

Genetic-Based IIR Filter Design for Efficient QRS Complex Detection using Neuro -Based Classifier

Jassim M. Abdul-Jabbar

drjssm@gmail.com

and

Omar Najeeb Saadi

onsa90@yahoo.com

Computer Engineering Department - College of Engineering-University of Mosul.

Abstract:

In this paper, a new method is proposed for QRS complex detection using a special kind of IIR filter called bi-reciprocal lattice wave digital filter (WDF). This filter has some attractive features that make it more efficient than other types of filters. One of these features is its sufficient linear phase in the passband, thus yielding a perfect reconstruction condition. Therefore, it is not required to cascade the designed filter with an all-pass filter for correcting the phase distortion. The coefficients of the designed filter are achieved by simulating the FIR response suggested in [1]. A least square method solution is used in such simulation with a genetic-based algorithm. A simplified structure for the designed filter is accomplished with less-complex realization. 50 records of European ST – T ECG database is classified into four classes (Normal, Left Bundle Branch Block (LBBB), ST segment elevation, and Left Ventricular Hypertrophy (LVH)). By applying the designed filter coefficients into neural network classifier, the results show that the accuracy of the classification process is 95.9 %.

Keywords: QRS Complex Detection, IIR Filter, Bi-Reciprocal Lattice WDF, Genetic Algorithm, Neural Network Classifier.

تصميم مرشح نوع IIR الخوارزميات الجينية للكشف الكفوء QRS باستخدام مصنف معتمد على الشبكات العصبية

عمر نجيب سعدي

*قسم هندسة الحاسوب- كلية الهندسة-

:

في هذا البحث، تم اقتراح طريقة جديدة لكشف إشارة QRS (bi-reciprocal lattice WDF). هذا المرشح لديه بعض المميزات (IIR) كافية في واحدة من هذه المميزات هي خطية . وعليه فليس مطلوباً . وكلي لتصحيح تشويه الطور. لقد تم الحصول على معاملات المرشح المصمم وذلك بمحاكاة الاستجابة الترددية للمرشح FIR [1]. وتم استخدام طريقة المربعات الصغرى لحل مثل هذه المحاكاة وبعتماد الخوارزميات الجينية. تم إنجاز هيكل مبسط للمرشح صمم مع تحقيق أقل تعقيداً. قاعدة بيانات ST-T ECG الأوروبية التي صنفتم إلى أربعة أصناف هي (LBBB) ST وتضخم البطين الأيسر (LVH). العصبية أظهرت النتائج أن دقة عملية التصنيف 95.9 % .

Received: 22 – 4 - 2014

Accepted: 7 – 10 – 2015

1. Introduction

ECG signal is usually used to check the electrical activity of the heart through number of leads lies on the skin of the body. The normal ECG shown in Fig. 1 consists of a P wave, a QRS complex, and a T wave. The QRS complex is often, but not always, includes three separate waves: the Q wave, the R wave, and the S wave [1], [2]. P wave is generated by electrical potentials appearance when the atria depolarizes before atrial contraction begins. The QRS complex is a result of potentials generated when the ventricles depolarize before contraction, *i.e.*, when the depolarization wave spreads through the ventricles. Therefore, both the P wave and the components of the QRS complex are depolarization waves. In addition, when the ventricles recover from the state of depolarization, the T wave appears. This process normally occurs in ventricular muscle within 0.25 to 0.35 second after depolarization, and the T wave is known as a repolarization wave. Thus, ECG is composed of both depolarization and repolarization waves [2].

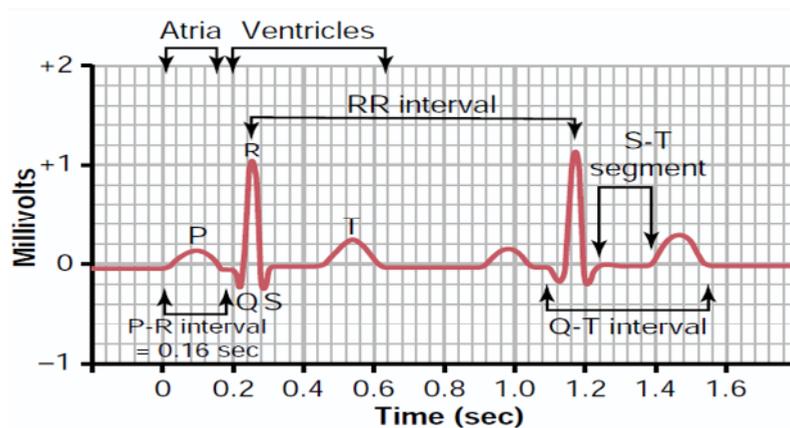


Fig. 1 Normal ECG signal.

In this paper, a genetic-based IIR filter design is proposed for efficient QRS complex detection with a neuro-based classifier. It is known that using IIR filters for QRS complex detection has many advantages such as low filter order which reflects a simple filter structure, excellent roll-off frequency characteristics for low orders, and efficient implementation on FPGA chips.

In addition to this introductory section, there are other six sections in this paper. Section 2 presents a related literature review. The bi-reciprocal lattice WDF design procedure is described in section 3. Section 4 explains the ECG data used in this paper with the standard normalization application on filter coefficients. Section 5 illustrates the trained neural network to work as an ECG classifier. In section 6, the designed system is executed using Matlab simulation. Finally, section 7 concludes this paper.

2. Literature Review

QRS complex detection researchers have been continued their development in the past decade due to their vital importance in the automated ECG analysis. Many of those researchers used FIR filters, filter banks or wavelet filtering to extract the features of the QRS complex. Among many methods of ECG signal classification, researchers recently prefer to utilize fuzzy classifiers [1], [3], neural network classifiers [4], [5] or even some extreme

learning machine [6]. Other researchers presented hybrid systems used as a diagnostic classifier for the ECG signals; such as a neuro-fuzzy network [7], [8] and a combined method of particle swarm with neural network [9].

In 2011, A. Pantelopoulos and N. Bourbakis [10], used wavelet with a 3 layer artificial neural network to classify 46 MIT – BIH ECG database into 5 classes with accuracy 94.9 %. Also in 2011, B. Abibullaev and H. Don [4], presented a method for QRS complex detection and ECG classification by the use of continuous wavelets and artificial neural networks. The resulting average accuracy is in the order of is 97.2% but the tests were only conducted for two categories of QRS complex classification (normal and abnormal). I. Saini *et al.* [11], used in 2012 a K-Nearest Neighbor algorithm as classifier for QRS complex detection in ECG signals. A CSE and MIT-BIH arrhythmia database was used to test this classifier. The results show that the QRS complex detection accuracy rate is 99.81%. It should be noted that the accuracy of this algorithm is largely dependent on the value of K and the type of distance metric. In 2013, S. Khoshnoud, and H. Ebrahimnezhad [12], proposed an algorithm consists of preprocessing block for noise elimination, multi-resolution wavelet for R-peak detection, and probabilistic neural network to classify four kinds of MIT-BIH ECG database. The results show that the accuracy is 92.9% and the sensitivity is 93.17%.

In 2014, J. M. Abdul-Jabbar and R. W. Hamad [1], designed an FIR filter bank with a fuzzy classifier to classify the ECG data into five classes with efficient classification rate. However, in that design, a small trained data is used. In 2015, a neuro-fuzzy classification method is used for identifications of ECG signals [8]. A feature extraction method with a QRS like filter is utilized. Five standard parameters (energy, mean value, standard deviation, maximum and minimum) are extracted from these disease features and then used as inputs to the neuro-fuzzy classification system. Again in 2015, K. Muthuvel and L. P. Suresh [13], developed a technique to classify ECG signal using Haar wavelet for features extraction and neural network classifier. An Artificial Bee Colony (ABC) combined with genetic algorithm (GA) was used to train the neural network. The accuracy of that technique was 93%, sensitivity was 90 % and specificity was 89% for the cross over rate of 0.8.

In this paper, the proposed classification system is composed of an IIR filter with approximate linear phase (perfect reconstruction) for QRS-complex detection, a standard normalization function to normalize the values of the filter coefficients, and a neural network to classify the data into four classes.

3. Filter Design Procedure

It is possible to obtain a bi-reciprocal lattice WDF with approximate linear phase by letting one of the branches $H_1(z^{-2})$ consist of pure delay ($z^{-(2R+1)}$). As shown in Fig. 2, the other branch $H_0(z^{-2})$, of even order $2N$, is a general all-pass function in z^2 [14].

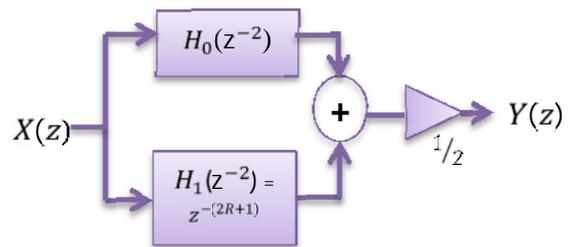


Fig. 2 Bi-reciprocal lattice WDF block diagram.

From Fig. 2, the transfer function of a linear phase low pass bi-reciprocal lattice WDF is

$$H(z) = \frac{Y(z)}{X(z)} = \frac{1}{2} [H_0(z^{-2}) + z^{-(2R+1)}] \quad (1)$$

where R is the number of attenuation zeros. The frequency response of such filter is given by

$$H(e^{j\omega T}) = \frac{1}{2} [H_0(e^{j2\omega T}) + e^{-(2R+1)\omega T}] \tag{2}$$

where

$$H_0(e^{j2\omega T}) = |H_0(e^{j2\omega T})| e^{j\Phi_0(2\omega T)} \tag{3}$$

where $|H_0(e^{j2\omega T})|$ is the magnitude response of $H_0(e^{j2\omega T})$. In the pass-band, the phase response of $H_0(e^{j2\omega T})$ branch $\Phi_0(2\omega T)$ must approximate the linear phase response of the other branch $-(2R + 1)\omega T$ [15]; that is:

$$\Phi_0(2\omega T) = -(2R + 1)\omega T \tag{4}$$

In this work, the order (N) of $H_0(z^{-2})$ is chosen to be 4. Two 2nd order identical all-pass filter sections are cascaded to minimize the number of multipliers (see Fig. 3). The order of delayer $z^{-(2R+1)}$ is 3, therefore, $R = 1$. The transfer function of the designed filter described in Fig. 3 is

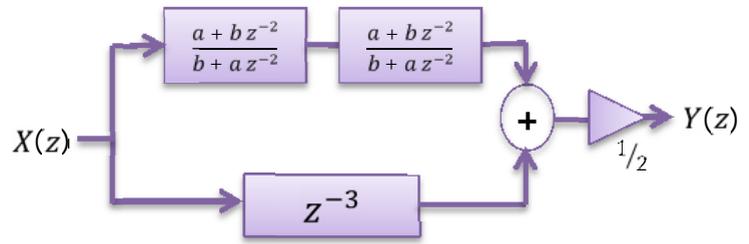


Fig. 3 Designed bi-reciprocal lattice WDF with approximate linear phase.

$$H(z) = \frac{Y(z)}{X(z)} = \frac{1}{2} [\left(\frac{a + bz^{-2}}{b + az^{-2}} \right)^2 + z^{-3}] \tag{5}$$

where a and b are all-pass filter coefficients.

$$H(e^{j\omega T}) = \frac{Y(e^{j\omega T})}{X(e^{j\omega T})} = \frac{1}{2} [\left(\frac{a + b e^{-j2\omega T}}{b + a e^{-j2\omega T}} \right)^2 + e^{-j3\omega T}] \tag{6}$$

The coefficients a, b , are determined by simulating the following transfer function of the FIR filter in [1].

$$H_f(z) = 0.001275 + 0.146 z^{-1} + 0.7092 z^{-2} + 0.146 z^{-3} + 0.001275 z^{-4} \tag{7}$$

Thus,

$$H_f(e^{j\omega T}) = 0.001275 + 0.146 e^{-j\omega T} + 0.7092 e^{-j2\omega T} + 0.146 e^{-j3\omega T} + 0.001275 e^{-j4\omega T} \tag{8}$$

Least square method solution is applied with the following error equation (here T is assumed to be equal 1)

$$E = \int_{-\pi}^{\pi} [H(e^{j\omega T}) - H_f(e^{j\omega T})]^2 \tag{9}$$

Equation (9) requires an optimization algorithm to minimize E . This is accomplished by the determination of the coefficients a, b that give minimum E . Genetic algorithm (GA) is used for that purpose. Using Matlab software, the proposed flowchart of Fig. 4 is used to minimize E in equation (9), and to determine the transfer function of the bi-reciprocal lattice WDF.

In Fig. 4, the number of variables of the fitness function is selected to be 2 (only the filter coefficients a and b as shown in equation (9)). Other options in the GA solver remain at their default cases. The optimization process is terminated after 51 iterations because the average change in the fitness value (FVC_{avg}) becomes less than options TolFun with an accepted E value and the results are as follows: $E = 0.08866$, $a = 0.45$ and $b = 4.212$.

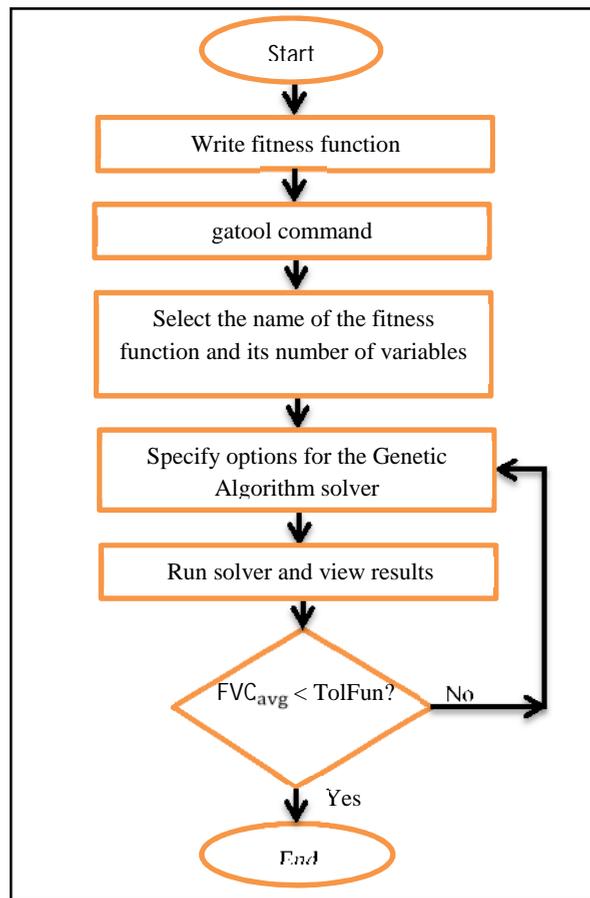


Fig. 4 GA flowchart.

Now, the transfer function of the bi-reciprocal lattice WDF can be formulated as

$$H(z) = \frac{1}{2} \left[\left(\frac{0.45 + 4.212z^{-2}}{4.212 + 0.45z^{-2}} \right)^2 + z^{-3} \right] \quad (10)$$

A simplified form of equation (10) can be given by

$$H(z) = \frac{1}{2} \left[\left(\frac{0.11 + z^{-2}}{1 + 0.11z^{-2}} \right)^2 + z^{-3} \right] \quad (11)$$

Fig. 5 illustrates the frequency response of the resulting filter transfer function equation (11).

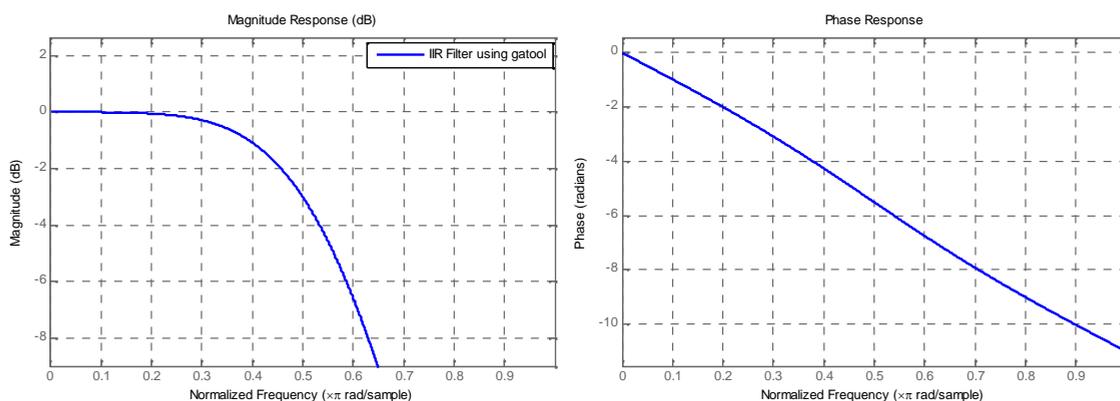


Fig. 5 Frequency response plot of equation (11).

