De-Noising of Electrocardiogram (ECG) with Adaptive Filter Using MATLAB

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***Abstract*- Problem associated with biomedical signal like ECG is to extract noise cause by high frequency interference, electromagnetic fields, power line interference and body movement. It is difficult to apply filters with fixed coefficients to reduce random noises. Adaptive filter technique is required to overcome this problem. This paper presents an innovative technique for estimation of ECG waves using Adaptive Noise Cancellation (ANC) algorithm, widrow-hoff LMS algorithm. Comparisons are made for original signal to noisy. Simulations are done for random noise pattern in matlab.**

***Keywords*- ECG, Adaptive filtering, random noise, LMS algorithm , MATLAB**

I. INTRODUCTION

Electrocardiogram (ECG) is a nearly periodic signal that reflects the activity of the heart. A lot of information on the normal and pathological physiology of heart can be obtained from ECG. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyze them. Thus the need is there for computer based methods for ECG signal Analysis.

The heart is divided into 4 chambers as shown in Fig.1. The two upper chambers the left and right atria are synchronized to act together. Similarly, the two lower chambers the ventricles operate together. The right atrium receives the blood from the veins of the body and pumps it into the right ventricle. The right ventricle pumps the blood through the lungs, where it is oxygenated. The oxygen-enriched blood then enters the left atrium, from which it is pumped into the left ventricle. The left ventricle pumps the blood into arteries to circulate throughout the body. For the cardiovascular system to function properly, both the atria and ventricles must operate in a proper time relationship. Each action potential in the heart originates near the top of the right atrium at a point called pacemaker or sinoatrial (SA) node. The pacemaker is a group of specialized cells that spontaneously generate action potentials at a regular rate. The biopotentials generated by the muscles of the heart result in the electrocardiogram. ECG signal is the electrical signal which occurs due to electrical activity of heart. This signal is measure by surface electrode on limb and chest. The typical ECG signal as shown in Figure 2, as it appears when recorded from the surface of the body. Alphabetic designations have been given to each of the prominent features. These can be identified with events related to the action potential propagation pattern. To facilitate analysis, the horizontal segment of this waveform preceding the P wave is designated as the baseline or the isopotential line.

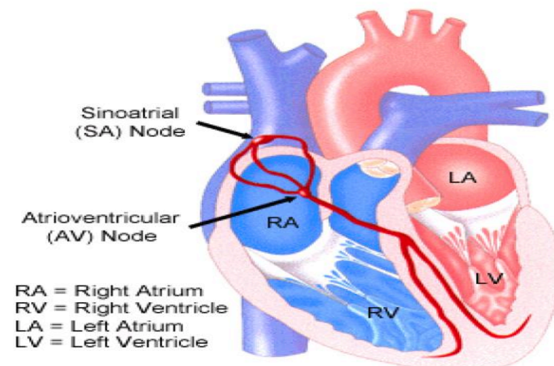

Figure 1: Conduction System of Heart

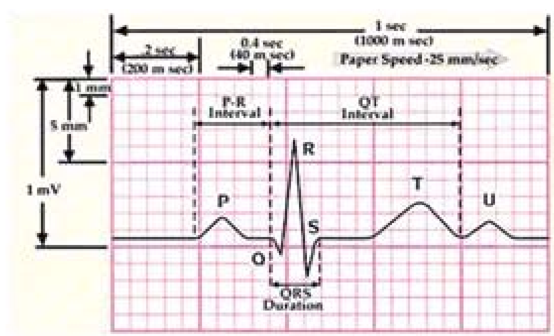

Figure 2: A Typical Cardiac Signal

The P wave represents repolarization of the atrial muscular. The QRS complex is the combined results of the repolarization of the atria and the repolarization of the ventricles, which occur almost simultaneously. The T wave is the wave of the ventricular repolarization, whereas the U wave, if present, is generally believed to be the result of after potentials in the ventricular muscle. The P-Q interval represents the time during which the excitation wave is delayed in the fibers near the AV node.

Signal processing (DSP) has been used for noise filtering, system identification, and voice prediction. Standard DSP techniques are not able to solve this problem accurately and quickly. Adaptive filtering technique is used to get accurate solutions.

In many applications for biomedical signal-processing the information-bearing signals are superposed by further components. Thus signals get distorted and the extraction of information is complicated. Commonly frequency selective filters with fixed coefficients are used to suppress a specific

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frequency range of a signal. If the frequency spectrum of signal and interference overlap or the characteristic of the interference is time dependent or not exactly known, filters with fixed coefficients can hardly meet the demand.

II. PROCEDURE

Filters with fixed characteristics (tap-weighted or coefficients) are suitable when the characteristics of the signal and noise (random or stationary) are stationary and known. Design of frequency domain filters requires detailed knowledge of the spectral contents of the signal and noise. Such filters are not applicable when the characteristics of the signal and or noise vary with time that is when they are non-stationary. They are also not suitable when the spectral contents of the signal and the interference overlap significantly.

I. Adaptive Noise Cancellation (ANC) algorithm

Figure shows a generic block diagram of an adaptive filter or ANC the primary input to the filter $x(n)$ is a mixture of the signal of interest $v(n)$ and the primary noise $m(n)$.

$$x(n) = v(n) + m(n) \quad (1)$$

$x(n)$ is the primary observed signal; it is desired that the interference or noise $m(n)$ be estimated and removed from $x(n)$ in order to obtain the signal of interest $v(n)$. It is assumed that $v(n)$ and $m(n)$ are uncorrelated. Adaptive filtering requires a second input, known as the reference input $r(n)$, that is uncorrelated with the signal of interest $v(n)$ but closely related to or correlated with the interference or noise $m(n)$ in some manner that need not be known. The ANC filters or modifies the reference input $r(n)$ to obtain a signal $y(n)$ that is as close to the noise $m(n)$ as possible. $y(n)$ is then subtracted from the primary input to estimate the desired signal:

$$y(n) = e(n) = x(n) - y(n) \quad (2)$$

Let us now analyze the function of the filter. Let us assume that the signal of interest $y(n)$, the primary noise $m(n)$, the reference input $r(n)$ and the primary noise estimate $y(n)$ are statically stationary and have zero means. We have already stated that $y(n)$ is uncorrelated with $m(n)$ and $r(n)$ is correlated with $m(n)$.The output of the ANC is

$$e(n) = x(n) - y(n)$$

$$e(n) = v(n) + m(n) - y(n) \quad (3)$$

Where $y(n) = m(n)$ is the estimate of the primary noise obtained at the output of the adaptive filter. By taking the square and expectation (statically average) of both sides of equation (3), we obtain.

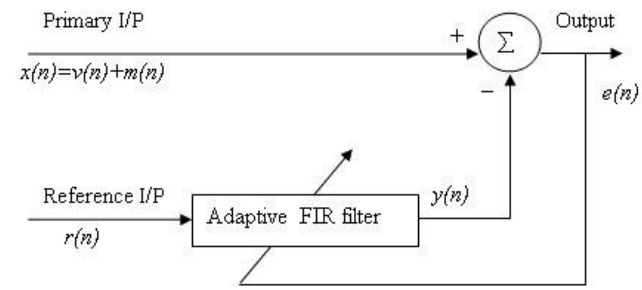

Figure 3: Block diagram of generic adaptive noise canceller (ANC) or adaptive filter

$$E[e^2(n)] = E[v^2(n)] + E[\{m(n) - y(n)\}^2] + 2E[v(n)\{m(n) - y(n)\}] \quad (4)$$

Since $y(n)$ is uncorrelated with $m(n)$ and $y(n)$ and all of them have zero means, we have

$$E[v(n)\{m(n) - y(n)\}] = E[v(n)]E[m(n) - y(n)] = 0 \quad (5)$$

Equation (4) can be rewritten as

$$E[e^2(n)] = E[v^2(n)] + E[\{m(n) - y(n)\}^2] \quad (6)$$

Note from figure 1. That the output $e(n)$ is used (fed back) to control the adaptive filter. In ANC applications, the objective is to obtain an output $e(n)$ that is a least-squares fit to the desired signal $v(n)$ this is achieved by feeling the output back to the adaptive filter and the filter is adjusted to minimize the total system output power. The system output serves as the error signal for the adaptive process.

$E[e^2(n)]$ is minimized therefore the signal power $E[v^2(n)]$ will be unaffected so the minimum output power is

$$\min\ E[e^2(n)] = E[v^2(n)] + \min\ E[\{m(n) - y(n)\}^2] \quad (7)$$

$E[\{m(n) - y(n)\}^2]$ is also minimized, therefore from Equation (3).

$$e(n) - v(n) = m(n) - y(n) \quad (8)$$

The output $e(n)$ will contain the signal of interest $v(n)$ and some noise. From equation (8), the output noise is given by $e(n) - v(n) = m(n) - y(n)$. Since minimizes $E[\{m(n) - y(n)\}^2]$, minimizing the total output power minimizes the output noise power. Since the signal component $y(n)$ in the output power minimizes the output noise power. Since the signal component $y(n)$ in the output remains unaffected, minimizing the total output power maximizing the output SNR.

Note from eq.(6) that the output power is minimum when $E[e^2(n)] = E[v^2(n)]$. When this condition is achieved, $E[\{m(n) - y(n)\}^2] = 0$. We then have $y(n) = m(n)$ and $e(n) = v(n)$; that is, the output is a perfect and noise-free estimate of the desired signal.

Optimization of the filter may be performed by expressing the error in terms of the tap-weight vector and applying the procedure of choice. The output $y(n)$ of the adaptive filter in response to its $r(n)$ is given by

$$y(n) = \sum_{k=0}^{M-1} w_k r(n-k) \qquad (9)$$

Where w_k, $k = 0,1,2,3\ldots M-1$, are the tap weight, and M is the order of the filter. The estimation error $e(n)$ or the ANC system is

$$e(n) = x(n) - y(n) \qquad (10)$$

For the sake of notational simplicity, let us define the tap-weight vector at time n

$$w(n) = [w^0(n), w^1(n), w^2(n), ...w^{M-1}(n-M+1)]^T \quad (11)$$

Similarly, the tap-weight vector at each time instant n may be defined as the M dimension vector

$$r(n) = [r(n)\, r(n-1)..........r(n-M+1)]^T \qquad (12)$$

Then the estimation error $e(n)$ given in equation (10) may be rewritten as

$$e(n) = x(n) - w^T(n).r(n) \qquad (13)$$

It is worth noting that the derivations made above required no knowledge about the processes behind $v(n), m(n)$ and $r(n)$ or their inter-relationship other than the assumptions of statically independence between $v(n), m(n)$ and so the form of correlation between $m(n)$ and $r(n)$. The arguments can be extended to situations where the primary and reverence inputs contain additive random noise processes that are mutually uncorrelated and also uncorrelated with $v(n), m(n)$ and $r(n)$. The procedures may also be extended to cases where $m(n)$ and $r(n)$ are deterministic or structured rather than stochastic, such as power- line interference or an ECG signal. Several methods are available to maximize the output SNR; two such methods based on the least mean squares (LMS) and the recursive least squares approaches are described in the following sections.

II. Least Mean Squares (LMS) algorithm

Adaptive filtering algorithm is used to minimized MSE by adjusting the tap-weight vector. By squaring the expression for the estimation error $e(n)$ given in equation (13), we get

$$e^2(n) = x^2(n) - 2.x(n)r^T(n)w(n) + w^T(n)r(n)r^T(n)w(n) \quad (14)$$

The squared error is a second order (quadratic) function of the tap weight vector (and the input) and may be depicted as a concave hyper-paraboloidal (bow like) surface that is never negative. The aim of the filter optimization procedure would be to reach the bottom of the bowl-like function. Gradient based methods may be used for this purpose.

By taking the expected values of the entities in equation (14) and taking the derivative with respect to the tap weight vector, we may derive the wiener hopf equation for the present application. The LMS algorithm takes a simpler approach by assuming the square of the instantaneous error as in eq. (14) to stand for an estimate of the MSE. The LMS algorithm is based on the method of steepest descent, where the new tap-weight vector $w(n-1)$ is given by the present tap-weight vector $w(n)$ plus a correction proportional to the negative of the gradient $\nabla(n)$ of the squared error:

$$w(n+1) = w(n) - \mu\nabla(n) \qquad (15)$$

The parameter µ controls the stability and rate of convergence of the algorithm: the larger the value of µ, the larger is the gradient of the noise that is introduced and the faster is the convergence of the algorithm, and vice-versa.

The LMS algorithm approximates

$$\tilde{\nabla}(n) = -2x(n)r(n) + 2\{w^T(n)r(n)\} = -2e(n)r(n) \qquad (16)$$

Using this estimate of the gradient in eq.(16) we get

$$w(n+1) = w(n) + 2\mu.e(n)r(n) \qquad (17)$$

The expression is known as the widrow-hoff LMS algorithm.

III. RESULT

This section presents results obtained on simulation of the proposed work. Figure 4-6 represent various results obtained and are in accordance with the theoretical expections.

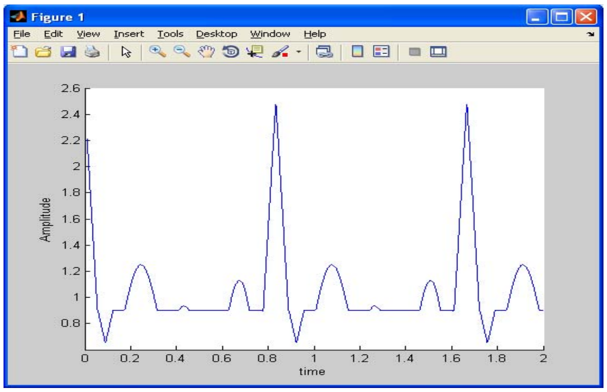

Figure 4: Implementation of ECG Signal

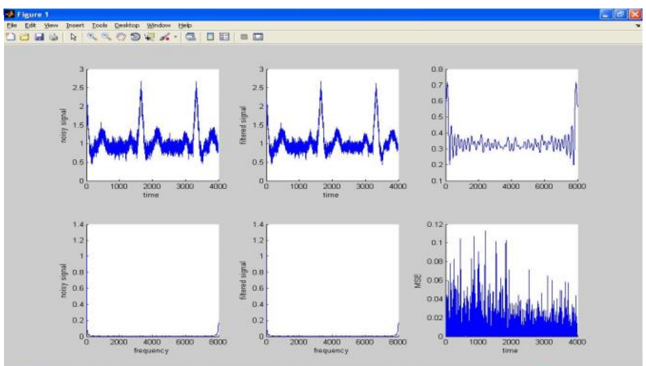

Figure 5: Implementation of ANC Algorithm

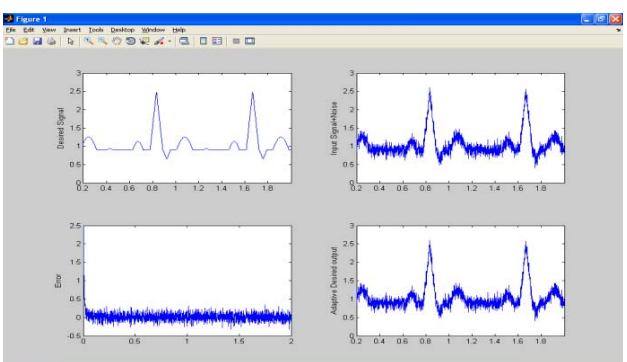

Figure 6: Implementation of LMS Algorithm

IV. CONCLUSION

In this paper adaptive filter is used for noise removal from ECG signal. For this, the original and the desired signals are selected in such a manner that the filter output is the least squared estimate of the original ECG signal. The paper proposed the modifications in the weight update formula for LMS based realizations. Our simulations, however, confirm that the SNR of the proposed algorithm gives better result. Biomedical signals play a crucial role in the diagnosis of patients. A new structure and algorithm for the LMS adaptive filter with a dynamic structure was suggested, as signal changes in time and can be variously mixed with noise depending on the environment and based on the patient's condition. Excessive filtering results in a distorted signal. The LMS adaptive filter is widely used to filter the ECG signal, but the existing LMS adaptive filters adapt to the environment showing limitations in the given filter, so its convergence and performance cause distortions and even poor performance, depending on the environment and the patient's condition.

The proposed treatment exploits the modifications in the weight update formula and thus pushes up the speed over the respective LMS based realizations. Our simulations, however, confirm that the SNR of the proposed algorithm gives better result.

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