Patients with Congestive Heart Failure*, Cardiology,106, 207–214, 2006.

[10] D. E. Vigo, S. M. Guinjoan, M. Scaramal, L. N. Siri, D. P. Cardinali, *Wavelet transform shows age-related changes of heart rate variability within independent frequency components*, Autonomic Neuroscience: Basic and Clinical 123, 94 – 100, 2005.

[11] www.physionet.org

[12] Peng C-K, Mietus JE, Liu Y, Khalsa G, Douglas PS, Benson H, Goldberger AL. *Exaggerated Heart Rate Oscillations During Two Meditation Techniques*, International Journal of Cardiology 70, 101-107, 1999.

[13] E. Toledo, O. Gurevitz, H. Hod, M. Eldar and S. Akselro, *Wavelet analysis of instantaneous heart rate: a study of autonomic control during thrombolysis*, Am J Physiol Regulatory Integrative Comp Physiol 284, 1079-1091, 2003.

[14] H. Burri, P. Chevalier, M. Arzi, P. Rubel, G. Kirkorian, P. Touboul, *Wavelet transform for analysis of heart rate variability preceding ventricular arrhythmias in patients with ischemic heart disease*, International Journal of Cardiology 109, 101 – 107, 2006.

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