Heart Rate Variability Analysis And The Structural Health Of The Heart

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Heart rate variability (HRV) represents the degree of change in the instantaneous heart rate or RR intervals, analysis of which can provide information about the effects of the autonomic nervous system. Power spectral density, calculated as the distribution of the power contained in a signal over frequency, has been used in HRV analysis to identify important frequency bands: The high frequency (HF) band (0.15-0.4 Hz) corresponds to the autonomic parasympathetic tone and respiratory frequency, while the low frequency (LF) band (0.04-0.15 Hz) corresponds to a complex measure of the autonomic sympathetic tone and vagal influence.

The angiotensin converting enzyme insertion/deletion (ACE I/D) genetic polymorphism was identified as a contributing factor influencing parasympathetic tone. Specifically the DD genotype, which is associated with increased risk or progression of cardiovascular disease, is associated with a decreased HF HRV. Spectral analyses have shown that diabetic neuropathy, myocardial dysfunction, older age, and an increased risk of post-myocardial infarction mortality are all associated with decreased HRV and spectral content from 0.04-0.32 Hz.

Traditionally, a Fast Fourier transform is used to decompose the time-domain signal into a frequency domain, but it is limited in that time information is hidden and a stationary signal is required since it is averaged. Instead, we are attempting to utilize a novel time-frequency analysis technique, wavelet transform analysis, which simultaneously provides information about time, frequency, and power and is appropriate for non-stationary signals as is the inter-beat interval data. We investigated the relationship and clustering between factors influencing heart rate variability, including pathophysiologic, pharmacologic, genetic, and demographic covariates. Because the beat to beat data recorded had different time length for each participant; the data was transformed in 32 scales using a wavelet debauchees transform. A conversion between scale and frequency exist. The 32 scales were divided into two groups in order to cluster the similar signatures in the low frequency range and in the high frequency range: Scales 3 through 10 (0.4706 Hz- 0.1412 Hz) represented the high frequency component, while scales 12 through 31 (0.1177 Hz- 0.0455 Hz) represented the low frequency component. For each scale, we designed a 2-D Kohonen layer, forming a 3D Kohonen representation for all the scales. Figure 1 represent the cluster analysis obtained in the high frequency range as indicated.

The optimal SOM (using baseline data) results were obtained with a 20x20 Kohonen map using batch training, linear initialization, and gauss neighborhood. The clusters obtained are independent of the Kohonen initialization values.

In addition to the Kohonen unsupervised net a Backpropagation (BP) net was trained to map the participant characteristics to the their beat to beat wavelet signatures. The BP net showed that wavelet scales 8, 15, and 17 had optimal separation for cluster identification; for example at those scales existed the larger difference between participant characteristics, such as smokers vs. non-smokers, young healthy vs. old non-healthy participants, and DD,DI, and II genotypes. Figure 2 shows the results of the BP for individuals of DI genotypes as indicated.

Subjects with multiple medical co-morbidities do not cluster, and remain as outliers. For example, participant 30 (blood pressure=258/105, BMI=16.2, male smoker with hypertension and diabetes mellitus on beta blocker and ACE Inhibitor medications) never clustered --in the low scales (high frequency range)—with the patients that had fewer medical co-morbidities. The results showed that there is not a single parameter distinguishing patients between clusters, rather the results are a combination of participant characteristics. The integration of the CWT and SOM techniques for HRV analysis represents a potentially useful paradigm to identify clinical characteristics and environmental factors that influence such measures.

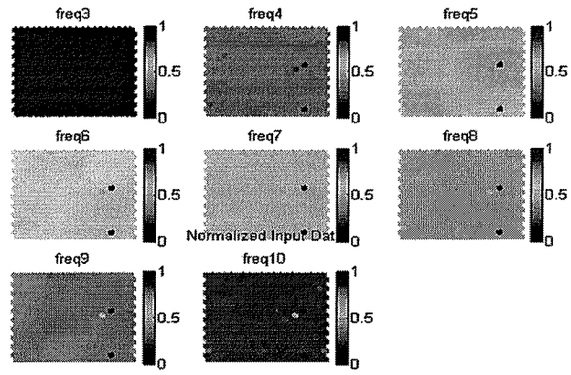

Figure 1: Variation of the patient clustering by scale in the frequency band of 0.15-0.4 Hz. The data is normalized between 0 and 1. Two main clusters are formed (darker points) indicating two main sets of patients with two main tone respiratory frequencies.

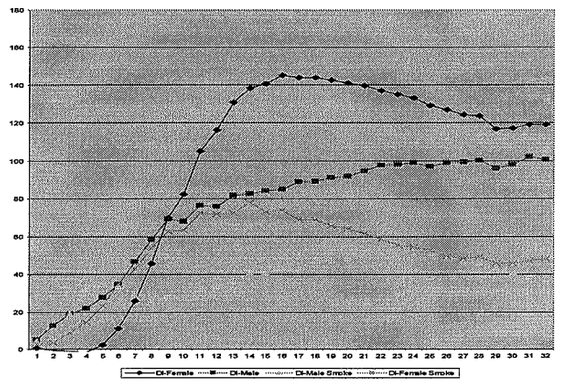

Figure 2. Selected participant Wavelet-magnitude representation versus wavelet-scale. Diamonds indicate females non-smoker; the squares indicate males non-smokers; the triangles indicate male smokers; and the crosses indicate female smokers. All patient of this group have a DI genotype, ages not more than 30 years, old and healthy. Scale 17 shows a large separation between groups.