Real-Time Discrimination of Multiple Cardiac Arrhythmias for Wearable Systems Based on Neural Networks

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Abstract

This paper aims at developing a wearable system able to recognize the most significant cardiac arrhythmias through an efficient algorithm, in terms of low computational cost and memory usage, implementable in a portable, real-time hardware. In addition, it must respect the specifications of good specificity and sensitivity, in order to permit a positive clinical validation. The hardware is constituted of a general purpose microcontroller, which is able to acquire electro-cardiogram signal (ECG), perform analog to digital conversion and extract QRS complex. The algorithm classifies QRS complexes as normal or pathologic by means of selected features obtained from Discrete Fourier Transform (DFT). Furthermore, a spatial wavelet pre-filter is also investigated to obtain an enhanced QRS complex discrimination. In particular, pattern recognition of QRS complex is performed from binding minimal architecture of neural network as Kohonen Self Organizing Map (KSOM).

Experimental results were validated by means of MIT-BIH Arrhythmias Database obtaining specificity and sensitivity up to 98%.

1. Introduction

In the last few years wearable systems have been achieved a large diffusion in research and business. They show many advantages in terms of portability and longevity for long-term monitoring. The most common applied fields concern biomechanical analysis, rehabilitation and portable non-invasive acquisitions of physiological parameters [1].

Nevertheless, wearable systems require small-sized hardware and low power consumption and this can limit a high level of local post-processing especially when real-time is required.

Advances in cardiology allow using wearable systems for non-invasive and long-term monitoring of acquired ECG signals with a local low-level processing (usually an alarm generation), recording and transmission to a remote workstation for a high post-processing analysis. Usually, detailed cardiac analysis is comprised of two phases: feature extraction and classification. The first phase could be performed in the time domain to obtain morphologic features (e.g. width, height and area of QRS complex, heart-rate variability etc..) [2,3], in the frequency domain in order to find changes in QRS-complex power spectra between normal and arrhythmia waveforms [4,5], in time-frequency domain [6,7] and spatial transformations [8,9]. The second phase could be achieved by means of several techniques, most of which cannot be implemented because do not respect real time requirement.

Therefore, the most interesting technique for our purpose is the artificial intelligence (AI) technique such as the Artificial Neural Network (ANN) that can be realized through different architectures such as Kohonen Self Organizing Map (KSOM) [10,11], MultiLayer Perceptron (MLP) [12,13], and Probabilistic Neural Network (PNN) [14]. Considering our hardware restrictions, many minimal architecture of KSOM (2x2 neurons) were combined in order to recognize pathologic QRS complex from features extracted in the frequency domain (that with minimal computational add-on minimize memory usage and enhance discrimination).

This simple signal processing let us to obtain an accurate real-time recognition of many cardiac arrhythmias. It was implemented in a portable general purpose microcontroller (Cypress PSoC [15]), which was chosen for its high small hardware-size. In particular, the analog modules and floating point operations are embedded inside the chip.

2. Methods

It is well known that ECG signal is the representation of the heart electric activity during the cardiac cycles. This signal is formed by various waves labelled P, Q, R, S and T. Many cardiac arrhythmias can be recognized through an analysis of the morphology of these waves (see fig.1) with automatic and nondeterministic methods [3], but not implantable into a wearable system.

The wearable system here proposed, is able to perform this classification. In this system six KSOM maps were implemented to discriminate each one of the six common

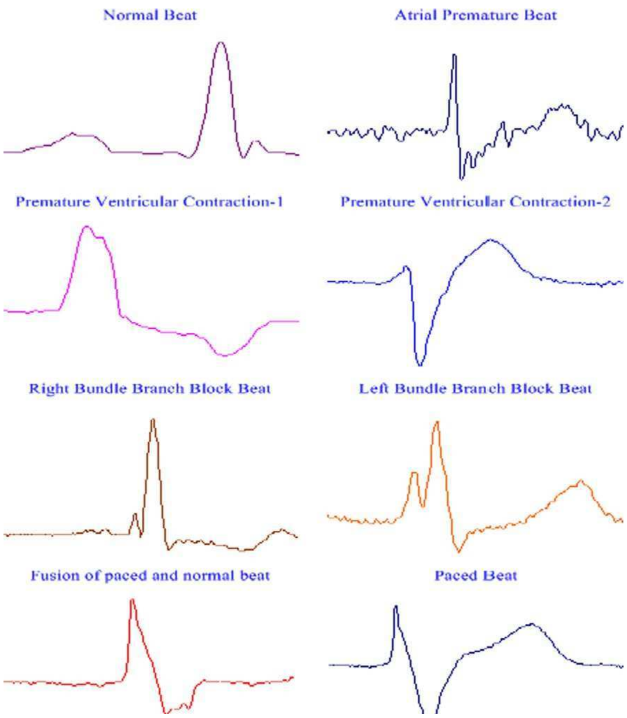

Fig. 1: Typical arrhythmias in time domain (from [14])

cardiac arrhythmias (see Fig.1). Every map is constituted of four neurons, which is the minimum number of neurons usable in this architecture.

In particular the system consists of three parts (see Fig.2):

- Analog block, which provides the signal conditioning and performs analog to digital conversion;
- Features extraction block, that extracts QRS complex from digitalized ECG and transforms data from time to frequency domain;
- Pattern recognition block, which classifies the features as normal or pathologic.

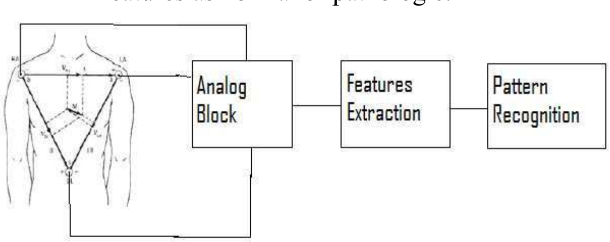

Fig.2: System setup

Regarding of first block, cardiac potential is acquired by means of surface electrodes and conditioned through circuit showed in Figure 3, which consists of a differential amplifier in 3 op-amp configuration (for a good rejection of common mode) with an integrator in feed-back chain in order for the baseline to be stationary.

Two low-pass filters (active and passive) are located at the end of this block, in order to minimize the high frequency noise. The output signal is digitalized through an incremental ADC with sampling rate of 360 Hz, according with MIT-BIH Arrhythmias Database records sampling rate, and 12 bit resolution.

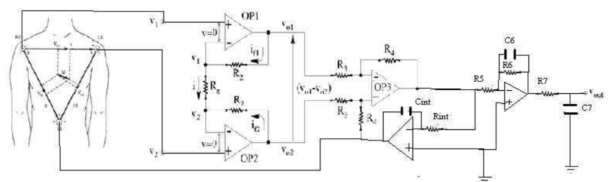

Fig.3: Analog circuit for conditioning ECG signal

This block was fully implemented into the PSoC, which takes advantages in term of small-size and low power consumption.

The second block performs the extraction of QRS complex through detecting of the R-wave and gathers the signal within a time window of about 280ms centred in the R-peak previously found. If the stationary condition is respected, then the R-wave can be detected through a simple threshold technique, allowing the real-time requirement and memory saving.

Memory usage (*Mu*) was evaluated in order to allocate the signal samples, the algorithm, the KSOM maps and the neurons weights, as follows:

$$Mu = Nn * Ns * Nm; \tag{1}$$

where *Nn* is the number of neurons, *Ns* is the number of samples and *Nm* is the number of KSOM.

Considering the time window and the sample rate the number of samples, *Ns,* is 100 for each QRS complex, the numbers of neurons, *Nn,* is 4 and the number of maps, *Nm*, is 6. Therefore *Mu* is about 8Kbyte, which exceeds chip capacity.

In order to minimize *Mu* and enhance feature discrimination a Discrete Fourier Transform (DFT) algorithm was applied in the time domain [16], obtaining a reduced number of samples in the frequency domain and a frequency resolution of 3.6 Hz.

DFT was implemented as follows:

$$X[k] = \frac{1}{N}\sum_{n=0}^{N-1} x[n] e^{-\frac{j2\pi k n}{N}} \tag{2}$$

For k=0…Ns-1.

Classifiers were trained with the first 10 samples [4].

In order to enhance spectral discrimination the use of wavelet spatial filter as Morlet wavelet (from [14]) was investigated:

$$\varphi(k) = \cos\left[\frac{5(x(k) - t(k))}{d}\right] e^{-\frac{(x(k)-t(k))^2}{2\sigma d^2}} \qquad (3)$$

For k=0…Ns-1.

Where d is the dilatation parameter, x is a sequence of samples obtained from the QRS complex; t is a sequence of samples obtained from the QRS complex of normal beat.

Pattern recognition block implements a minimal Kohonen Self-Organizing Map (2x2 neurons for two input classes) for each cardiac arrhythmia. This choice of neural network is justified because KSOM requires only the storage of weight and label array and the output is performed with a simple sum of products. Nevertheless, KSOM requires a long training phase with many examples. Training phase was performed in offline mode.

A KSOM maps the original space into a two-dimensional net of neurons in such a way that close neurons respond to similar signals, in order to solve classification tasks and to find structures in data. In this work the integrate-and-fire neuron model was used, the winner-takes-it-all training strategy was adopted using a distance-based learning method. A decay factor over epoch time was used for both the learning rate and the learning radius. According to the Kohonen map topology, all the elements of the input vector are connected to all the artificial neurons of the KSOM.

After training process, a supervised labelling step is performed. Cluster labels are assigned to the individual artificial neurons. This is done via the interpretation of the content of the synaptic weight vectors (feature vectors) of the artificial neurons. Here the same label can be assigned to several artificial neurons so that clusters can be represented by several artificial neurons. After validation of the KSOM through samples extracted by a test data set, performance of the classification task were evaluated using the above mentioned confusion matrix. In order to check the generalization capability of the neural network, a cross-validation process is carried out.

3. Results

As above mentioned, results were performed by applying the system to the MIT-BIH arrhythmia database records. Indeed only the cases showed in Table1 are processed.

Results showed both accurate discriminations (see Table 2) and faster processing time during pathological QRS classification, when used FFT and KSOM.

Considering the wavelet filter application, whose results are also reported in Table 2, results showed good specificity, but in some cases lower sensitivity. The hardware here realized showed high portability with low power consumption, suitable for wearable system applications.

Heartbeat	N. QRS	Record	Patient
Normal	1543 1743 2621 923 244 2031 314 2230	MIT-119 MIT-200 MIT-209 MIT-212 MIT-217 MIT-221 MIT-231 MIT-233	Female,age51 Male, age 64 Male, age 62 Female,age32 Male, age 65 Male, age 83 Female,age72 Male, age 57
Paced	2078 1542	MIT-107 MIT-217	Male, age 63 Male, age 65
Left Bundle Branch block	2492 2123 2003	MIT-109 MIT-111 MIT-214	Female,age64 Female,age47 Male, age 53
Fusion of Paced and Normal	260	MIT-217	Male, age 65
Right Bundle Branch block	2166 1531 1825 1254 397	MIT-118 MIT-124 MIT-212 MIT-231 MIT-232	Male, age 69 Male, age 77 Female,age32 Female,age72 Female,age76
Premature Ventricular Contraction	444 826 256 396 831	MIT-119 MIT-200 MIT-214 MIT-221 MIT-233	Female,age51 Male, age 64 Male, age 53 Male, age 83 Male, age 57
Atrial Premature Contraction	96 30 383 1382	MIT-118 MIT-200 MIT-209 MIT-232	Male, age 69 Male, age 64 Male, age 62 Female,age76

Table 1: MIT-BIH arrhythmia database records included in our dataset

4. Discussion and conclusions

A simple algorithm able to discriminate in real-time normal and pathologic QRS complex was rightly implemented into a portable hardware, thanks to small memory usage and lower complexity. The QRS complexes were effectively extracted by means of a threshold method to find the R-peaks. FFT algorithm was applied in order to extract and decimate sample features and minimal KSOMs were used to pattern recognition.

Wavelet spatial filter tested showed lower frequency discrimination. Therefore for this wearable system wavelet filter method is not acceptable.

	FFT – KOH		WAV – FFT - KOH	
Heartbeat	Specificity	Sensitivity	Specificity	Sensitivity
Paced	99.99%	99.94%	99.97%	99.50%
Left Bundle Branch block	99.62%	97.34%	99.28%	93.59%
Fusion of Paced and Normal	99.85%	92.30%	94.23%	98.46%
Right Bundle Branch block	99.91%	98.49%	99.23%	83.59%
Premature Ventricular Contraction	98.50%	90.07%	96.74%	90.49%
Atrial Premature Contraction	99.61%	99.88%	n.c.	n.c.

Table 2: Experimental results

Experimental results demonstrated that our system have specificity and sensibility up to 99% for Paced beat and Atrial Premature Contraction arrhythmia, up to 97% for Left Bundle Branch block and Right Bundle Branch block and up to 90% for Premature Ventricular Contraction and Fusion of Paced and Normal.

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