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ORIGINAL PAPER

An Intelligent Ballistocardiographic Chair using a Novel SF-ART Neural Network and Biorthogonal Wavelets

Alireza Akhbardeh · Sakari Junnila · Teemu Koivistoinen · Alpo Värri

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Abstract This paper presents a comparative analysis of novel supervised fuzzy adaptive resonance theory (SF-ART), multilayer perceptron (MLP) and Multi Layer Perceptrons (MLP) neural networks over Ballistocardiogram (BCG) signal recognition. To extract essential features of the BCG signal, we applied Biorthogonal wavelets. SF-ART performs classification on two levels. At first level, pre-classifier which is self-organized fuzzy ART tuned for fast learning classifies the input data roughly to arbitrary (M) classes. At the second level, post-classification level, a special array called Affine Look-up Table (ALT) with M elements stores the labels of corresponding input samples in the address equal to the index of fuzzy ART winner. However, in running (testing) mode, the content of an ALT cell with address equal to the index of fuzzy ART winner output will be read. The read value declares the final class that input data belongs to. In this paper, we used two well-known patterns (IRIS and Vowel data) and a medical application (Ballistocardiogram data) to evaluate and check SF-ART stability, reliability, learning speed and computational load. Initial tests with BCG from six subjects (both healthy and unhealthy people) indicate that the SF-ART is capable to perform with a high classification performance, high learning speed (elapsed time for learning around half second), and very low computational load compared to the well-known neural networks such as MLP which needs minutes to learn the training material. Moreover, to extract essential features of the BCG signal, we applied Biorthogonal wavelets. The applied wavelet transform requires no prior knowledge of the statistical distribution of data samples.

Keywords Ballistocardiogram · Intelligent chair · Classification · Novel SF-ART neural network · Biorthogonal wavelet transform

A. Akhbardeh (✉) · S. Junnila · A. Värri
Institute of Signal processing, Tampere University of Technology, Tampere 33101, Finland
e-mail: akhbarde@cs.tut.fi

T. Koivistoinen
Department of Clinical Physiology, Tampere University Hospital, Tampere 33521, Finland

Introduction

Ballistocardiogram (BCG) reflects the mechanical activity of the heart. As the heart is pumping blood out of the heart, a reaction force opposite to the force moving the blood is generated [1, 2]. This force, among with the forces generated by the respiration and disturbances caused by body movements, can be measured in the spine axis using some sensitive force sensor. BCG measurement was invented and used in the first half of 20th century, but was later surpassed by the simpler to measure electrocardiogram (ECG). BCG is difficult to analyze visually, and its use in medical diagnosis has never been very common. With the development of computer processing power and signal processing algorithms, new interest to BCG has risen. The classic BCG measurement, a freely suspended bed, has been surpassed by more advanced and easier to use sensors, like the static-charge sensitive bed (SCSB). However, a bed size sensor still requires quite a lot of space to operate, which has motivated us to develop a chair based sensor system. The developed EMFi-sensor based chair can be made very light and easily transportable, and using wireless data transmission even indistinguishable from a normal chair [3]. No electrodes are needed, and the patient can even be measured fully clothed, although very thick clothing does dampen the signal. An example of the BCG signal is shown in Fig. 1.

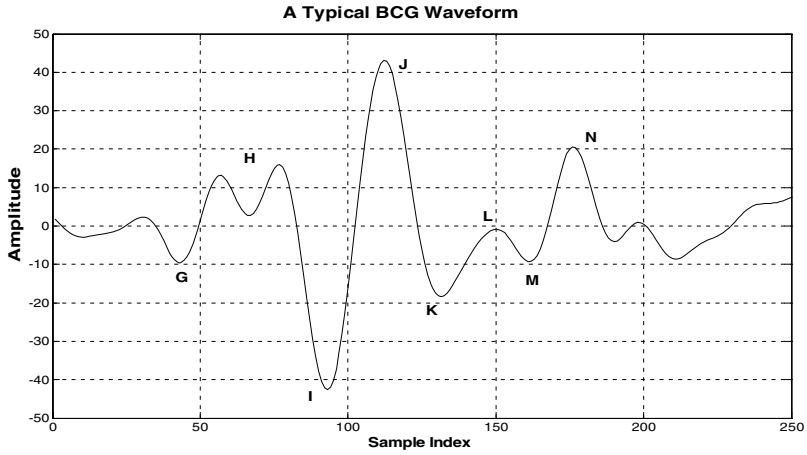

Fig. 1 An example of BCG signal including spikes, and wave complexes called G, H, I, J, K, L, M, and N components

During the past several years, some classical as well as intelligent pattern recognition methods have been developed for BCG analysis. Yu and Dent [4, 5], and Jansen et al. [6] listed some of these methods in more details. The performance of some of the existing methods is very good whilst not considering electromechanical drifts, BCG cycle's latency, motion artifacts, or other kinds of non-linear disturbances [7]. The results will have some errors if not counting such important factors. Another important limitation of the existing approaches is their unsuitability for fast implementation as well as on-line processing.

To overcome these problems, in our previously developed systems, we used some high resolution methods including different kinds of wavelet transforms as well as novel Time-frequency moments singular value decomposition (TFM-SVD) to compute the most important BCG waveform features and then cluster them using well known Artificial Neural Networks (ANNs) such as Multilayer perceptrons (MLP) and Radial basis functions (RBF). To find performance of the combined approach, several test subjects from three groups were used: two healthy young persons, two healthy old men and two old men with a past infarct in their heart. The results showed that our developed methods have higher performance than other existing methods, but, learning speed and computational loads are still not solved [8–10].

To solve these two remaining problems, we applied our newly developed neural network called Supervised Fuzzy Adaptive Resonance Theory (SF-ART) [11] and biorthogonal wavelet transform [12–14] to classify the BCG cycles with high learning speed and low computational loads. In Section 2, the used measurement system is presented. The developed signal processing methods are presented in Section 3, followed by results and discussion.

Measurement system

The BCG measurement is done using a normal office chair with 30 × 29 cm size EMFi-sensor films fitted under the upholstery on the seat and the backrest. The signal from the EMFi-sensors is amplified and converted to a voltage signal using a charge amplifier unit. Output of the amplifier is fed into a commercial medical data-acquisition device, which is controlled by a laptop-PC. The recorded data are stored in the laptop PC. A diagram of the measurement system is presented in Fig. 2. The system has been presented in [15, 16].

EMFi-sensor

EMFi sensor film [3] is an elastic electret material consisting of three distinct layers: two smooth and homogeneous surface layers, and a thicker mid section full of flat air voids separated by leaf-like polypropylene layers. External force supplied to the film surface changes the thickness of the air voids and causes charges residing on the polypropylene/ void interfaces to move with respect to each other. As a result, a charge proportional to the force (pressure) applied to the film is generated to the film electrodes [13].

Charge amplifier

To measure the weak charge changes produced by the EMFi-film, a charge amplifier type of pre-amplifier is needed. The amplifier design is based on the recommendations of EMFi-film manufacturer Emfit Ltd, with increased gain and low-pass amplifier in output. The charge amplifier produces a $+5$ V $\cdots$ -5 V voltage output signal, which is then fed to a medical data acquisition device. The battery-operated amplifier unit was accepted for medical use in Tampere University Hospital.

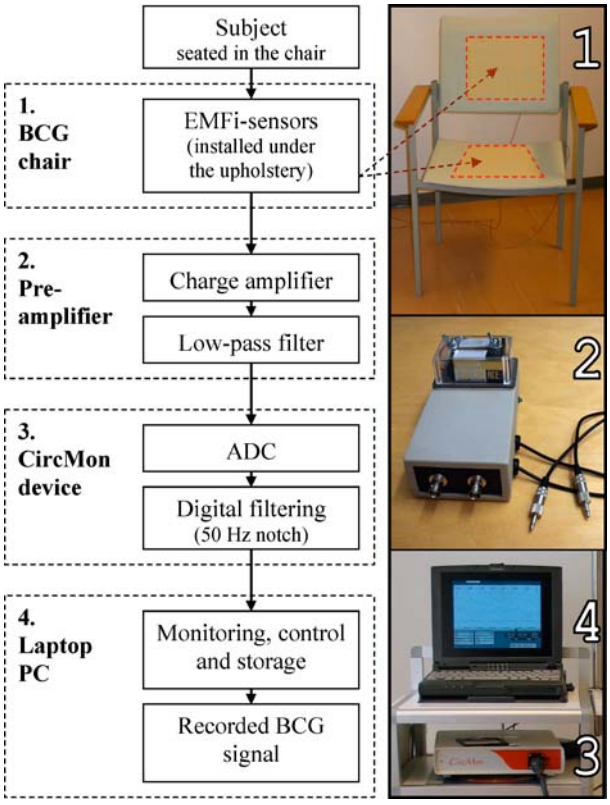

Fig. 2 The measurement system

Data acquisition

The output of the charge amplifier is connected to the CircMon circulation monitor, a medical data acquisition device developed by JR Medical Ltd, Tallinn, Estonia. Besides BCG from the measurement chair, CircMon is able to record electrocardiogram (ECG), impedancecardiogram (ICG) and other biosignals simultaneously. The data from all the inputs is sampled with CircMon's internal 12 bit A/D-converter with a fixed sampling frequency of 200 Hz. CircMon is connected via a serial interface to a laptop PC, which is used to display signals and parameters calculated from the measurement in real-time, and to store recorded data for analysis.

Patient recordings

Ballistocardiogram of test subjects was recorded in a clinical trial at Tampere University Hospital in 2004–2005 with a chair fitted with EMFi-film sensors using the measurement hardware presented in this section. A reference ECG signal was recorded simultaneously from the chest of subject's body. Several different subject groups were measured, but only three groups were used in the study presented in this paper. These were: (1) Group 1: Healthy young males and females. Age between 20 and 30; (2) Group 2: 50–70 year-old males. No coronary artery disease and no myocardial infarction in the past, no asthma or no ongoing dialysis treatment; (3) Group 3: 50–70 year-old males with myocardial infarction in the past. Fig. 3 shows a typical BCG signal for an old man with past cardiac infarct.

Intelligent signal processing methods

Overview

As shown in Fig. 4, our suggested procedure includes three stages: 1-BCG cycle extraction using a blind segmentation

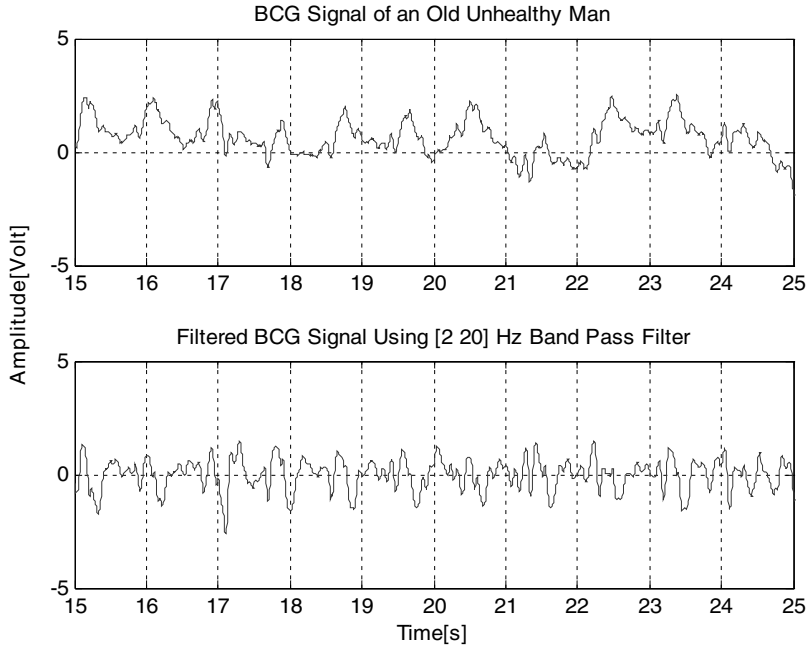

Fig. 3 Typical raw and filtered (band pass filter 2–20 Hz) BCG signals for an old unhealthy man. As can be seen, there are some motion artifacts in the BCG signal, not removed by filtering

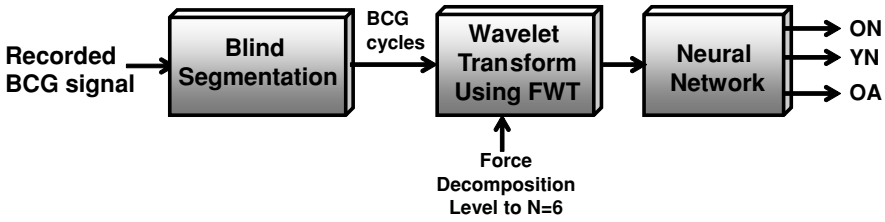

Fig. 4 Block diagram of our system to classify BCG data to three classes; YN: Young Normal, ON: Old Normal, and OA: Old Abnormal classes

method; 2-The BCG feature computing using a biorthogonal wavelet transform to eliminate non BCG related components as well as reducing the dimension of SF-ART neural network inputs; 3-Classification of BCG cycles using neural networks. The segmentation stage uses only coarse components of the BCG signal and amplitude separation/threshold detection method to extract BCG templates (BCG waveforms for every cardiac cycle).

Blind segmentation of BCG data

A recorded BCG signal consists of components attributable to cardiac activity, respiration, and body movements. To have a pure BCG signal and to remove additional components including background noise as well as respiration, we used a band pass filter with a passing band from 2 to 20 Hz. However, body movements during recording destroy some BCG cycles (increasing high amplitude components to signal). These parts of recorded BCG signal are useless and must be eliminated by amplitude thresholds for accounting only valid parts of signal. This method is useful because body movements usually cause bigger signal changes compared to normal cardiac activities.

To perform BCG data segmentation in a blind way without using any other synchronization signal, such as ECG first, we extracted a coarse BCG signal using a narrow band pass filter with 1 and 2 Hz cutting frequencies. Then, we used absolute values of this BCG coarse signal and its peaks between a lower and upper amplitude threshold as synchronization points. Based on our experience, peaks out of this range are not related to BCG cycles, being background noises or motion artifacts. Fig. 5 shows typical filtered (2–20 Hz) BCG and absolute values of BCG coarse signal for an old man with past cardiac infarct. A uniform windows with length of 250 samples (1.2 s) and the computed synchronization points are used to find central points of these windows and then counting 125 samples before and 124 samples after these central points to create BCG cycles with the same lengths (1.2 s for every cycle). BCG cycle extraction for an unhealthy subject is more difficult than healthy one. Therefore, we only show extracted cycles for an old man with past cardiac infarct in Fig. 6.

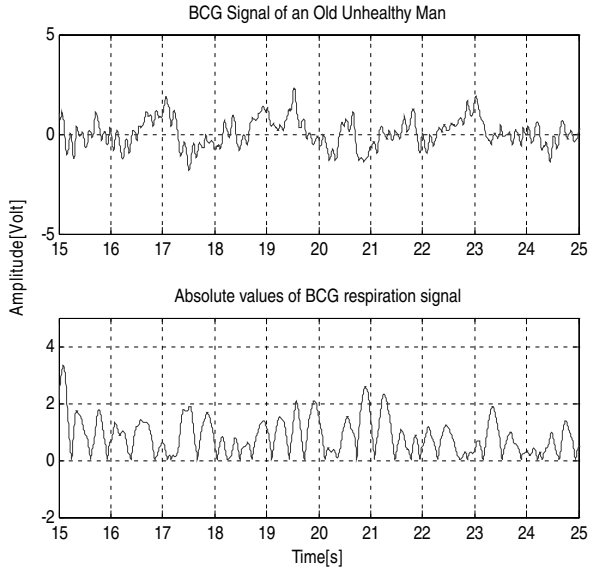

Fig. 5 Typical BCG and corresponding absolute values of coarse signal for an old man with past cardiac infarct

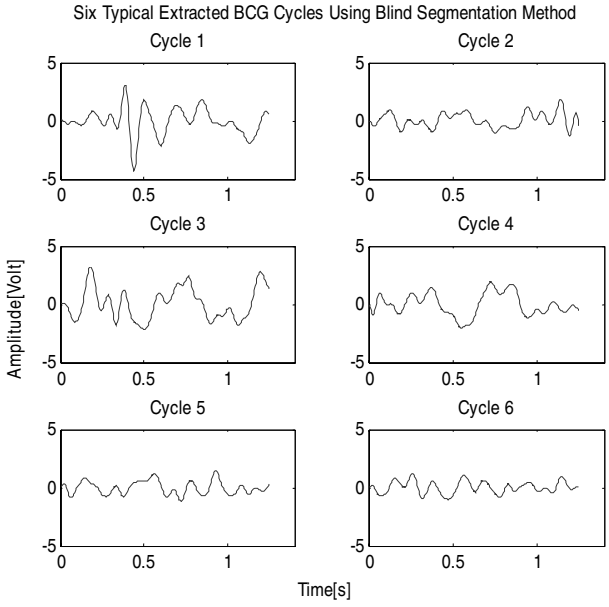

Fig. 6 Typical four BCG cycles of an old man with past cardiac infarct

Computing BCG features based on shift-invariant biorthonormal wavelet transform

The suggested high-resolution method for features computing is using a special kind of wavelet, called Shift-Invariant Biorthonormal Wavelet Transform [12–14]. The properties of this kind of wavelet are suitable for our application because we would like to reduce the dimensions of the BCG cycle optimally. The method does not affect the phase or cause shifting of waveforms.

There are several parameters that affect the wavelet characteristics and behavior. In real applications such as feature extraction, we would like to decrease the number of the high amplitude values (singularities) of the wavelet coefficients as well as to increase the number of around-zero coefficients, but because of the tradeoffs in parameter choices we cannot completely fulfill both interests.

If a wavelet gives us only one or two factors to control its behaviors, it is recommended to choose it for our application because of this benefit. In biorthogonal wavelet, it is possible to control its behaviors using two factors (p and $\tilde{p}$). The nonlinearity increases by p. The number of around-zero wavelet coefficients as well as number of high amplitudes increases by $\tilde{p}$ (trade's off). Thus, we must be aware about singularities of signal and generating high amplitude coefficients while increasing $\tilde{p}$ (only increasing $\tilde{p}$ till generating enough around-zero wavelet coefficients).

BCG classification using Supervised Fuzzy Adaptive Resonance Theory (SF-ART) and multi layer perceptrons (MLP) neural networks

In this work, we used both Supervised Fuzzy Adaptive Resonance Theory (SF-ART) and Multi Layer Perceptrons (MLP) Neural Networks for BCG classification. MLP and back propagation algorithm are very well known neural networks [17], but SF-ART is new. In our previous work, we proposed a novel neural network called Supervised Fuzzy Adaptive Resonance Theory (SF-ART) [11] which enables Fuzzy Adaptive Resonance Theory (F-ART) [18] for supervised incremental learning by adding another module to it, an array with M cells called Affine Lookup Table (ALT). ALT plays very important role to enable classifier to learn incrementally when new data become available. It protects previously acquired knowledge and avoids forgetting it during incremental learning phase (catastrophic forgetting). As shown in Fig. 7, in pre-classifier level, a self-organized F-ART Neural Network [18] is used to classify data primarily to M arbitrary classes. Based on our experience, to increase learning speed, clustering resolution and to create an automatic learning algorithm, which is free from any parameter's adjustment for different applications, F-ART's learning parameters (learning factor η and vigilance parameter ρ) must be always just under 1. In post (affine)-classification level, it uses an array with M cells called ALT, without any special learning algorithm run on it. In training mode, the index of

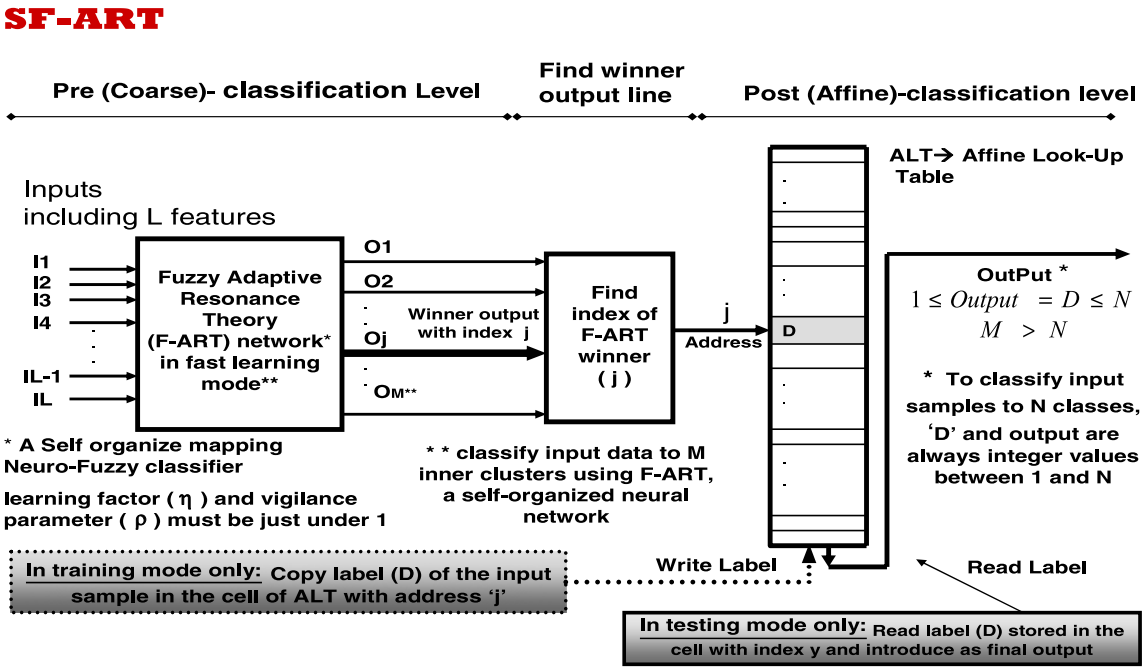

Fig. 7 Supervised Fuzzy Adaptive Resonance Theory (SF-ART) structure: it is an automatic (supervised) learning algorithm and free from any adjusting learning parameters: learning factor (η) and vigilance parameter (ρ) must be just under 1

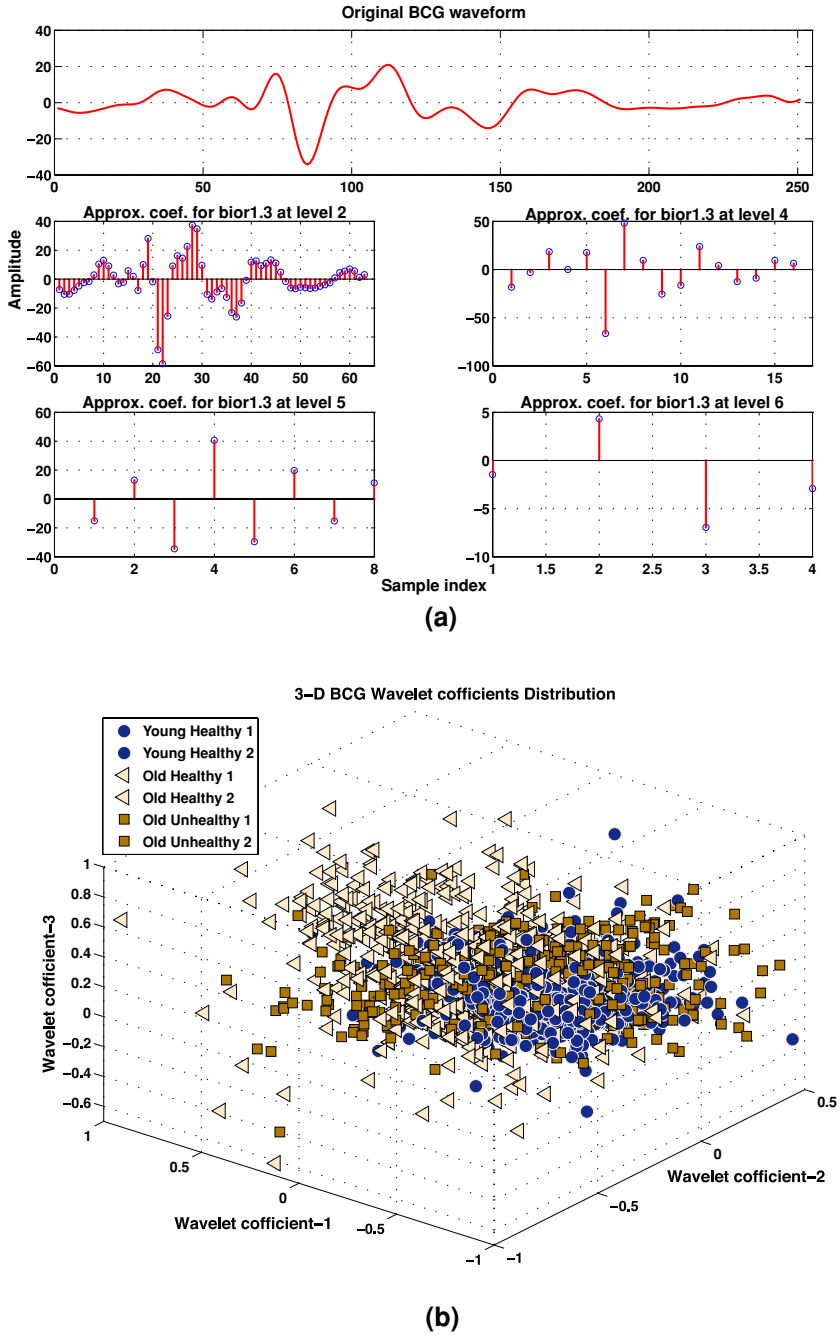

Fig. 8 (a) Wavelet Coefficients (WCs) at four different levels for a typical BCG cycle. (b) 3-D representation of BCG cycle's WCs (in level 6) for six subjects of three categories: young Normal, Old Normal, and Old Abnormal

winning output line of the first stage is used as index of the ALT cell to copy the label (output desired value) of the corresponding input sample into it. In testing mode, the index of first stage's winning output line will be used as index of the ALT cell to recall and declare formerly stored label as the final output (final winning class).

Results

In this work we used compactly supported Biorthogonal Spline wavelets with $p = 2$, $\tilde{p} = 4$ to find the wavelet coefficient of every BCG cycle $x[n]$ at level 6 using the iterative FWT algorithm (pyramidal multi-resolution wavelet analysis) [12–14]. Our practical experiences showed that using $p = 2$, $\tilde{p} = 4$ is enough and the most important features of the BCG waveforms were saved at level six of iteration FWT, decreasing the signal dimension (N) from 250 to 4. Fig. 8a shows wavelet coefficients at four different levels for a typical BCG cycle. Fig. 8b also shows 3-D representation of BCG cycle's wavelet coefficients (in level 6) for six subjects of three categories: young normal, old normal and old abnormal subjects.

Table 1 Results of BCG classification when using

		Class 1	Class 2	Class 3	Overall
(A) Supervised fuzzy adaptive resonance theory (SF-ART)					
Class 1	SBJ1	97.93 ± 2.28	2.07 ± 2.28	–	
	SBJ2	94.94 ± 2.83	5.06 ± 2.83	–	
Class 2	SBJ1	–	61.72 ± 36.8	38.28 ± 36.8	
	SBJ2	–	89.87 ± 1.53	10.13 ± 1.53	
Class 3	SBJ1	–	21.34 ± 6.90	78.66 ± 6.90	
	SBJ2	–	3.46 ± 0.94	96.54 ± 0.94	
Overall					94.70 ± 0.86
(B) Multi layer perceptrons (MLP) neural network					
Class 1	SBJ1	96.26 ± 3.06	3.74 ± 3.06	–	
	SBJ2	83.13 ± 5.99	16.87 ± 5.99	–	
Class 2	SBJ1	–	99.40 ± 0.26	0.60 ± 0.26	
	SBJ2	–	77.80 ± 4.29	22.20 ± 4.29	
Class 3	SBJ1	–	3.54 ± 1.37	96.46 ± 1.37	
	SBJ2	–	5.20 ± 0.48	94.80 ± 0.48	
Overall					90.65 ± 1.51

Note. Classification of the BCG data of six subjects to three classes using SF-ART (SF) and MLP classifiers and Biorthogonl wavelets. SBJ mean 'subject number.' O.P means 'overall performance (averaged)' after k-fold (five times) cross validation tests: '±' shows a 95% confidence interval on the average performance (mean). Structures: SF, η and $\rho \rightarrow 1$; MLP, Nh1 = 15, Nh2 = 10, learning rate of 0.001 for all layers

To demonstrate performance of our approach, and to compare results, we used both Supervised Fuzzy Adaptive Resonance Theory (SF-ART) and Multi Layer Perceptrons (MLP) Neural Networks for BCG classification. Based on our experience, level six wavelet coefficients of BCG cycles are optimized for our application in which we classify subjects using neural networks (4 inputs/3outputs) to three categories. These three categories are: 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 a history of heart infarct. SF-ART structure has fixed structure, but for MLP, our previous works showed that structure with Tanh() to simulate nonlinearity of neurons and two hidden layers (relatively 15, and 10 neurons) is also optimized.

For every subject of the three categories, the wavelet decompositions stage gave us features of every BCG cycle (dimension of data reduced from 250 to 4). These data were normalized, mapped to area $[-1, 1]$, and finally saved randomly into a unique data matrix.

We used a small part of data (300 BCG cycles) for training the SF-ART and the MLP nets. All tests were done in the 3 GHz Pentium 4 computer. Learning speed is low for MLP with back propagation and convergence occurred after 10000 learning cycles. Training time for learning was around five minutes while SF-ART needed 470 ms (seven learning cycles) for convergence. Another factor that affects learning speed is computational load. MLP is a heavy structure, but SF-ART is not. The computational loads of the SF-ART is N*Ni*M*L, where N is number of learning cycles (Typically less than 10 cycles for most pattern recognition problems: elapsed time above few seconds to train a fresh classifier), Ni is number of training samples, $M = 7$ is number of mathematical calculations (sum, subtraction, division and multiplying) and $L = 2$ is logical/comparative calculations ($>$, $<$, $=$, Min and Max). It means that in SF-ART, first stage (F-ART) has low computational load and second stage is only a set of simple memory cells and they are easy to implement on chip [19, 20].

In testing mode, the rest of the data (2000 BCG cycles) were used to check the performance of the neural networks, not using the same data for training or testing the system although the BCG cycles were obtained from the same subjects as the training data. Table 1 shows the performance of the classifiers under test. It can be seen that the performance of systems is high, but SF-ART learnt very fast. When the highest proportion of cycles in a class is taken as the classification result of the subject, no classification errors are made for both MLP and SF-ART.

Discussion

The proposed Ballistocardiogram analysis system consists of a sensitive EMFi-film based movement sensor, amplifiers and ADC, wavelet-based feature extraction and neural network classification of the features to three classes. Here the EMFi sensor has been fitted to an office chair but it could be installed to chairs for homes or even to cars. The advantage of BCG analysis to ECG analysis is that no electrodes are needed to be attached to the subject.

The wavelets are known to be efficient in many signal processing applications but choosing the appropriate type of wavelets is not a trivial task. The applied biorthogonal spline wavelets are not noticeably affected by latencies or nonlinear disturbances in the signal.

The results show that the three classes could be separated quite well from each other. The "scattegrams" of Fig. 8b indicate, however, that the classification is not reliable on the basis of a single BCG cycle but a number of them are needed to estimate the center of the distribution.

For this study BCG signals of six subjects from three classes were used to train and test well-known Multi layer Perceptrons (MLP) as well as novel Supervised Fuzzy Adaptive Resonance Theory (SF-ART) neural networks. SF-ART has two inner modules to classify input data to desired classes. The SF-ART performs hierarchical clustering by employing Fuzzy Adaptive Resonance Theory (F-ART) neural network as an unsupervised learning at the pre-classification level. Another stage, post (affine)-classifier, using a special look-up table called Affine Look-up Table (ALT) and downloading/uploading output desired values (labels) tries to perform final classification. In first level, it is possible to use any kind of classic, statistical or intelligent classifier. But in the second level, the ALT is neither a classifier nor a learning algorithm, only a readable/writable look-up table memory.

The results indicated that SF-ART learnt BCG patterns very fast in less than one second while MLP need several minutes to train. MLP or other existing neural networks except SF-ART are very sensitive to volume of training set as well as number of adaptation cycles during training mode and they suffer from tradeoffs between learning speed and performance [11]. SF-ART is an automatic classifier and it is free from adjusting net's parameters, only adjusting learning and vigilance factors in values near to 1 is enough. The result showed that SF-ART learnt patterns with lower volume of training frames and overtraining occurred faster than with other tested methods.

One interesting benefit of SF-ART, because of ALT, is incremental learning when new data become available (on-line learning) [11]. Therefore, our future aim is to apply SF-ART for classifying more subjects, especially testing its reliability, stability and performance for on-line learning. In order to extend the system into a complete "heart disease diagnosing system" several steps are necessary. First, a representative BCG data set of normal subjects of both sexes and all adult age groups needs to be collected. Additionally a representative data set of each heart disease category to be diagnosed needs to be collected and the neural network needs to be trained with the whole material. Finally, the system has to be validated with an independent set of normal subjects and heart patients before it can be taken into clinical use. Even then the system can only serve as a part of the set of tests which confirms the diagnosis although its ease of use suggests that it could have value alone, too, as a screening device of the general population.

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