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Detection of heart murmurs based on radial wavelet neural network with Kalman learning

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ABSTRACT

In general, heart medical diagnosis devices are reliable and efficient; however, they are only present in huge or modern hospitals. Heart murmurs are one of the typical heart problems. In this paper, we propose a radial wavelet neural network (RWNN) classifier for heart murmurs (pulmonary insufficiency and tricuspid insufficiency). The extended Kalman filter (EKF) is used as a learning algorithm for the RWNN. The network inputs are dimensional features, extracted from real cardiac cycles, and three classification outputs. Proposed model classification accuracy is compared with a multilayer perceptron trained with Levenberg–Marquardt training algorithm and with extreme learning machine one. The proposed model is trained and tested using real heart cycles in order to show the applicability of the proposed scheme.

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1. Introduction

There are many efficient and reliable heart diagnosis devices. Unfortunately, this modern technology is not available in all hospitals. Cardiac diagnosis is typically started by an auscultation where heart sounds are captured by a stethoscope, from which a medical doctor, depending on his hearing capabilities and training, listens and interprets the acoustic signal. This method of diagnostic is uncertain [1], mostly due to the fact that human ear loses the acoustic frequency sensitivity through the years [2]. Even though auscultation is not the only way for cardiac diagnosis, it is considered as a primary tool due to its simplicity. Phonocardiography is a technique where heart sounds are registered [2]; this method has an important place as a fortifier of the acoustic interpretation throughout sound graphics (phonocardiogram) from an acoustic-electric transducer. Through a phonocardiogram (PCG), it is possible to analyze the heart acoustic signal from timing, frequency and location point of view and its components in an objective and repetitive form. Heart murmurs are abnormal sounds, which are appreciable in some parts of the vascular system. Neural networks have demonstrated adequate results in PCG's classification [3,4].

Due to their nonlinear modeling characteristics, neural networks have been successfully implemented in control systems, pattern classification and time series forecasting applications. Wavelet transform has been used as signal pre-processor and in neural network classifiers as input space feeders with 90% classification accuracy [5–7]. Wavelet neural networks have been used as classifiers in real applications [8–10] due to their advantages of fitting functions and dealing with information [11]; higher prediction accuracy and better fault tolerance to meet the uncertainty, nonlinearity, and complexity in real-world systems [12].

The typical training approach for multilayer perceptrons is the back propagation through time. However, it is a first order gradient descent method, and hence its learning speed could be very slow [13]. Another well-known training algorithm is the Levenberg–Marquardt one [14]; its principal disadvantage is that global minimum is not guaranteed and its learning speed could be slow too, depending on the initialization. In the past years, extended Kalman filter (EKF) based algorithm has been introduced to train neural networks [15]. With the EKF based algorithm, the learning convergence is improved [13]. The EKF training of neural networks has proven to be reliable for many applications over the past 10 years [15]. However, EKF training requires the heuristic selection of some design parameters which is not always an easy task [16]. Finally, extreme learning machine (ELM) has been recently proposed to develop a very fast learning for feedforward neural network. In theory, this algorithm is able to supply good generalization capability at extremely fast learning speed [17,18].

In this paper we propose a wavelet neural network (WNN) architecture with EKF training algorithm for classifying heart cycles with murmurs. In order to get the real cardiac sound registers, a

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monitoring cardiac platform was designed and built. The neural network input vectors are amplitude features extracted from segmented cardiac cycles, which are obtained via wavelet transform. The applicability of this architecture is illustrated via simulations of the proposed WNN with real heart murmurs in order to show the potential applications for medical cardiac diagnosis devices. The remainder of this paper is organized as follows. Section 2 describes methodology used in this scheme. It also describes the platform built to acquire and analyze heart sounds and murmurs, in union with medical and mathematical background. In addition, explains the segmentation and feature extraction algorithms, respectively, performed in order to divide cardiac cycles from PCG's and to extract features from segmented cardiac cycles. Section 3 is dedicated to describe the neural model, where the training phase relies on an extended Kalman filter which is able to deal with the nonlinearity of the model. Lastly, Section 4 reports the experimental analysis of the proposed scheme applied to the problem of classifying real heart murmurs.

2. Methodology

As first step, real phonocardiograms with murmurs are registered from patients with the cardiac monitoring platform. For the registered data, the continuous time wavelet transform is applied for analysis via software as part of the segmentation stage. Then, the feature extraction algorithm is applied and features for every cardiac cycle are computed. Some cardiac cycles are selected to train the neural networks, and the remaining of the data is used to test the neural networks performance.

2.1. Heart sounds and murmurs

Blood circulation through the human body is possible due to the organ that functions as a pump: the heart. Heart is compound of two separate pumps and four chambers, each side of the heart is compounded of two cavities. This organ has four valves, two per side. In the right side, we have aortic and tricuspid valves. In the left side, we have pulmonary and mitral valves. All the events related from the start of a heartbeat till the beginning of another compose the cardiac cycle. Cardiac cycle (CC) duration varies depending on the patient. The normal heart rate is 72 beats/min, the duration of the cardiac cycle is 1/72 beats/min-about 0.0139 min per beat, or 833 milliseconds per beat [19]. Heart sounds (HS) are listened by a stethoscope, which is used as main diagnostic tool. It is possible to distinguish four HS, but only the first two are sufficient to describe the cardiac valves activity. The first heart sound (S1) is produced by the closure of the mitral and tricuspid valves, it is followed by the second heart sound (S2), produced by the closure of the pulmonary and aortic valves. A cardiac cycle is accomplished with the occurrence of one S1 to another S1 where the heart sounds frequency ranges within 30–600 Hz [2]. A microphone within that range is necessary to be employed for cardiac sounds measurement. The graphical record for heart sounds is called a phonocardiogram.

Heart murmurs are abnormal sounds within the cardiac cycle. When the hole of a valve is squeezed, it is called stenosis. When the valve is incompetent to close; this is called insufficiency or regurgitation. Normal and abnormal heart sounds can be analyzed in a phonocardiogram, see Fig. 3. From [20] is known that S1's and S2's frequency range is within 50–200 Hz.

2.2. Cardiac monitoring platform

In order to register and capture heart sounds in a phonocardiogram, it is necessary to have a hardware platform. For this study, a cardiac monitoring platform (CMP) is built. It covers an acoustic-electric transducer, a signal conditioning process and a microcontroller. The transducer is composed by a stethoscope coupled with an Electret microphone to register the cardiac sounds and connected to the signal conditioner. The sensor covers the cardiac sounds bandwidth from 30 Hz to 600 Hz [2]. A signal conditioner is used to amplify the electric signal from this sensor (Electret) and includes an anti-aliasing filter (4 kHz cutoff low pass filter) for the $f_s = 8$ kHz sampling frequency chosen. Finally, a USB-microcontroller (uC) is used in order to receive the signal from signal conditioner, which is connected to the analog to digital converter (ADC) built-in the uC and send it to computer via USB. In the computer, HS are shown as graphical signals and stored via Matlab interface software. The cardiac monitoring platform is shown in Fig. 4. Cardiac registers are stored in the computer to be analyzed. The signal flow diagram of every PCG register is shown in Fig. 1 and block diagram of the whole classification system is shown in Fig. 2.

Every phonocardiogram stored by the cardiac monitoring platform has a duration of 15 s and is compounded of many cardiac cycles. Every cardiac cycle has similar behavior about the heart valve where it comes from. It is necessary to make a segmentation of every phonocardiogram in single cardiac cycles in order to perform a medical diagnosis. The cardiac signal, like other biomedical signals, is non-stationary and changes its properties through time. Spectral analysis methods give information about frequency content but they do not involve the time. Continuous time wavelet transform (CWT) performs time domain analysis on different scales (frequencies), what allows a time space–frequency analysis of a signal. Due to time–frequency analysis and non-stationary behavior of cardiac signal, CWT is frequently used in the analysis of biomedical signals [21].

2.2.1. Wavelets

Wavelets are a class of functions used to place a given function in both position and scaling. They are used in applications such as signal processing and time series analysis [22]. A wavelet is a small wave function, usually denoted $\psi(\cdot)$. A small wave grows and decays in a finite time period, as opposed to a large wave, such as the sine wave, which grows and decays repeatedly over an infinite time period. For a function $\psi(\cdot)$, defined over the real axis $(-\infty, \infty)$, to be classified as a wavelet, it must satisfy the following

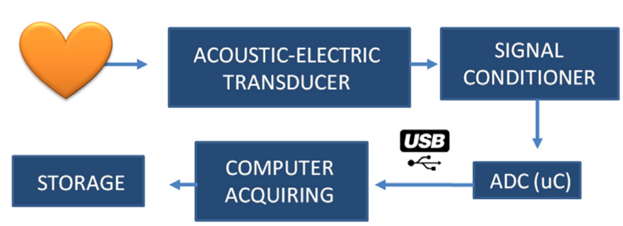

Fig. 1. Signal flow diagram of acquiring of every PCG register.

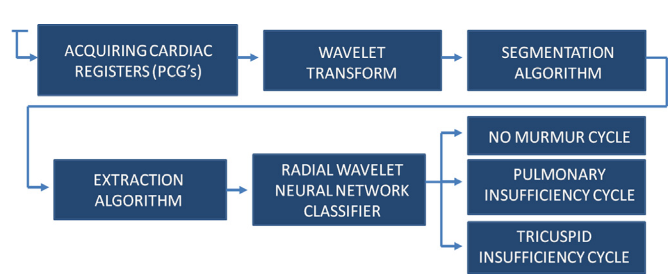

Fig. 2. Block diagram of the whole classification system.

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