

An Objective Approach towards Assessment of the Physiological Age of Heart

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Abstract

A novel objective methodology is proposed for the assessment of the physiological age of the heart which is based on extraction of wavelet features from sternal ballistocardiogram and classification of these features using neural networks and k-nearest neighbor classifiers. Some promising preliminary results suggest that the proposed methodology is feasible to be developed to a tool for assessment of the physiological age of the heart independent of its chronological age and present a new tool for the assessment of the cardiac performance.

Index terms: Ballistocardiogram (BCG), Debauches wavelets, Neural networks, K-nearest neighbor classifier.

Introduction

Cardiac failure has been identified as a serious international problem, in particular for aging groups, causing an increasing number of patients on hospitals waiting lists. It is useful to develop a marker that can identify such problems at an earlier stage. It is known that the hearts of certain persons are found to be much older physiologically than chronologically. The goal of this research is to use the mechanical vibration of the body recorded from the sternum, ballistocardiogram, to assess the physiological age of the heart as a marker of cardiac health.

The ballistocardiogram is a vital signal in the 1-20 Hz frequency range created by the movements of the heart and blood, and can be recorded from the human body by noninvasive means. In the early 1930s Isaac Starr recognized that BCG signals closely reflect the strength of myocardial contraction and function of the heart as a pump [1]. However, due to the unrefined nature of the previous BCG signal acquisition technologies, the lack of interpretation algorithms, and the lack of practical

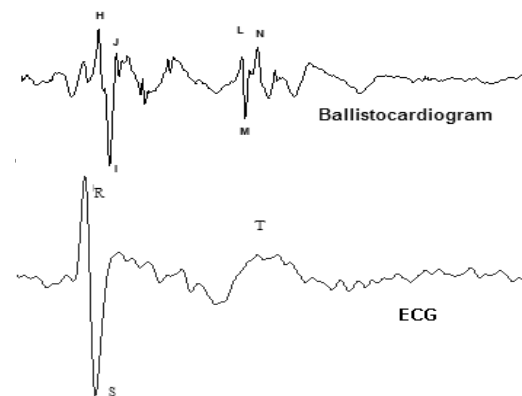


Figure.1. The accelerometer sensor was placed on the sternum while the subject was in supine position and BCG signal was recorded together with the ECG signal.

devices, our current health care systems do not use BCG for clinical purposes.

New micro-sensor and digital wireless technologies provide more accurate BCG signal acquisition, and thereby open new possibilities to use BCG, and in general the mechanical signals of the heart, clinically. Considering these new possibilities, our research focus in CiBER is on developing appropriate new devices [2] and algorithms [3] followed by clinical tests [4] to allow adoption of BCG as a new additional tool in diagnosis and identification of cardiac malfunctions.

Everybody knows what strength and weakness are. A strong man can lift weights that would be impossible for a weak man; or that a strong man can support a burden for a long time, a weak man for a lesser time. The same reasoning is true observing the mechanical vibration of the body created by heart beats, as a marker of cardiac strength. Longitudinal research in ballistocardiography has shown that the amplitude and morphology of the signal changes with age [1].

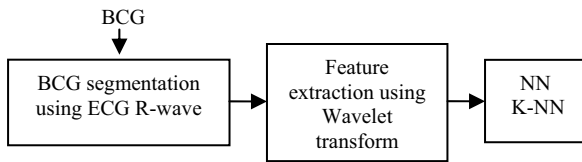


Figure.2. The BCG signal gets segmented using the R wave of the ECG signals, wavelet features get extracted from the segmented cycles, the extracted feature vectors get classified using neural network (NN) or k-nearest neighbor classifiers (K-NN).

The BCG signal noninvasively presents this mechanical strength while ECG signal only reflects the electrical activity of the heart and doesn't give us any information about the heart's contractility. There are imaging methods such as echocardiograph that can be used for the same purpose but this methodology is very expensive and hard to be performed on daily basis while new sensor technology offers us the possibility to have portable BCG instruments that can be used for monitoring of the heart using BCG signal.

In our new objective approach at CiBER to processing of BCG signal we are trying to derive an estimation of the physiological age of the heart that gives information to the user about the performance of their heart. As the first step for development of a system which can assess the physiological age of the heart we thought to develop a set of classifiers that can reliably distinguish between BCG signals of different healthy heart age groups. Considering the complexity of the problem we decided to use artificial intelligence techniques as explained in this paper.

Data Acquisition Setup

The BCG dataset was acquired from subjects without heart-related pathologies, most of whom were patients of Burnaby General Hospital (old), or students at SFU campus (Young). Out of the 38 subjects taking part in our study, 31 were healthy male subjects younger than thirty years old and 7 were healthy male subjects older than seventy. The ethical approval for this data acquisition was granted by Simon Fraser University and the Fraser Health Authority of British Columbia, Canada.

The data acquisition involved measurement of BCG, twelve lead ECG, pulse oximetry, respiration and heart sounds. All of the signals were acquired by a Biopac biological data acquisition system with sampling rate of 2 KHz [5]. A single cycle of synchronous BCG and ECG signals can be seen in Figure 1.

The BCG signal was measured using a high sensitivity (1000 milivolts/g) accelerometer which was positioned on the sternum. The accelerometer sensor was factory calibrated, weighed 54grams, and was connected to a charge amplifier [6]. The ECG signal was measured in twelve leads and the R-wave of the second lead of the ECG signal was used to identify BCG cycles.

Methodology

The BCG signal was recorded together with ECG signal as explained before and the methodology proposed in Figure 2 was followed to classify this signal.

BCG Cycle Segmentation

From lead II of the ECG signal the QRS complexes were identified using a technique based on filter banks [7] and the BCG signal was segmented using the R waves detected on the synchronous ECG signal. The minimum R-R interval for each subject was considered as the window length and each BCG cycle was considered to start fifty samples before the corresponding R wave on ECG and for the length of the window.

BCG Feature Extraction

The suggested high-resolution method for feature extraction is a special kind of wavelet, called Daubechies Wavelet which is an orthogonal transform [8]. The properties of this kind of wavelet are suitable for our application because we seek to reduce the dimensions of the BCG cycle optimally. The continuous wavelet transform of a square-integrable function $f(t)$ is defined as:

$$wf(s,t) = \int_{-\infty}^{\infty} f(\tau) \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right) d\tau$$

Where s and t are the scale (or frequency) and time variable, respectively. The function $\psi(t)$, called wavelet mother function, must satisfy the admissibility condition, i.e. it must be a zero-mean, square-integrable function. In practical applications the parameters s and t must be discrete values.

BCG Classification

In this research we used two different classifiers to classify the BCG signal. For the first classifier we used feed forward neural networks trained by a back propagation algorithm; for the second classifier we used k-nearest neighbor classifier [9]. Both classifiers are supervised networks so they require a desired response to be trained. They learn how to transform input data into a desired response, so they are widely used for pattern classification.

Results

In this research Daubechies (db) Wavelet was used to extract important information from each BCG cardiac cycle. Referring to our investigation db with control parameter $p=8$ provides better result for our application. After feature extraction, a feed forward neural network with 20 neurons in the hidden layer and two neurons in the output layer, each corresponding to one age group, were used to classify the BCG signal.

Table 1. The results of classification of BCG signal to two different classes of healthy male older than 70 and younger than 30 years old. Subjects 1-31 are the younger group and 32-38 are the older group. With the neural network an average accuracy of 97.61% and with K-NN an average accuracy of 98.6% was achieved.

Subject	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
NN	91.5	100	100	100	100	98.1	100	100	100	100	100	100	98.5	97.8	100	100	95.7	100	100
K-NN	78.97	100	100	100	100	98.15	100	100	100	100	100	100	98.48	100	100	100	100	98.66	100
Subject	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
NN	100	100	100	100	100	100	100	100	100	100	100	100	100	69	100	87.3	100	100	100
K-NN	100	100	100	100	100	100	100	100	100	100	100	100	100	79.31	100	100	100	93.33	100

A cross validation method was used to divide the dataset in training and test data in which one subject was kept outside the data and the neural network was trained on the rest of the subjects and then the feature vectors of the left out subject were applied to the network to test its ability to distinguish the age of that vector.

The same procedure was repeated for the k-nearest neighbor classifier and the results of Table 1 for each subject were produced. The percentages reported in the table represents the ratio of correctly classifies vectors to the total number of vectors for that individual subject.

Depending on the heart rate different subjects had different numbers of feature vectors but the same vectors were used for both classifiers in order to compare the performances. The neural network accuracy over all feature vectors extracted from all subjects was calculated to be 97.61% with the ninety five percent confidence interval of 1.75% and the k-nearest neighbor's accuracy was calculated to be 98.6% with the ninety five percent confidence interval of 1.52%. The results obtained by the neural network are very close to the k-nearest neighbor classifier but neural network is substantially slower compared to k-nearest neighbor in classification.

Conclusion

In this research a novel objective methodology was proposed for the assessment of the physiological age of the heart using BCG signal and artificial intelligence and the promising preliminary results presented in Table 2 confirms the possibility of reliably separating healthy people of different age groups from each other using our methodology. The BCG signal was chosen for this study as this signal reflects the mechanical performance of the heart which is proven to be modulated by age and on the other hand provides a inexpensive and noninvasive methodology for monitoring cardiac activity. The results of classification of BCG signal to two different classes of healthy male older than 70 and younger than 30 years old lead to more than 97.61% percent accuracy.

This is an objective approach to the subjective observations in the past that the morphology of the BCG signals change by age. The next important step of this research is to further develop the BCG dataset to include healthy subjects of both sexes and of different age

categories to be able to train the neural network over all these categories. After this training stage we would be able to assign the signal acquired from each individual's heart to a specific age group that the neural network assigns it to, which will in turn be considered as an index reflecting the physiological age of the heart rather than its chronological age.

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