# BALLISTOCARDIOGRAM DIAGNOSIS USING NEURAL NETWORKS AND SHIFT-INVARIANT DAUBECHIES WAVELET TRANSFORM

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## ABSTRACT

One of critical problem causing death of humankind is heart disease. To help Medical doctors to find patient heart conditions and monitoring their body's signals, several electronic devices have been developed over several decades. Among different methods used for these purposes, Ballistocardiography (BCG) has an interesting measurement feature that no electrodes are needed to be attached to the body during recording. Therefore, it is provides a strong potential possibility to evaluate the patients heart condition in the homeear, or his office. In this research, we used Shift Invariant Daubechies wavelet transform to extract essential BCG features and Artificial Neural Networks to classify them. The results show that our method using wavelet transform and neural network classifier has a reliable and high performance, no sensitive to BCG waveform latency as well as non-linear disturbance. Moreover, the wavelet transform requires no prior knowledge of the statistical distribution of data samples and the computation complexity and training time are reduced.

## 1. INTRODUCTION

Ballistocardiography is one of the newest clinical tools for diagnosing, monitoring and managing myocardial disorders related to heart disease. The disorders because of disease are characterized by sudden recurrent and transient disturbances of myocardial function and/or mechanical movements of the heart. The presence of any abnormal disorders in the Ballistocardiogram (BCG) confirms heart diagnosis, which sometimes can be confused with other disorders because of some special situation for subject producing similar disturbances in BCG. An example of BCG waveform is shown in Fig. 1 [1]. During the past several years, a large number of Bio-signal classification methods have been developed, including single and multi channel template matching, principle component analysis, amplitude separation, Fourier analysis, linear filtering autoregressive modeling, neural networks, and maximum likelihood. Some of methods used for BCG features Extraction and classification have been reviewed by Xinsheng Yu [2]. Most of the existing methods perform very well when the problem of Motion artifacts, and BCG waveforms latency as well as non-linear disturbance such as electrical drifting of electronic devices and adding noises with different recourses to recorded signal is not considered. However, methods that do not deal with such an important issue may potentially give us untrue information about patient. Other limitations of the existing techniques concern their degree of success in the case of special situation of subject such as stress, their ease of hardware and/or software implementation, their portability across platforms, and their suitability for real-time processing.

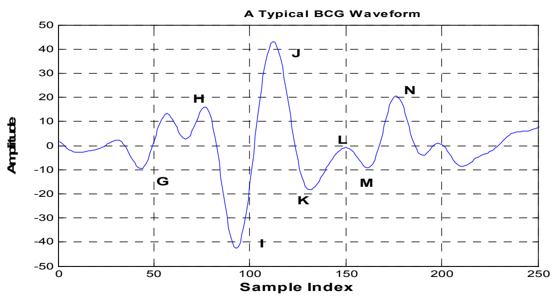


Fig. 1. Example of BCG signal including spikes, and wave complexes called G,H,I, J, K, L, M, and N components[1].

We have proposed some new method of BCG features extraction and classification using a well-known artificial neural network (ANN) so-called Multi-Layer Percepteron (MLP). To recognize the most important BCG features and decreasing information redundancy and presenting to ANN for signal classification, the shift-invariant wavelet transforms also have been used. We used 6 subjects including to these categories: young healthy, old healthy and old men with some infarct in their heart.

## 2. PROCEDURES

*2.1 Overview*

As can be seen in Fig. 2, our suggested procedure includes three stages: 1- BCG segmentation stage to extract BCG cycles and specify its waveforms; 2- The BCG features computing using shift-invariant wavelet transform to eliminate not importance or disturbances of BCG waveforms as well as reducing dimension of ANN inputs; 3- Classification stage to clarify class of every BCG spike and clustering them using artificial intelligence. The segmentation stage only uses R spike of ECG signal and amplitude separation/threshold detecting method to extract templates. Well-known artificial neural networks (ANN) so-called Multi-Layer Percepterons (MLP) have been used to classify BCG Waveforms. Moreover, the ECG signal in segmentation stage is only for extraction of BCG templates not for classification purposes.

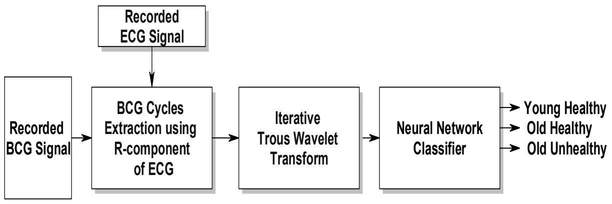


Fig. 2.Block diagram of our system to classify BCG data to three classes.

*2.2 BCG cycles Extraction Using ECG R Spike and the amplitude separation method (Segmentation Stage)*

The BCG data set used in this study was provided by ProHemon research team located at Tampere University hospital and Tampere University of Technology-Digital Media institute using a chair fitted with Electro-Mechanical Sensor so-called EMFI and a Data acquisition so-called CircMon developed by Jr Medical Ltd, Tallinn/Estonia [1,3,4].The signals was sampled at 200 samples/Second from the seat of the chair in a clinical trial. During the BCG recording, the references ECG signal were recorded simultaneously form the chest of subject's body at the same sampling rate. Fig.3 shows one typical recording of BCG and ECG records of a young healthy man. The R-Component of the ECG signal is used to identify each BCG cycle using amplitude/ threshold separation method to extract BCG waveforms into a unique 250 points window size. The BCG cycles are filtered to reduce the background noise and were then normalized into the range [0, 1]. Altogether, there are 6 normal subjects,

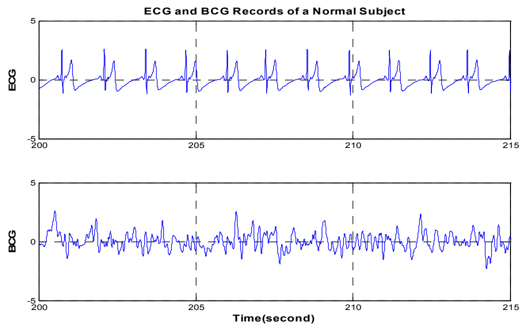


Fig. 3. ECG and BCG records of a Filtered Normal young subject using Band pass filter [1, 45] for ECG & [1, 10] HZ for BCG. As can be seen, there are some motion artifacts in BCG signal, not being possible to remove using filtering.

who were included to three categories: young healthy, old healthy and old men with some infarct in their heart.

*2.3Computing BCG Features Based on Shift-Invariant Daubechies compactly supported Wavelet* Transform

The suggested high-resolution method for features computing is using a special kind of wavelet, called on Shift-Invariant Daubechies compactly supported Wavelet *Transform* [5,6,7,8]. The properties of this kind of wavelet are good for our application because we would like to reduce optimally dimension of BCG cycle and not effecting phase or shifting of waveforms in our method's performance.

*2.3.1 Trous- Fast Wavelet Transform (T-FWT) [5,7,8]*

To implement shift invariant wavelet transform, an algorithm called Trous is presented in [5,7,8]. Suppose $a_0[n]$ is a sequence of input signal samples. For $j>0$, we denote: $a_j[n]=\int_{-\infty}^{+\infty} f(t)\psi(n-t)dt$, where $\psi$ is wavelet base. The dyadic wavelet coefficients are computed for $j>0$ over the integer grid

$$d_j(n)=wf(n,k^j)=\langle f(t),\psi_2(t-n)\rangle$$

For any filter $x[n]$, we denote by $x_j[n]$ the filters obtained by inserting $2^j-1$ zeros between samples of $x[n]$ with Fourier transform equal to $X(k^j\omega)$. Inserting zeros in the samples of $x[n]$ creates holes. Now, let $\bar{x}_j[n]=x_j[-n]$. By using the following equation, we can compute a dyadic wavelet transform and its inverse:

$$a_{j+1}[n]=a_j[n]*\bar{h}_i[n],\quad g_{j+1}[n]=a_j[n]*\bar{g}[n].$$

Filter $h[n]$ so-called conjugate mirror filter is a low-pass filter and hence only low frequency components can pass through it; on the other hand $g[n]$ is a high-pass filter to pass high frequency components. The dyadic wavelet representation of signal $a_0$ is defined as the set of wavelet coefficients up to a scale $k^J$ plus the remaining low-frequency information $a_J : \left[ \{d_j\}_{1\le j\le J}, a_J \right]$. Fig. 4 shows block diagram of such operations, where $J = \log_2 N$ and $\tilde{x}[n]$ is the duality of $x[n]$.

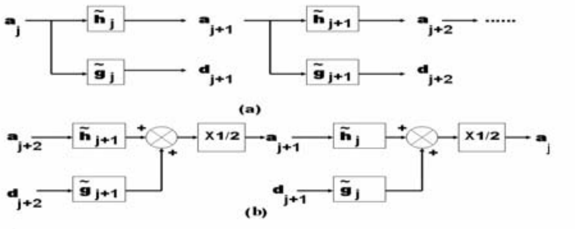


Fig. 4. (a). Fast Wavelet Transform (FWT) algorithm to find coefficients based on repeatable method using contracted filters.
(b). Signal reconstruction based on repeatable method using contracted filters.

*2.3.2 Daubechies compactly supported Wavelets [5,7,8]:*
The h, and g filters that we used in this paper are constructed form a strong wavelet bases so-called daubechies wavelets. These bases are orthogonal wavelets and have less information redundancy than other wavelet transforms. Daubechies wavelets have a support (width) of minimum size for any given number of vanishing moments (P). Definition of vanishing moments is: $\psi$ (wavelet base) has P vanishing point if $\int_{-\infty}^{+\infty} t^k \psi(t)dt = 0 \;\; for \;\; 0 \le k < p$. The number of vanishing moments of $\psi$ affects in increasing number of negligible and almost zero wavelet coefficients.

*2.33 BCG Features computing using Shift-Invariant Daubechies Wavelets with P=2*
In this research work we used shift invariant Daubechies Wavelets with P=2 (db2) and Trous algorithm (Fig.4) to find wavelet coefficient of every BCG cycle $x[n]$ at level 6. Our practical experiences showed that using p=2 is enough and the most important features of BCG waveforms were saved at level 6 of iteration T-FWT. It is possible to decrease cycle dimension (N) from 250 to 4 by saving only local maxima coefficients without losing important information [5,7,8]. Fig 5 shows wavelet coefficients at 2 different levels for a typical wavelet waveform. Moreover, the results for 6 typical subjects are showed in Fig.6.

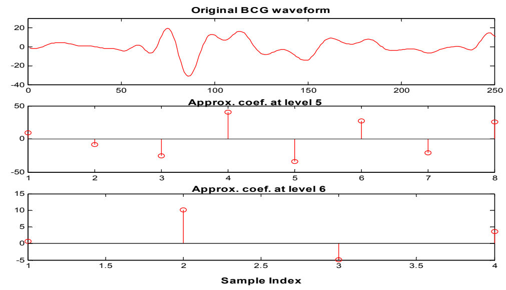


Fig. 5. Local maxima Wavelet coefficients at 2 different levels for a typical wavelet waveform

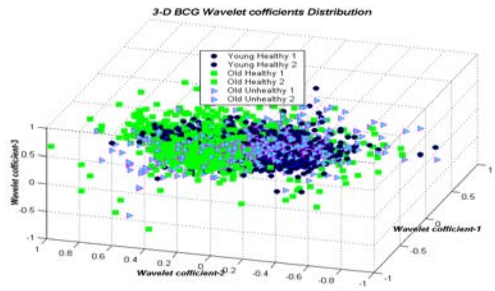


Fig. 6. 3-D Representation of BCG cycles Daubechies Wavelet Coefficients (level 6) for 6 subjects of 3 categories: Young Normal, Old Normal, and Old Abnormal Subjects.

*2.4 BCG Spike Classification Using Multi-Layer Percepterons (MLP) Artificial Neural Network [8,9]*

Multilayer perceptrons (MLPs) are feed forward neural networks trained with the standard back propagation algorithm. They 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. With one or two hidden layers, they can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems. Most neural network applications involve MLPs.

## 3. RESULTS

To demonstrate performance of approaches and comparing results, we used MLP Neural Networks with 4 inputs, Tanh() to simulate non-linearity of neurons, two hidden layer (relatively 15, and 10 neurons), and 3 outputs for classifying 6 subjects to 3 categories: young healthy students with age between 20-30 years old (2 subjects), old healthy men with age between 50-70 years old (2 subjects) and two old Subjects (50-70 years old) with some infarct in their hearts.

For every subject of three categories, the previous stage (Wavelet Decompositions) give us features of the every BCG cycle (dimension of data reduced from 250 to 4). These data are normalized, mapping to area [-1, 1], and finally saved randomly in unique data matrix. We used small part of data for training Artificial Neural Network (ANN) and rest of data for testing performance of ANN classifier, not using same data for training or testing the system. Table 1 shows performances of approaches. It has been seen that the performance of our developed system is very high and can be used in diagnosing applications using BCG signal. According to the our experiences, some of BCG waveforms have latency or non-linear disturbance such as motion artifacts and electro-mechanical drifts, but the proposed method in this paper, as shown in table 1, is able to discriminate them with high accuracy.

TABLE 1
RESULTS OF BCG CLASSIFICATION USING NEURAL NETWORKS AND BCG CYCLES IN FIG. 4. SHIFT-INVARIANT DAUBECHIES WAVELET TRANSFORMS ARE USED FOR COMPUTING BCG WAVEFORMS FEATURES

| | | Class1 | Class2 | Class3 | Overall |
|---|---|---|---|---|---|
| Class 1 | SBJ1 | 100% | - | - | |
| | SBJ2 | 97% | 3% | - | |
| Class 2 | SBJ1 | - | 90% | 10% | |
| | SBJ2 | - | 87% | 13% | |
| Class 3 | SBJ1 | - | 34% | 66% | |
| | SBJ2 | - | 12% | 88% | |
| Overall | | | | | 92% |

SBJ=Subject, Every cell show correct classification percentage for every class; Class 1: Young healthy student with age between 20-30 years old (2 subjects), Class 2: Old healthy men with age between 50-70 years old (2 subjects), class 3: Two old Subjects (50-70 years old) with some infarct in their hearts, Overall (%): performance computed using randomly selected training and testing BCG data of 6 subjects.

## 4. CONCLUSION

To discriminate BEG features, researchers have presented different methods. Most of the Existing methods have high accuracy in the BCG features discrimination whilst not considering BCG waveforms have latency or non-linear disturbance such as motion artifacts and electro-mechanical drifts/noises. However, ignoring these kinds of important issues may potentially give us untrue information about patients. In this paper, we developed approaches, which have very high performance, even for the case of non-linear disturbance or latency. In our approach to overcome these kinds of phenomena, we used very strong time-frequency signal processing/feature extraction method so-called Shift invariant Daubechies compactly supported Wavelets.

Truly BCG cycles classification is very important in finding intensity of disease and the kind of it. The first stage of our diagnosing system is segmentation stage using R-components of ECG signal of the same subjects. To reduce dimension of BCG waveforms as well as eliminating/decreasing latency, and non-linear disturbances, the Daubechies compactly supported Wavelet transforms are used as second stage (pre-processing stages). Neuro-classifier (MLP NET) is used to classify BCG cycles. The result showed that this classifier-multi-layer network has very high performance, even with non-linear disturbance or latency. It should be mentioned that the developed method in this paper is not limited to BCG data classification and can be used to other examples of signal processing such as evoke potentials, EEG, EOG, and EMG.


## 5. ACKNOWLEDGMENT

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