Removing 0.5 Hz Baseline Wander From ECG Signal Using Multistage Adaptive Filter

Dr. H. H. Abbas*

Received on: 7/2/2010 Accepted on: 5/5/2011

Abstract

This paper deals with the implementation of software system to remove 0.5 Hz baseline wander noise from the ECG signal using multistage adaptive filter.

At start, a single stage adaptive filter has been implemented and the performance of the implemented system has been checked for changing the values of noise levels, the convergence factor of the adaptive algorithm, and the length of the adaptive filter.

From testing results it is clear that the performance of the implemented system changes by the above factors values.

Then an adaptive filter with the best values for the above factors has been used as a prototype to build multistage filter.

The resulted multistage adaptive filter has been tested to prove its capability to remove 0.5 Hz baseline wander noise as compared with single stage adaptive filter.

From testing results, it is clear that multistage filter gives better results than single stage filter.

Keywords: Adaptive filtering, ECG signal, Baseline wander noise, LMS algorithm.

إزالة الضوضاء بتردد 0.5 هرتز الناتجة عن التأرجح عن خط الأساس (Baseline Wander) من أشارة تخطيط القلب باستعمال المرشح الاعتمادي متعدد المراحل

الخلاصة

أن هذا البحث يتناول بناء نظام برمجي لإزالة الضوضاء بتردد 0.5 هرتز ناتجة عن التأرجح عن خط الأساس (Baseline Wander) من أشارة تخطيط القلب باستعمال المرشح الاعتمادي متعدد المراحل.

في البداية تم بناء مرشح اعتمادي أحادي المرحلة و من ثم فحص تأثير تغيير قيم كل من مستوى الضوضاء، عامل التقارب للخوارزمية الاعتمادية و طول المرشح الاعتمادي (عدد معاملات المرشح) على أداء النظام الذي تم بناءه.

أن من الواضح من نتائج الفحص أن أداء النظام الذي تم بناءه يتأثر بقيم العوامل السابقة. بعد ذلك تم استخدام مرشح اعتمادي بأحسن قيم للعوامل السابقة كنموذج ابتدائي لبناء مرشح متعدد المراحل.

أن المرشح الاعتمادي المتعدد المراحل الذي تم بناءه تم اختباره للبر هنة على قابليته على إزالة الضوضاء بتردد 0.5 هرتز ناتجة عن التأرجح عن خط الأساس (Baseline Wander) مقارنة بالمرشح الاعتمادي الأحادي المرحلة.

*Al- Mansour University College/Baghdad

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https://doi.org/10.30684/etj.29.11.18

2412-0758/University of Technology-Iraq, Baghdad, Iraq This is an open access article under the CC BY 4.0 license <u>http://creativecommons.org/licenses/by/4.0</u> من الواضح من نتائج المقارنة أن المرشح المتعدد المراحـــل يعطي نتائج أفضل بكثير من المرشح الأحادي المرشح

Introduction

The aim of this paper is to implement a computer program to remove 0.5 Hz baseline wander noise from the ECG signal using multistage adaptive filter.

At start, a single stage adaptive filter has been implemented and the performance of the implemented system has been tested under many circumstances and conditions. Then from testing results many points are concluded. Then a prototype single stage adaptive filter with the best performance is used to build multistage filter.

Then the resulted multistage adaptive filter has been tested to prove its capability to remove 0.5 Hz baseline wander noise.

From testing results, it is clear that multistage filter gives better results than single stage filter for all cases.

An Introduction To Ecg

The electrocardiogram (ECG) is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax. The surface ECG is obtained by recording the potential difference between two electrodes placed on the surface of the skin. A single normal cycle of the ECG represents the successive atrial depolarization /

repolarization and ventricular depolarization / repolarization which occurs with every heart beat. Then simply, the ECG (EKG) is a device that measures and records the electrical activity of the heart from electrodes placed on the skin in specific locations [1, 2].

The ECG is used for:

a. Screening test for coronary artery disease, cardiomyopathies, left ventricular hypertrophy.

b. Preoperatively to rule out coronary artery disease.

c. Can provide information in the precence of metabolic alterations such as hyper/hypo calcemia / kalemia etc.

d. With known heart disease, monitor progression of the disease.

e. Discovery of heart disease; infarction, coronal insufficiency as well as myocardial, valvular and cognitial heart disease.

f. Evaluation of ryhthm disorders.

g. Finally, it is the basic cardiologic test and is widely applied in patients with suspected or known heart disease.

Typical ECG period consists of P, Q, R, S, T and U waves as shown in Figure (1). The ECG waves are as given below:

a. P wave: the sequential activation (depolarization) of the right and left atria.

b. QRS complex: right and left ventricular depolarization.

c. T wave: ventricular repolarization.

d. U wave: origin not clear, probably "after depolarizations" in the ventrices [1, 2].

Ecg Filtering

There are two common noise sources which are:

a. Baseline wander.

b. Power line interference.

When filtering any biomedical signal care should be taken not to alter the desired information in any way. A major concern is how the QRS complex influences the output of the filter since they often pose a large unwanted impulse. Possible distortion caused by the filter should be carefully quantified. In this paper only baseline wander noise is taken in to account [3].

Basline Wander

Baseline wander which is the extragenoeous low-frequency highbandwidth components, can be caused by:

a. Perspiration (effects electrode impedance).

b. Respiration.

c. Body movements.

Baseline wander can cause problems to analysis, especially when exmining the low-frequency ST-T segment. There are two main approaches used for baseline wander filtering which are linear filtering (time-invariant and time-variant) and polynomial fitting [1, 2].

Linear Time-Invariant Filtering Of Baseline Wander

Basically one can create a highpass filter to cut of the lower-frequency components (the baseline wander). The cut-off frequency should be selected so as the ECG signal information remains undistorted while as much as possible of the baseline wander is removed; hence the lowest-frequency component of the ECG should be noticed. This is generally thought to be definded by the slowest heart rate. The heart rate can drop to 40 bpm, implying the lowest frequency to be 0.67 Hz. Again as it is not percise, a sufficiently lower cutoff

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frequency of about 0.5 Hz should be used.

A filter with linear phase is desirable in order to avoid phase distortion that can alter various temporal realtionships in the cardiac cycle. Linear phase response can be obtained with finite impulse response, but the order needed will easily grow very high.

This complexity can be reduced by for example forward-backward IIR filtering. This has some drawbacks, which are:

a. not real-time (the backward part...). b. application becomes increasingly difficult at higher sampling rates as poles move closer to the unit circle, resulting in unstability.

c. hard to extend to time-varying cutoffs.

Yet another way of reducing filter complexity is by first decimating and then again interpolating the signal. Decimation removes the highfrequency content, and now a lowpass filter can be used to output an estimate of the baseline wander. The estimate is interpolated back to the original sampling rate and subtracted from the original signal as shown in Figure (2) [3, 4, and 5].

Linear, Time-Variant Filtering Of Baseline Wander

Baseline wander can also be of higher frequency, for example in stress tests, and in such situations using the minimal heart rate for the base can be inefficeient. By noting how the ECG spectrum shifts in frequency when heart rate increases, one may suggest coupling the cut-off frequency with the prevailing heart rate instead as shown in Figure (3).

There are two approaches to represent

the "prevailing heart rate":

1. A simple but useful approach is just to estimate the length of the interval between R peaks, the RR interval as shown in Figure (4).

2. Linear interpolation for interior values.

Time varying cut-off frequency should be inversely proportional to the distance between the RR peaks but in practise an upper limit must be set to avoid distortion in very short RR intervals.

A single prototype filter can be designed and subjected to simple transformations to yield the other filters [4, 5].

Polynomial Fitting Of Baseline Wander

One alternative approach to basline wander removal is to fit polynomials to representative points in the ECG such as knots selected from a "silent" segment, often the best choise is the PQ interval as shown in Figure (5). A polynomial is fitted so that it passes throught every knot in a smooth fashion. This type of baseline removal requires the QRS complexes to have been identified and the PQ interval localized. Higher-order polynomials can provide a more accurate estimate but at the cost of additional computational complexity. A popular approach is the cubic spline estimation technique [3,4, and 5].

Polynomial fitting can also adapt to the heart rate (as the heart rate increases, more knots are available), but performs poorly when too few knots are available.

Adaptive Filtering

Digital signal processing (DSP) has been a major player in the current technical advancements such as noise filtering, system identification, and voice prediction. Standard DSP techniques, however, are not enough to solve these problems quickly and obtain acceptable results. Adaptive filtering techniques must be implemented to promote accurate solutions and a timely convergence to that solution.

Adaptive Filtering System Configurations

There are four major types of adaptive configurations; filtering adaptive system identification [6], adaptive noise cancellation [7], adaptive linear prediction [8], and adaptive inverse system [9]. All of the above systems are similar in the implementation of the algorithm, but different in system configuration. All four systems have the same general parts; an input x(n), a desired result d(n), an output y(n), an adaptive transfer function w(n), and an error signal e(n) which is the difference between the desired output d(n) and the actual output y(n).

In this paper only adaptive noise cancellation configuration is given.

For details about other configurations on can see [6, 8, and 9].

Adaptive Noise Cancellation Configuration

The adaptive noise cancellation configuration is as shown in Figure (6). In this configuration the input x(n), a noise source $N_1(n)$, is compared with a desired signal d(n), which consists of a signal s(n) corrupted by another noise $N_0(n)$. The adaptive filter coefficients adapt to cause the error signal to be a noiseless version of the signal s(n).

Both of the noise signals for this configuration need to be uncorrelated

to the signal s(n). In addition, the noise sources must be correlated to each other in some way, preferably equal, to get the best results.

Due to the nature of the error signal, the error signal will never become zero. The error signal should converge to the signal s(n), but not converge to the exact signal. In other words, the difference between the signal s(n) and the error signal e(n) will always be greater than zero. The only option is to minimize the difference between those two signals [6, 7, 8, 9, and 10].

Adaptive Filter Algorithms

There are two categories of adaptive filter algorithms which are:

1. Finite Impulse Response (FIR) algorithms which can be subdivided into:

a. Least Mean Squares (LMS) Gradient Approximation Method.

b. Transform Domain Adaptive Filter (TDAF).

c. Quasi-Newton Adaptive Algorithms.

d. Adaptive Lattice Algorithms.

2. Infinite Impulse Response (IIR) algorithms.

In this paper Least Mean Squares (LMS) gradient approximation method is used to build the adaptive filter and for this reason it will discussed in details in the next subsection [6, 7, 8, 9, and 10].

Least Mean Squares (Lms) Gradient **Approximation Method**

Given an adaptive filter with an input x(n), an impulse response w(n) and an output v(n) you will get a mathematical relation for the transfer function of the system:

$$y(n) = \mathbf{w}^{\mathrm{T}}(n)\mathbf{x}(n) \tag{1}$$
 and

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$$\mathbf{x}(n) = [\mathbf{x}(n), \mathbf{x}(n-1), \mathbf{x}(n-2), \dots, \mathbf{x}(n-(N-1))]$$
 (2)

Where: $\mathbf{w}^{T}(n) = [w_0(n), w_1(n), w_2(n)]$ $w_{N-1}(n)$] are the time domain coefficients for an N^{th} order FIR filter.

Using an estimate of the ideal cost function the following equation can be derived.

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu \Delta_{E[e]}^{2}(n)$$
(3)

In the above equation w(n+1)represents the new coefficient values for the next time interval, μ is a scaling factor, and $\Delta_{E[e]}^{2}(n)$ is the ideal cost function with respect to the vector $\mathbf{w}(\mathbf{n})$. From the above formula one can derive the estimate for the ideal cost function

 $\boldsymbol{w}(n+1) = \boldsymbol{w}(n) - \mu \boldsymbol{e}(n)\boldsymbol{x}(n) \quad (4)$ Where

$$e(n)=d(n)-y(n)$$
 (5)

and

 $y(n) = \mathbf{x}^{T}(n)\mathbf{w}(n)$

(6)In summary, in the Least Mean Squares Gradient Approximation Method, often referred to as the Method of Steepest Descent, a guess based on the current filter coefficients is made, and the gradient vector, the derivative of the MSE with respect to the filter coefficients, is calculated from the guess. Then a second guess is made at the tap-weight vector by making a change in the present guess in a direction opposite to the gradient vector.

This process is repeated until the derivative of the MSE is zero [11, 12, 13, 14, and 15].

Software Implementation And Testing For Single Stage Adaptive Filter

In this section, a computer program is implemented to remove noise (0.5 Hz baseline wander) from ECG signal using single stage adaptive filter. Then the implemented computer program is tested for many conditions and from the results many points are concluded.

Software Implementation For Single Stage Adaptive Filter

The flowchart of the implemented software for this part is shown in Figure (7).

This software (computer program) is implemented by using the Matlab package programming language.

Software Testing For Single Stage Adaptive Filter

The implementd software is tested for the following parameters:

- 1. The sampling frequency = 1000 Hz.
- 2. The heart beat per minute = 72.
- 3. The ECG duration = 1.5 sec.
- 4. The ECG amplitude = $1000 \mu V$.
- 5. Different noise levels are considered $(10, 30, 80, \text{ and } 100\mu V)$.
- 6. Different values for the convergence factor are considered (0.0001, 0.00001, 0.000001, 0.0000001, 0.0000001, 0.00000001).
- 7. Different values for filter length are used (20 and 40).

The results for the above parameters are shown in Table (1). The results from program execution for the case when noise level = $80 \mu V$, filter length = 40, and convergence factor = 0.000000001 are shown in Figure (8).

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From Table (1), the following points are

concluded:

- 1. The adaptive algorithm was convergent for large values of the convergence factor. The reason of this behavior is that the frequency of the noise (0.5 Hz) is so close to the frequency of the ECG signal.
- 2. Increasing the length of the adaptive filter improves the performance.
- 3. Increasing the noise levels degrades the performance.

Software Implementation And Testing For Multistage Adaptive Filter

In this section, a computer program is implemented to remove noise (0.5 Hz baseline wander) from ECG signal using multistage adaptive filter. Then the implemented computer program is tested for many conditions and from the results many points are concluded.

Software Implementation For Multistage Adaptive Filter

The flowchart of the implemented software for this part is shown in Figure (9).

This software (computer program) is implemented by using the Matlab package programming language.

Software Testing For Multistage Adaptive Filter

The implementd software is tested for the following parameters:

- 1. The sampling frequency = 1000 Hz.
- 2. The heart beat per minute = 72.
- 3. The ECG duration = 1.5 sec.
- 4. The ECG amplitude = $1000 \mu V$.

- 5. Different noise levels are considered (20, 35, 50, and 80μ V).
- 6. The convergence factor = 0.000000001).
- 7. Filter length = 40.
- 8. Number of stages is from 1 to 5.

The above parameters are used for both single stage and multistage adaptive filters. Then the Mean Squared Error (MSE) is calculated in Table (2). The results from program execution for the case when noise level = 35μ V, filter length = 40, and convergence factor = 0.000000001 are shown in Figure (10). From testing results (Table (2)), it is clear that multistage filter gives better results than single stage filter for all cases.

Conclusions

The following points are concluded from this work:

- 1. Increasing of noise levels degrades the performance of single stage adaptive filter.
- 2. The adaptive algorithm is convergent when the convergence factor values are decreased up to 0.000000001. Then it diverges for higher convergence factor values.
- 3. The performance of single stage adaptive filter is improved with increasing of the filter length. This is because that increasing the filter length will increase the convergence rate.
- 4. The multistage filter gives better results than single stage filter for all cases.

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Table (1) Testing results for single stage adaptive filter for the following noise levels: (a) Noise level = 10 micro volts. (b) Noise level = 30 micro volts. (c) Noise level = 80 micro volts. (d) Noise level = 100 micro volts.

filter length factor factor 0.0001	20	40		
0.0001	The algorithm diverge	The algorithm diverge		
0.00001	The algorithm diverge	The algorithm diverge		
0.000001	The algorithm diverge	The algorithm diverge		
0.0000001	The algorithm diverge	The algorithm diverge		
0.00000001	The algorithm Coverage With noise removal	The algorithm Coverage With noise removal		
0.000000001	The algorithm Coverage With noise removal	The algorithm Coverage With noise removal		
	(a)			
filter GU length Hactor 0.0001	20	40		
0.0001	The algorithm diverge	The algorithm diverge		
0.00001	01 The algorithm The al diverge div			
0.000001	The algorithm diverge	The algorithm diverge		
0.0000001	The algorithm diverge	The algorithm diverge		
0.00000001	The algorithm Coverage With noise removal	The algorithm Coverage With noise removal		
0.000000001	The algorithm Coverage With noise removal	The algorithm Coverage With noise removal		
(b)				

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filter length Factor and the second	20	40		
0.0001	The algorithm diverge	The algorithm diverge		
0.00001	The algorithm diverge	The algorithm diverge		
0.000001	The algorithm diverge	The algorithm diverge		
0.0000001	The algorithm diverge	The algorithm diverge		
0.00000001	The algorithm diverge	The algorithm diverge		
0.000000001	The algorithm Coverage With noise removal	The algorithm Coverage With noise removal (better than20)		
(c)				

(\mathbf{C})				
filter Outength Factor	20	40		
0.0001	The algorithm diverge	The algorithm diverge		
0.00001 The algorithm diverge		The algorithm diverge		
0.000001 The algorithm diverge		The algorithm diverge		
0.0000001	The algorithm diverge	The algorithm diverge		
0.00000001	The algorithm diverge	The algorithm diverge		
0.000000001	The algorithm Coverage With noise removal	The algorithm Coverage With noise removal (better than20)		

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number of stages noise level	Single stage adaptive filter	2	3	4	5
20	$MSE = 1.65 \times 10^{-4}$	MSE = 1.98 ×10 ⁻⁶	MSE = 1.87 ×10 ⁻⁶	MSE = 1.77×10 ⁻⁶	MSE = 1.67×10 ⁻⁶
35	$MSE = 4.02 \times 10^{-4}$	MSE = 2.37×10 ⁻⁵	MSE = 1.99×10 ⁻⁵	MSE = 1.68 ×10 ⁻⁵	MSE = 1.42×10 ⁻⁵
50	MSE = 6.16 ×10 ⁻⁴	$MSE = 1.03 \times 10^{-4}$	$MSE = 7.35 \times 10^{-5}$	MSE = 5.27×10 ⁻⁵	MSE = 3.87 ×10 ⁻⁵
80	$MSE = 8.3 \times 10^{-4}$	$MSE = 4.96 \times 10^{-4}$	MSE = 2.36×10^{-4}	MSE = 1.39 ×10 ⁻⁴	MSE = 1.07 ×10 ⁻⁴

Table (2) Testing results for multistage adaptive filter for different noise levels

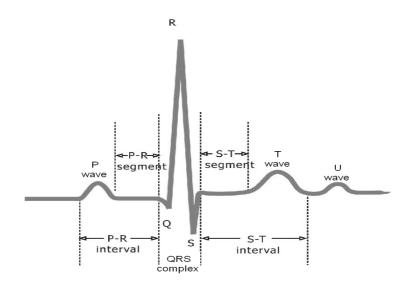


Figure (1) Typical ECG period.



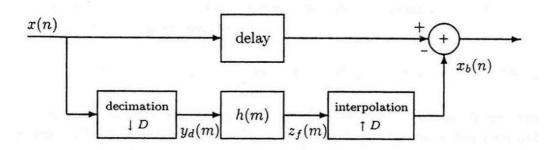


Figure (2) Decimation and Interpolation to remove baseline wander.

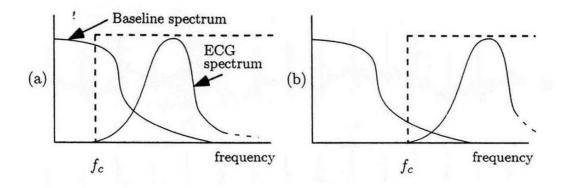


Figure (3) Schematic example of baseline noise and the ECG Spectrum at a (a) Lower heart rate, and (b) Higher heart rate.

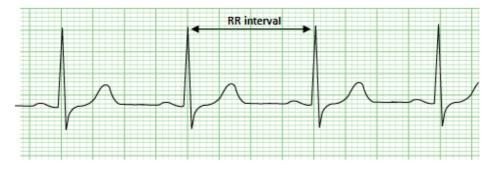


Figure (4) Illustration of the RR interval.

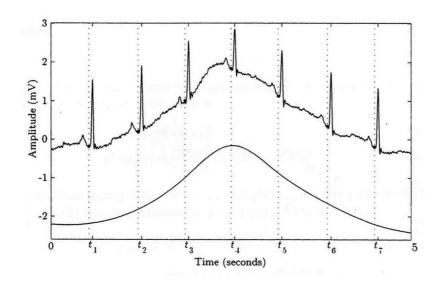


Figure (5) Fitting polynomials to the PQ interval.

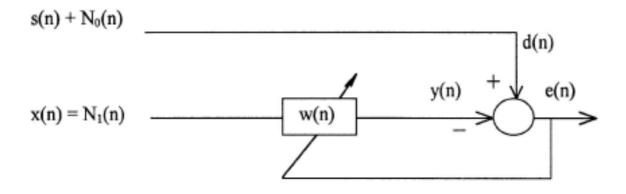


Figure (6) Adaptive Noise Cancellation Configuration.

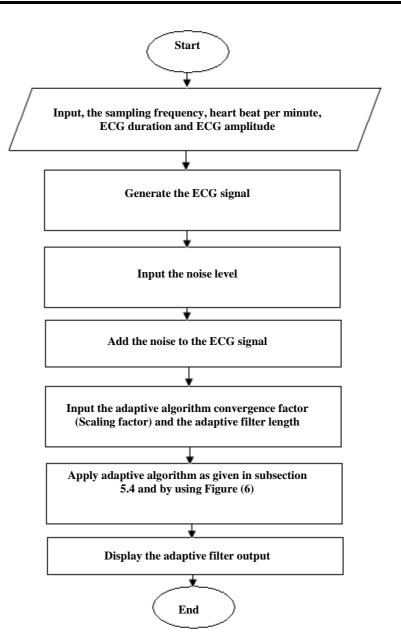
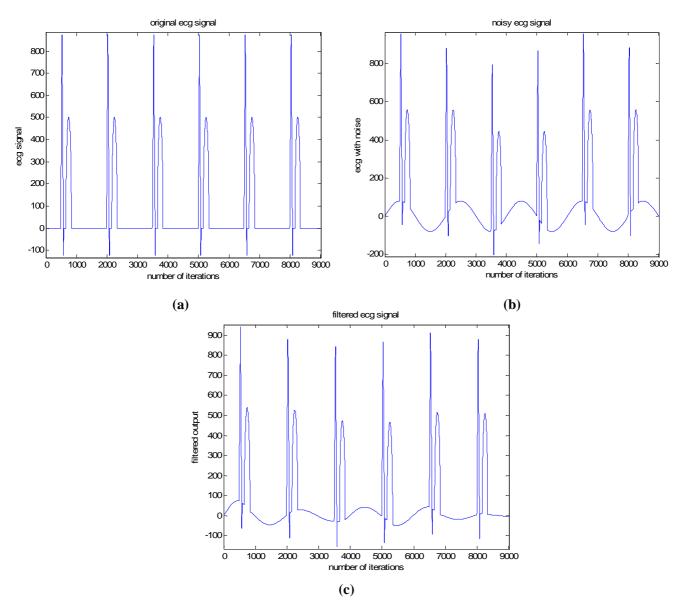
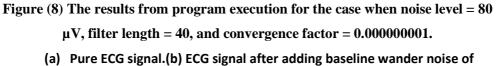


Figure (7) The flowchart of single stage adaptive filter.

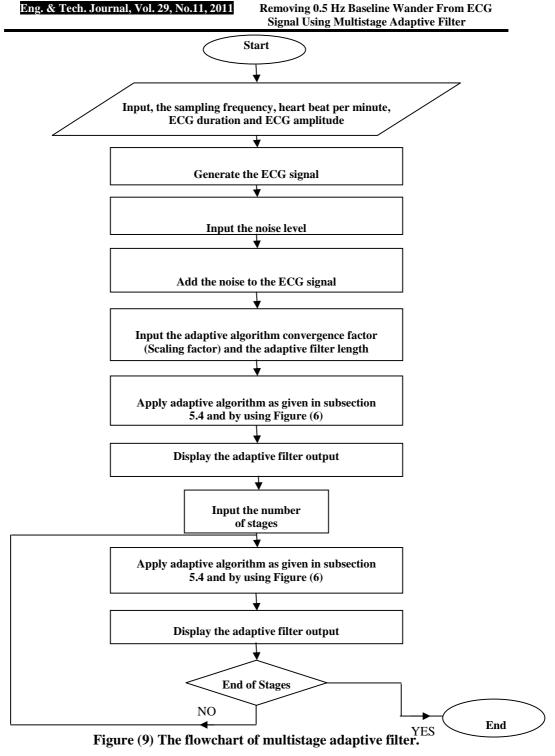


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amplitude = 80 μ V.(c) Filtered ECG signal.



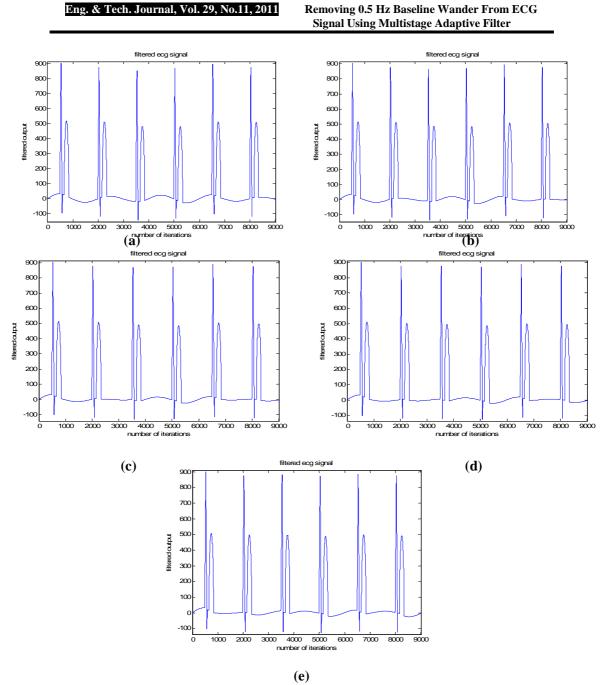


Figure (10) The results from program execution for the case when noise level = 35 μ V, filter length = 40, and convergence factor = 0.000000001 and the numberfstages is from 1 to 5.