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Analysis of ECG Using Filter Bank Approach

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ABSTRACT
In recent years scientists and engineers are facing several problems in the biomedical field. However Digital Signal Processing is solving many of those problems easily and effectively. The signal processing of ECG is very useful in detecting selected arrhythmia conditions from a patient's electrocardiograph (ECG) signals. In this paper we performed analysis of noisy ECG by filtering of 50 Hz power line interference using an adaptive LMS notch filter. This is very meaningful in the measurement of biomedical events, particularly when the recorded ECG signal is very weak. The basic ECG has the frequency range from 5 Hz to 100 Hz. It becomes difficult for the Specialist to diagnose the diseases if the artifacts are present in the ECG signal. Methods of noise reduction have decisive influence on performance of all electro-cardio-graphic (ECG) signal processing systems. After removing 50/60 Hz powerline interference, the ECG is lowpass filtered in a digital FIR filter. We designed a Filter Bank to separate frequency ranges of ECG signal to enhance the occurrences QRS complexes. Later the positions of R-peaks are identified and shown plotted. The result shows the ECG signal before filtering and after filtering with their frequency spectrums which clearly indicates the reduction of the power line interference in the ECG signal and a filtered ECG with identified R-peaks.
Keywords – ECG, Arrhythmia, QRS, Filter Bank, Adaptive LMS filter, Downsampling, spectrum, MATLAB.

I. INTRODUCTION

The recording of bioelectrical potentials generated on the surface of the body by the heart is called ECG (Electro-Cardio-Gram). ECG is an important tool to know about the functional and structural status of the heart. In healthcare, the diagnosis of cardiac diseases accurately through an automated method of analysis of ECG signals is crucial, especially for real-time processing. The heart rate signal detects the QRS wave of the ECG and calculates inter-beat intervals [1]. The classification of cardiac rhythms is based on the detection of the different types of arrhythmia from the ECG waveforms. Normally the ECG is corrupted by various noises such as 50/60 Hz power line signals, the baseline drift caused by patient breathing, bad electrodes and improper electrode location. Due to these types of noises detection of QRS complexes becomes difficult or may be false one. Thus, some studies have compared the robust performance of different algorithms for QRS wave detection. Trahanias used the mathematical morphology of the QRS complex to detect heart rates. Chang used the ensemble empirical model decomposition to reduce noises in arrhythmia ECGs. Fan used approximate entropy (ApEn) and Lempel-Ziv complexity as a nonlinear quantification to measure the depth of anaesthesia. Several researchers have extracted the features of ECG waveforms to detect the QRS complexes based on the arrhythmia database. Dr. Li, proposed the wavelet transforms method for detecting the QRS complex from ECG having high P or T waves, noise, and baseline drift. Yeh and Wang proposed the difference operation method to detect the QRS complex waves. Mehta and Lingayat used the support vector machine (SVM) method to detect the QRS complexes from a 12-leads ECG [2]. They also used the K-mean algorithm for the detection of QRS complexes in ECG signals. In these studies, the normal sinus ECG signal added different noise types and energy was used to evaluate the performance of these algorithms.

Arrhythmia can be defined as either an irregular single heartbeat or a group of heartbeats. Some classification techniques are based on the ECG beat-by-beat classification with each beat being classified into several different arrhythmic beat types. These include classification based on artificial neural networks [3], fuzzy neural networks, Hermite functions combined with self-organizing maps, and wavelet analysis combined with radial basis function neural networks. In these methods, the ECG waveform of each beat was picked up and different features were extracted to classify the arrhythmic types. Tsipouras used the RR-interval signal to classify certain types of arrhythmia based on a group of heartbeats.

In this paper we proposed an approach in which the ECG signal is processed with adaptive filter and a lowpass to remove noise due to powerline interference, baseline drift, motion artifacts and other noise sources filter. Later a Filter Bank and a simple QRS detection algorithm are used to detect R-peaks.

II. ECG BASICS

The human heart is a cone-shaped muscular pump located in the mediastinal cavity of the thorax between the lungs and beneath the sternum [4]. In a healthy heart a sequence of electrical impulses is generated by the natural pacemaker in the right atrium, which is called sinoatrial node (SA). This impulse sequence then flows down natural conduction pathways between the atria to the atrioventricular node and from there to both ventricles. Atria and ventricles contract coordinately as the impulses spread through the natural conduction paths in an orderly fashion. The flow of electrical impulses creates unique deflections in the ECG that gives the information about heart function and health. Fig.1 shows the cross section of human heart and the ECG signal generated from the various parts of the heart.

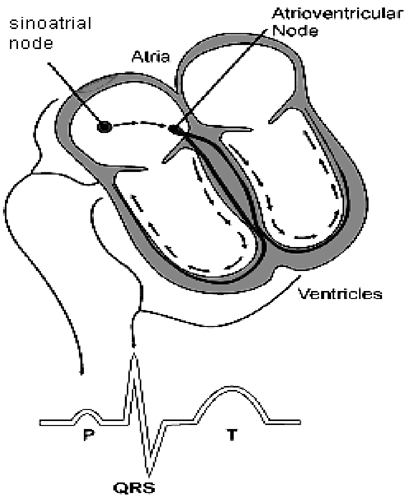

Fig. 1 cross section of human heart and the ECG signal

A typical ECG tracing of a single beat are traditionally recognized and labeled as a P wave, a QRS complex, a T wave, and a U wave [5]. The peak labeled P corresponds to the initial electrical pulse triggering the heart's contraction. The interval from P to Q corresponds to the spreading of the depolarization across the smaller chambers of the heart (the atria—singular atrium), and is typically very small because the atria are only a small fraction of the heart. The QRS complex, the great big feature in any ECG trace, shows where the ventricles contract. These are the largest, lower chambers of the heart, explaining why this feature is bigger than the P feature for the atria. The T wave shows where the ventricles re-polarize in preparation for the next heartbeat to occur and where the muscles are relaxing after contraction. We can calculate the rate by looking at several beats. With the help of ECG, doctors and other trained personnel can analyse ECG tracing and find out the reasons for functional and structural disorders of the heart such as abnormal speeding, slowing, irregular rhythms, injury to muscle tissue (angina), and death of muscle tissue (myocardial infarction) etc. The length of intervals gives the information about the conduction lengths of the flow of electrical impulses from SA node. If an impulse is following its normal pathway then the length of an interval is normal. If an impulse has taken a longer route or has been slowed then the interval is long. If an impulse has taken a shorter route or has been speeded up then the interval is short. When the electrical impulse did not rise normally or was blocked at that part of the heart QRS complex becomes absent. The P-wave will be absent when there is a lack of normal depolarization of the atria. If QRS complex is absent after a normal P wave then it indicates that the electrical impulse was blocked before it reaches the ventricles. When the heart tissue is dead or injured, the impulses will spread abnormally through the muscle tissue and produces abnormally shaped complexes in ECG. Such situation is called as myocardial infarction. Metabolic abnormalities and various medicines may also change electrical signal pattern of ECG.

III. METHOD

In this paper the ECG signal is analysed based on frequency content. The power spectrum of ECG signal may extend up to 100 Hz with QRS complex concentrating up to 50 Hz. Depending upon the sharpness of the morphology of Q, R and S waves the frequency content may extend even beyond 50 Hz with considerable magnitude. In general, the energy of P and T waves will be up to 10 Hz significantly. Hence the best way is to detect heartbeats is to analyze ECG signal based on different sub-bands of the ECG using FIR filters in the form of a filter bank [6], instead of considering just the output of one filter which maximizes SNR of the QRS [7].

Fig.2 shows the block diagram of our method used for analyzing ECG signal.

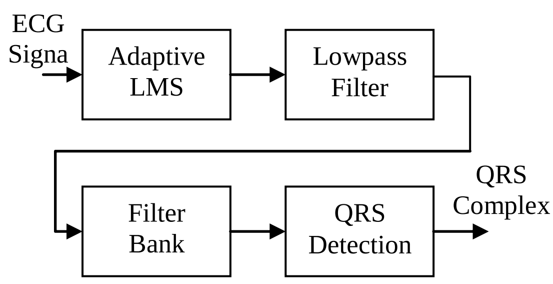

Fig.2 Block diagram of the proposed method

In order to remove 50 Hz (60 Hz) powerline interference an adaptive LMS filter is used [8]. The adaptive filter using LMS algorithm [9][10] is shown in Fig.3. The adaptive filter would take input both from the patient and from the power supply directly and would thus be able to track the actual frequency of the noise as it fluctuates. Such an adaptive technique generally allows for a filter with a smaller rejection range, which means, in our case, that the quality of the output signal is more accurate for medical diagnoses. The idea behind the block diagram is that a variable filter extracts an estimate of the desired signal.

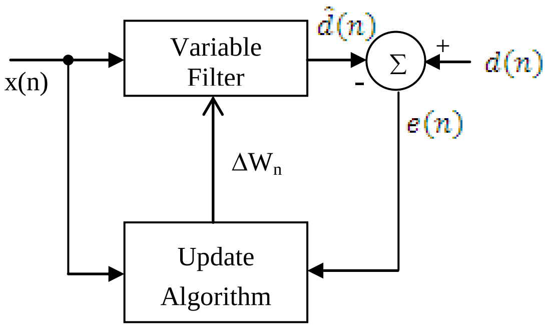

Fig.4 Block diagram of adaptive LMS filter

The input signal is the sum of a desired signal d(n) and interfering noise v(n). The adaptive filter is FIR structure [11] defined with filter coefficients as:

$$W_n = [W_n(0), W_n(1), ... W_n(p)]^T \tag{1}$$

The error signal is obtained from the difference between the desired and the estimated signal as:

$$e(n) = d(n) - \hat{d}(n) \tag{2}$$

The adaptive filter estimates the desired signal by convolving the input signal with the impulse response. In vector notation this is expressed as:

$$\hat{d}(n) = W_n * X(n) \tag{3}$$

Where X(n) is an input signal vector and given by:

$$X(n) = [x(n), x(n-1), ... x(n-p)]^T \tag{4}$$

Moreover, the variable filter updates the filter coefficients at every time instant according to the equation:

$$W_{n+1} = W_n + \Delta W_n \tag{5}$$

where ΔW_n is a correction factor for the filter coefficients. The adaptive algorithm generates this correction factor based on the input and error signals. The adaptive LMS filter can be implemented by using MATLAB. The desired estimate is then filtered through a lowpass filter to remove high frequency noise above 60 Hz.

The low-pass filter designed by Lynn is represented in simple and effective form with the following transfer function [12].

$$H_1(z) = \frac{(1-z^{-6})^2}{(1-z^{-1})^2} \tag{6}$$

$$H_1(\omega) = \frac{(1-e^{-j6\omega})^2}{(1-e^{-j\omega})^2} \tag{7}$$

The corresponding difference equation is as follows:

$$y(n)= 2y(n-1)-y(n-2)+x(n)-2x(n-4)+x(n-8) \tag{8}$$

The desired lowpass filter can be designed using MATLAB.After lowpass filtering the ECG signal is decomposed into different frequency bands using Filter Bank [13]. In this filter bank analysis technique we used 4 sub-bands; each one has bandwidth 6 Hz. The ECG signal is processed by those 4 sub-band filters and downsampled [14]. Thus The processing of ECG signal is carried out by using analysis and synthesis filters, each of length L, The analysis filters are bandpass filters whose ideal magnitude response $H_n(w)$, n =0,1,2,…,(N-1) is shown in the Fig.4.

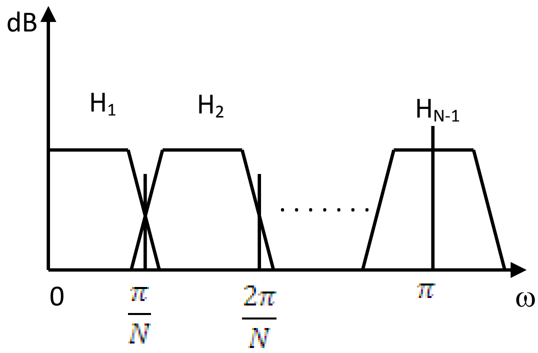

Fig.4 Ideal Magnitude response of a Filter Bank

If X(f) is the input signal then this filter bank decompose the input signal and produces the subband signals as follows:

$$Y_n(z) = H_n(z) X(z) \quad n=0,1,2,3,...,N-1 \tag{9}$$

The downsampling process keeps one sample out of samples. The downsampled signal is given as follows:

$$Z_n(z) = \frac{1}{N} \sum_{n=0}^{N-1} Y_n(z^{\frac{1}{N}} e^{\frac{j2\pi}{N}}) \quad n=0,1,2,...,N-1 \tag{10}$$

Since the downsampled signal has lower rate than subbands of input ECG signal the filtering process can be efficiently done at the input rate by taking advantage of the downsampling.

With the help of these subbands interesting features QRS complex can be extracted by combining these subbands in different ways. For example by using subbands 1, 2, 3 and 4 we can calculate the feature sum-of-absolute values, P_1, as [15]:

$$P_1 = \sum_{k=1}^{4} |Z_k(z)| \tag{11}$$

P_1 gives the energy in the frequency band [4, 28] Hz. Similarly, P_2 and P_3 can be computed using sub-bands {1, 2, 3}, and {2, 3, 4}, respectively as:

$$P_2 = \sum_k |Z_k(z)| \qquad k = 1,2,3 \tag{12}$$

$$P_3 = \sum_k |Z_k(z)| \qquad k = 1,3,4 \tag{13}$$

And these values are proportional to the energy in their respective sub-bands.

Similarly the features mean-of-sum-of-squares P_4, P_5 and P_6 can be computed using subbands {1, 2, 3, 4}, {1, 2, 3} and {2, 3, 4}, respectively as:

$$P_4 = \frac{1}{4} \sum_k (Z_k(z))^2 \qquad k = 1,2,3,4 \tag{14}$$

$$P_5 = \frac{1}{3} \sum_k (Z_k(z))^2 \qquad k = 1,2,3 \tag{15}$$

$$P_6 = \frac{1}{3} \sum_k (Z_k(z))^2 \qquad k = 1,2,3,4 \tag{16}$$

These features represent the energy of the QRS complex. An heuristic beat detection logic can be developed to maximize the number of true positives (TP's), while keeping the number of false negatives (FN's) and false positives (FP's) to a minimum by computing the detection strength (D) of an incoming feature (e.g., P_1, P_2, P_3) with the help of signal and noise levels as:

$$D = \frac{P - N}{S - N} \tag{17}$$

Where

S = Signal Level
N= Noise Level

The value of D is limited at 0 if a feature's value is less than N and limited to 1when a feature's value is above S. The signal history is updated with the feature's value if the value of D is greater than the threshold and noise history is updated with the feature's value if the value of D is less than the threshold. After extracting the ECG signal with isolated QRS energies, the R-peaks are detected by simple algorithm where a dynamic threshold is used.

IV. RESULTS

In this paper first we implemented an adaptive filter using MATLAB built-in function and adaptive.lms on input noisy ECG signal to reduce noises that resulted from 50 Hz power lines and baseline drift and then filtered in a lowpass filter to remove high frequency noise above 60 Hz. Finally the ECG signal is processed with a filter bank to separate QRS complexes and then the R-peak positions from QRS complex were detected. The Fig.5 shows the noisy ECG signal and its spectrum, ECG after removing 50 Hz powerline interference and its spectrum.

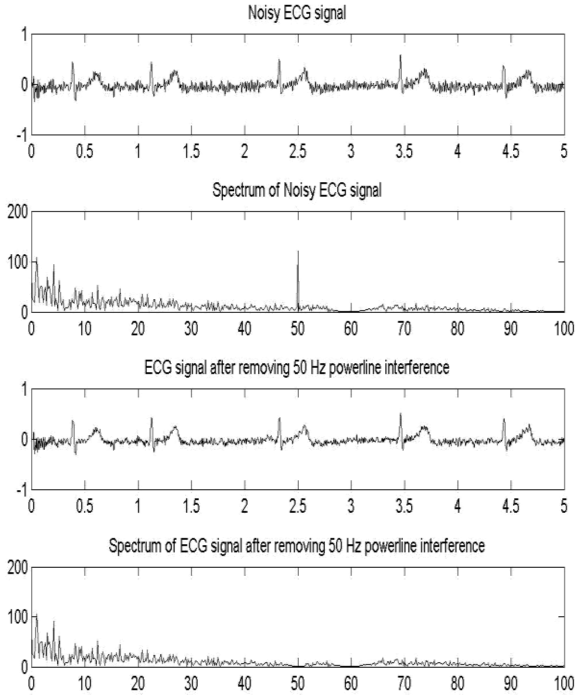

Fig. 5 ECG and its soectrum after removing 50 Hz powerline interfence

Fig.6 shows the ECG signal after processing with a filter bank and R-peaks detected.

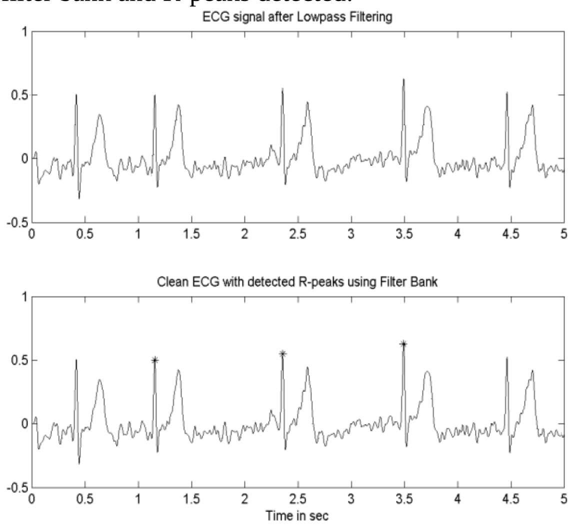

Fig.6 Lowpass filtered ECG and Cleaned ECG with detected R-peaks

V. CONCLUSION

Normally signals from ECG electrodes are brought to simple electrical circuits with amplifiers and analogue to digital converters. The main problem of digitalized signal is interference with other noisy signals like power supply network 50 Hz frequency and breathing muscle artifacts. These noisy elements have to be removed before the signal is used for next data processing like heart rate frequency detection. Digital filters and signal processing should be designed very effective for next real-time applications in embedded device.

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REFERENCES

[1] M. Jannett T.C. Jadallah M.A., Yates S.L. Quint S.R. Troynagle H. A comparison of the noise sensitivity of nine QRS detection algorithms, *IEEE Trans. Biomed. Eng. 1990;37:85–98*.

[2] T.B. Garcia and N.E. Holtz, *12-lead ECG: The Art of Interpretation*, (Jones & Bartlett Publ. Sudbury, MA.236 pp. ISBN 0-7637-1284-1).

[3] P. S. Hamilton, W. J. Tompkins, (1986). Using MIT/BIH Arrhythmia Database, *IEEE Transactions on Biomedical Engineering, Vol.31, No.3, (March 2007), pp. 1157-1165, ISSN 0018-9294.*

[4] T.C Ruch, H.DPatton, *Physiology and Biophysics* (Philadelphia, W. B. Saunders, 1982).

[5] N. Goldschlager, *Principles of Clinical Electrocardiography* (Connecticut, USA, ISBN 978-083-8579-510)

[6] H. S. Malvar, *Signal Processing with Lapped Transforms* (Norwood, MA: Artech House, 1992)

[7] P. S. Hamilton and W. J. Tompkins, Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database, *IEEE Trans. Biomed. Eng., vol. BME-33, pp. 1157–1165, 1986.*

[8] Haykin, Simon S, *Adaptive Filter Theory* (4th ed. Englewood Cliffs, New Jersey: Prentice Hall), 2001.

[9] J. R. Glover. Adaptive noise canceling applied to sinusoidal interferences, *IEEE Trans. Acoustical., Speech, Signal Processing, and ASSP-25 (12):484–491, Dec. 1977*.

[10] D.R Morgan, An analysis of multiple correlation cancellation loops with a filter in the auxiliary path, *IEEE Transactions on Acoustics, Speech and Signal Processing, ASSP-28(4):454–467, August 1980*.

[11] C.C. Boucher, S.J. Elliott, and P.A. Nelson. Effect of errors in the plant model on the performance of algorithms for adaptive feedforward control. *Proceedings of Institution of Electrical Engineers, volume 138, pages 313–319, 1991*.

[12] J. Pan, and W. J. Tompkins, A Real-Time QRS Detection Algorithm. *IEEE Transactions on Biomedical Engineering, 1985; 32(3): 230-2.*

[13] Nguyen, Truong T., and Soontorn Oraintara, Multidimensional filter banks design by direct optimization, *IEEE International Symposium on Circuits and Systems, pp. 1090-1093. May, 2005*.

[14] P. P. Vaidyanathan, *Multirate Systems and Filter Banks* (Englewood Cliffs, NJ: Prentice-Hall, 1993)

[15] C. Rebai, D. Dallet, P. Marchegay, *proceeding of: Instrumentation and Measurement Technology Conference, 2002. IMTC/2002*.