ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

Buse BOZOK

TREND REMOVAL OF ECG SIGNAL WITH LMS ALGORITHM

DEPARTMENT OF ELECTRICAL AND ELECTRONICS
ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on 12/05/2020.

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ABSTRACT

MSc. THESIS

TREND REMOVAL OF ECG SIGNAL WITH LMS ALGORITM

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In this study, the LMS algorithm was applied to detect and track baseline introduced by involuntary movements during the acquisition of electrocardiogram signals, skin mismatch with electrode, or any movement caused by breathing or breathing of the patient (baseline wander). The baseline wander was removed from the signal and corrected. For this purpose, the baseline signal was described using two models: a varying constant and a line with a varying slope and constant. The latter is not found in the literature and is the contribution of this study. A fixed length window moved along the signal and the model parameters corresponding to the each segment were computed. The constant directly provided the baseline and the end of line of each window plotted the baseline wander. The results were reported by applying this approach to a simulated electrocardiogram signal and a real signal received from MIH-BIH database records. The outcome shows that modelling signal segment with a line adopts to the baseline faster than the constant model.

Key Words: LMS algorithm; ECG; baseline signal suppression; adaptive filter.

ÖZ

YÜKSEK LİSANS TEZİ

EKG İŞARETİNİN TABAN SEVİYESİNİN LMS ALGORİTMASI İLE DÜZELTİLMESİ

Buse BOZOK

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
ELEKTRİK-ELEKTRONİK MÜHENDİSLİĞİ BÖLÜMÜ

Danışman : Doç. Dr. Sami ARICA
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Bu çalışmada elektrokardiyogram sinyallerinin alınması esnasında istemsiz hareketlerden, elektrot ile cilt uyumsuzluğu veya hastanın nefes alıp vermesinden kaynaklanan herhangi bir hareket yüzünden sinyalin tabanında oluşan kaymalar LMS algoritması ile takip edilmiş ve tespit edilmiştir. Taban kayması işaretten çıkarılarak düzeltilmiştir. Bu amaçla taban işareti sabit ve doğrusal olarak iki şekilde modellenmiştir. İkinci model literatürde bulunmaz ve bu çalışmaya katkıda bulunmuştur. Sinyal boyunca sabit uzunluktakı bir pencere hareket etti ve her bir bölüme karşılık gelen model parametreleri hesaplanmıştır. Sabit model taban kaymasını doğrudan destekledi ve her pencerenin satır sonunda taban çizgisini çizdi. Bu yaklaşım MIH-BIH veri tabanı kayıtlarından alınan işaretlere uygulanmıştır. Sonuçlar gösterdiki doğrusal model sabit modelden daha hızlı uyum sağlamıştır.

Anahtar Kelimeler: LMS algoritması; EKG; taban sinyali bastırma; uyarlamalı süzgeç.

EXTENDED ABSTRACT

Today, the most of the sudden death events are caused by heart diseases. That ECG signals can be accurately monitored have an important role in treatment ways and early diagnosis by the physiological and heart beat disorder. Therefore, electrocardiography devices have been developed for monitoring ECG signals. The electrical signals produce by the heart are sensored by the electrode which are replace in the body by means of electrocardiography functioned and monitored in the device and make it capable of recording.

ECG is at the micro and mili levels, and consist of noise and base shift. The base of electrocardiogram (ECG) signal may shift due to electrode resistance, skin contact, movement, etc. Therefore, it hinders R peak detection and correctly estimate the variation of heart rate. Thus, base signal should be excluded from ECG.

ECG signal are not stable like many other medical signal. It is not effective method to remove baseline wander with stable filters. However, some filters which are suitable for the changeable functions in time can be used. By this method, ECG signal determine baseline wander, is removed from signal with slope algorithms. Slope algorithm as the advantages of less operations load, are preferred in the speed of high convergence and mostly in adaptive signal processing and communication applications. These are LMS, NLMS and AP (Affine Projection). That's why we used LMS algorithm in this study is that high convergence despite of higher processing load is much better than slope algorithm.

In this study baseline signals are removed from the signal by using LMS algorithm. A window of the signal was modelled as constant traditionally and as a line. The window was shifted by unit sample and the parameters of the model was adopted. In case of line approximation, the tip of the line sketched the baseline. Matlab program is used for these processes.

In the comparison, initially a trend removal operation is processed by using

a constant polynomial on a synthetic signal. Secondly, trend removal operation is processed by using a first rank polynomial sampled from the ECG signals of a diseased individual in MIH-BIH database.

Some studies are carried on the data from person 1 from Physio.net website 'ecgiddb/Person_01/rec_1', 1'. All the diagrams are released in the part of results/outcomes. As in the graphics, linear method is successful in capturing a trend.

The tracking of the baseline signal will be carried out by utilizing the current value of the ECG signal. The linear (consist of two-variables) baseline model is the contribution of this study to the existing studies.

As the result of this study, we are able to reduce to the lowest level of baseline wander which is an appearing noise while monitoring the ECG device and this may be utilized in clinical diagnosis of heart diseases.

ACKNOWLEDGEMENTS

I would like to express thank to our supervisor Assoc. Prof. Dr. Sami ARICA for all of his supports, suggestions, patience and encouragement this study. I would like to also extend my deep appreciation to my parents for their love, moral and support.

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LIST OF ABBREVIATIONS

ECG	: Electrocardiogram
LMS	: Least mean square
NLMS	: Normalized LMS

1. INTRODUCTION

Medical signals are generally low-intensity signals at the micro and mili levels, and consist of noise and base shift. Base shift masks the rich physiological information contained in the noisy medical signal and prevents its occurrence. The base of electrocardiogram (ECG) signal may shift due to electrode resistance, skin contact, movement, etc. Therefore, it hinders R peak detection and correctly estimate the variation of heart rate. Thus, base signal should be excluded from ECG.

There are so many methods to stop the baseline signal. These methods are grouped as non-causal and causal methods. In non-causal techniques, the calculations are made over the entire signal and these methods are not proper for real-time practices. On the other hand, least mean square (LMS), recursive least squares (RLS), and Kalman adaptive filter/algorithm are causal techniques which are also utilized to remove baseline signal. In these approaches, mainly, the baseline signal is expressed as a constant and adapted or changed over time (varying with time) regarding the signal. These approaches can be used in real-time applications.

ECG signal is not stationary as well as many other medical signals, it changes its characteristic over time. Therefore, the removal of baseline signal does not give successful result for the entire signal with constant coefficient filters. Thus, filters whose coefficients are adapted to suit the time-varying properties of the signal should be used. LMS is the easiest and well-known adaptive filtering algorithm. In this study, the baseline of the ECG signal will be determined with LMS algorithm and removed from the signal. To achieve this aim, the base signal in the present time will be modeled in two different ways as constant and linear. The tracking of the baseline signal will be carried out by utilizing the current value of the ECG signal. The linear (consist of two-variables) baseline model is the contribution of this study to the existing studies.

Electrocardiogram (ECG) device is important in the diagnosis of many hearts proliferating, such as rapid heartbeat or slow heartbeat. The amplitude, duration and frequency of the signal provide information about the physiology of the heart. In this thesis the baseline of an ECG signal was detected and removed by using two approaches: a constant and line. The results were reported by applying this approach to the signals received from MIH-BIH database records.

1.1. ECG (Electrocardiogram)

The electrocardiogram can be defined as the measurement of the heart's electrical activity over time on the skin surface. In ECG measurements, it is recorded or displayed by the medical device with the help of electrodes. ECG has become a routine part of medical evaluation. The ECG detects the transmission of ions through the heart muscle, which differs by heartbeat. Doctors use ECG to detect conditions such as abnormal heart rhythms and heartbeats.

The ECG signal may be distorted by various noises. Known basic noise (artifacts) are as follows: network noise (power-line interference); Electrode contact noise, Motion artifacts, Muscle contraction; Baseline drift; Electronic signal processing devices, Electrocautery noise.

The purpose of this thesis is to investigate techniques and methods to identify ECG signals and eliminate distortion in these signals.

1.2. Baseline wander

Since the goal of the study removal of baseline wander, which a type of ECG artifact, this section is devoted to the baseline wander and it is discussed in more details. The baseline wander via respiration can be explained by the interference of the sinusoidal component in the respiratory frequency with the ECG signal. Figure 1.1 shows the baseline wander. The frequency and amplitude of the sinusoidal component must be nonstable. In addition, the amplitude of the ECG signal changes by 15% with respiration. This change is regenerated by implementing amplitude modulation between the sinusoidal component added to the baseline and ECG. Parameters related to this signal:

Amplitude change: 15% of peak - peak value of ECG amplitude.

Baseline change: 15% of the peak – peak value of ECG amplitude between 0.15-0.3Hz.

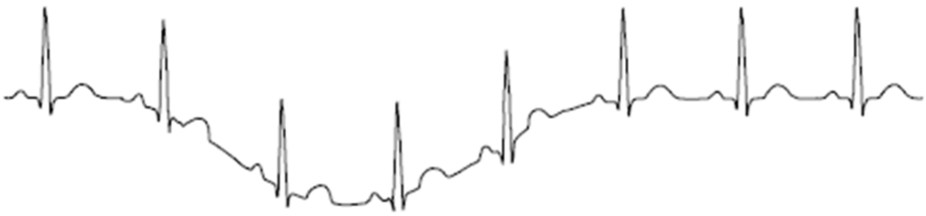

Figure 1.1. Baseline wander (Möngü, 2003)

In this thesis, all parameters were calculated for the ECG data obtained from MIH-BIH database using Matlab V5.3 program. Noises interfering with ECG signal were examined before calculation of parameters. Accordingly, the known basic noise; network noise (power-line interference), electrode contact noise, motion artifacts, muscle contraction, baseline wander, electronic signal processing devices, and electrocautery noise. The reasons for the occurrence of these noises are explained, frequency and amplitude components are given and the degree to which they can distort the ECG signal is emphasized. These noises are largely removed by the filters used during the QRS detection process. However, since ECG parameters are based on amplitude and time analysis, correction of baseline wander is of particular importance. The curve should be placed on the base by removing this noise in order to calculate these parameters correctly. To achieve this aim, LMS algorithm was used.

Baseline wander (BW) is a low frequency signal in a patient's electrocardiogram (ECG) signal recordings. Removing BW is an important step in processing ECG signals because BW makes it difficult to interpret ECG recordings. The main cause of BW in the ECG signal is the patient's movement and breathing.

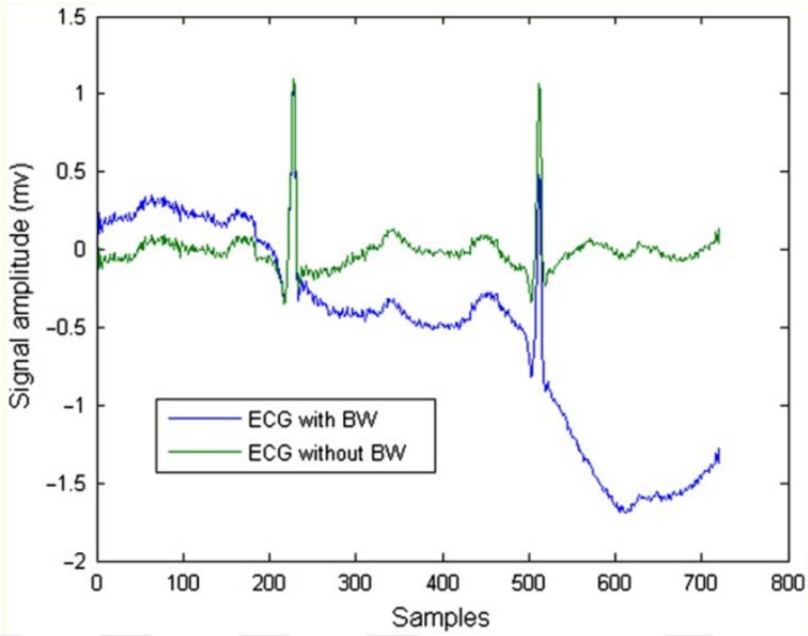

Figure 1.2. Sample of baseline wander (Gupta, Sharma and Joshi, 2015)

1.3. Adaptive filters

Adaptive filters are filters that can automatically adjust, change the filter coefficients according to some coefficients and allow the filter to adapt the changes on the input signal. Due to their performance, they can be used in many different applications such as signal processing, noise canceling and biomedical signal enhancement. Any noise is removed using different techniques and algorithms. (Yadav, 2014)

In an adaptive filter, there are basically two processes:

- To apply filtering process,
- To apply a process algorithm.

We tested the adaptive filter with the LMS algorithm to remove noise types such as baseline wander. Adaptive filter coefficients divided to two groups: slope algorithms and least squares algorithms. These algorithms are used to iteratively adjust the filter parameters as shown in the figure 1.3 below.

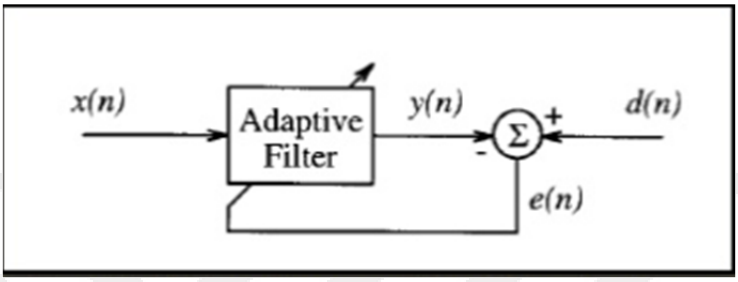

Figure 1.3. Block diagram of the adaptive filter (Al-Rale, 2017)

Here x (n) is the discrete-time input signal of the adaptive filter, y (n) is the output signal calculated using the estimated parameters, and d (n) is the desired signal that the adaptive filter is to follow. Parameter estimation by parameter setting algorithms that minimizes the expected value of the square of the error signal defined as e (n) = d (n) - y (n) between the signal y (n) calculated using the estimated parameters and the signal d (n) to be monitored by the adaptive filter iteratively calculated. (Hatun and Koçal, 2005)

Slope algorithms have advantage of low processing and high sampling rates and mostly use signal processing and communication applications. These are LMS (Least Mean Squares), NLMS (Normalized LMS), and AP (Affine Projection) algorithms. These algorithms have disadvantage of slow convergence. Least squares algorithms are preferred high convergence rather than slope algorithm. RLS (Recursive Least Squares) algorithm is included in this group. But high sample rates aren't all applications area.

The present study aimed to determine the base signal of the ECG signal in real time and to remove it from the signal with LMS algorithm. To achieve this aim, the base signal will be modeled in two different ways as a constant and a correct one. Tracking of the base signal will be conducted by considering the current value of the read ECG signal. Linear (two-variable) base model is the contribution of this study to the existing studies. (Tiryaki, Hatun and Koçal, 2008)

1.4. Lms algorithm

The LMS algorithm is an estimated version of the step-down method. In order to find the optimum parameters in the step-down method, the direction and magnitude of the next step are determined in the calculation of the next parameter value, starting from the initial value. The direction of the next step is determined by the derivative of the mean square error function. Step-down optimization method which makes mean square error function minimum,

$$w(n+1) = w(n) + \mu[p - Rw(n)] \tag{1.1}$$

is provided. Here μ the step size to be taken in the selected direction, R is the auto-correlation matrix of the input signal of the adaptive filter, and p is the counter-correlation vector between the signal that adaptive filter should follow and the input signal, is defined as respectively;

$$R = E[X(n)X^T(n)] \tag{1.2}$$

$$p = E[X(n)d(n)] \tag{1.3}$$

Here E is the expected value operator. The length of the adaptive filter is M, adaptive FIR (Finite Impulse Response) filter input signal x(n) and coefficient vector w(n), is defined as;

$$X^T(n) = [x(n)\; x(n-1) \ldots\ldots x(n-M+1)] \tag{1.4}$$

$$w^T(n) = [w_1(n)w_2(n) \dots \dots w_m(n)] \tag{1.5}$$

The estimated value is used since the exact value of the correlation coefficient R and the correlation vector p is unknown in practice. In step-down optimization algorithm, the instantaneous estimations of R and p matrices,

$$R(n) \triangleq [X(n)X^T(n)] \tag{1.6}$$

$$p(n) \triangleq [X(n)d(n)] \tag{1.7}$$

the following algorithm obtained using the form is known as the LMS algorithm.

$$w(n+1) = w(n) + \mu x(n)e(n) \tag{1.8}$$

The key advantage of LMS algorithm is to perform multiplication (2M+1) while implementing the algorithm. μ step parameter which enables to converge the estimates of LMS algorithm to optimum parameter values steadily,

$$0 < \mu < 2/\lambda_{\max}$$

Here as the values of R and p are instantaneous estimated values, the algorithm seems to be unable to perform well at first glance. However, the algorithm is inherently self-adaptive, and it takes these estimates to moderate during the adaptation, which improves the performance. The processes described for finding the LMS presented here may in fact be seen as a different approach to the steepest decreasing method. Unlike the steepest decreasing method, the correlation matrix R of the tap input vector and the cross-correlation vector p between the tap input vector and the desired response are calculated from the instantaneous estimates.

There are considerations in real-time implementations. An algorithm which can perform well in the computer environment may experience loss of performance due to the limitations in equipment in real time. While implementing, as an alternative to LMS for adaptive filters, adaptive filters such as RLS (Recursive Least Squares) can be considered and RLS is generally referred to when comparing with adaptive filters. The RLS can be faster and better than LMS in achieving Wiener solution; however, LMS is more preferred in practice. RLS is more difficult in implementation. The reason behind this, the LMS has a simpler structure, less processing load, and rounding and bit length errors affect performance more in RLS. RLS may reach LMS with a number of structural additions; however, the stability in the LMS is better. When these additions are made, a number of assumptions are also made, and these assumptions disrupt the structure of the self-adaptive filter by including statistical knowledge. When statistical knowledge is used, filters such as RLS in time-varying systems cannot follow the minimum error curve as successfully as LMS. (Hassibi, 2003)

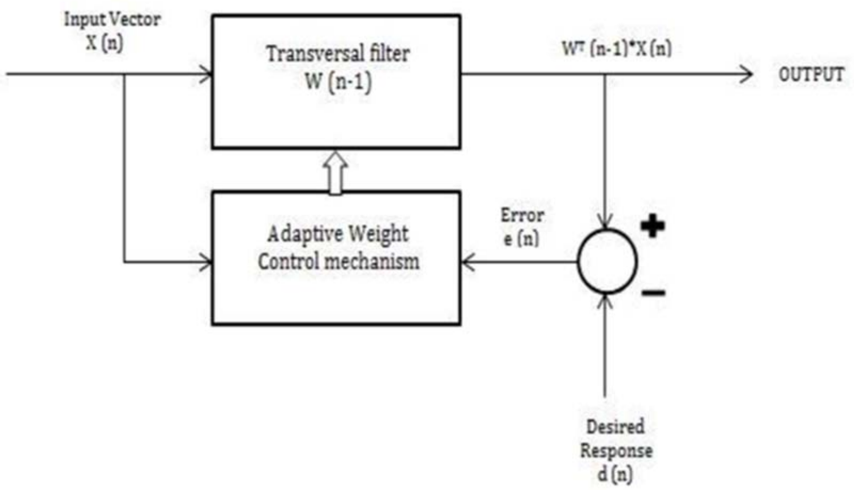

Figure 1.4. Block diagram of lms algorithm (Kundu and Jain, 2013)

2. PREVIOUS STUDIES

The initial correct samples of EKG signals were recorded in the early 20th century. Some studies were carried out for reducing the noises in ECG device by using various logarithm and techniques. These are the following ones:

Kaur and his friends (Kaur, R. Kaur and Singh, 2016) argued various logarithms in order to eliminate the noise in ECG signals and found out that the rate of signal/noise was highly amelıorated by using a normalized least mean square (NLMS) logarithms in proportion to the other ones.

Abbas (Abbas, 2011) endeavoured to minimalize the noise of ECG signal using single stage logarithm and multiple stage logarithm he got various outcomes and proposed that multiple stage filtration has better results than single stage filtration.

Saxena and his friends (Saxena, Upadhyaya, Gupta and Sharma, 2018) found out that NLMS logarithm have successfully reduced the noise on both stable and unstable signals.

Kaur and his friends (Kaur, Seema and Singh, 2011) realized that EKG band form went highly wrong when they first applied conventional IIR and FIR-High pass filter in order to eliminate the baseline dislocation. On the purpose of managing this effect, a digital filtration within zero phase was used and they pointed that this gives better outcomes.

Saxena and his friends (Saxena, Murarka and Gupta, 2017) compared LMS wşth NLMS and concluded that sensitivity went up with increased filters and increasing length of lay in convergence speed appeared rapidly. Within the same parameters, they argued that NLMS logaritmas gave better outcomes than LMS did.

Maniruzzaman and his friends (Maniruzzaman, Billah, Biswas and Gain, 2012) determined that it is successful to destroy the disarrengement in the ecg signals of 50 Hz power line by using NLMS logaritmas.

Sharma and Sidhu (Sharma and Sidhu, 2016) reveals that time zone analysis properly extinguishes 50 Hz power line parasite of NLMS logarithms, baseline circulation and muscle contraction noise. İn this way, they concluded the results that applicable NLMS logarithms which is based upon noise cancellation is an effective technique to get the optimum filtration by removing 50 Hz BW from LMS filtration technique.

Rahman and his friends (Rahman, Shaik and Reddy, 2009) suggested regresör LMS (NSRLMS) logarithm to be able to remove the noise from ecg signal. İt has a better filtration capability due to normalized term. It is obvious that NSRLMS can effectively remove nonstationary noise in the simulated results.

Biswas and his friends (Biswas, Anupdas, Debnath and Oishee, 2015), In order to remove the noises LMS and NLMS are employed two applicable filter. To have a better explanation, it is totally compared in point of various performing parameters like PSD, spektrogram, frequency specturum and convergence. It is stated that The analysis of ecg signal has accordingly decreased noisy ecg signal filtered signal; White noise, colorful noise, muscle artefact noise, elektrode motion noise, baseline circulation noise, komposite noise and power line parazite in both noisy ecg signal and filtered signal.

In this thesis similar to the studies described above we implemented LMS algorithm to remove the noise and baseline wander from a noisy ECG signal. In the all of the above studies baseline wander was approximated as a DC component varying (adapting) in time. Beside this commonly used LMS technique we considered a window with a fixed length moving along ECG baseline of the signal segment in this window was modelled a line. The window shifted one sample every time increment and this process was repeated. The end of the line followed the baseline. This approach makes adaptation faster than the custom method.

3. MATERIAL AND METHOD

3.1. Material

A synthetic noisy ECG signal was generated for testing and next a real ECG signal obtained from the MIH-BIH database was used for investigating the approach.

The MATLAB technical programing platform was preferred because of its rapid and extensive content in biomedical signal processing.

3.2. Method

ECG signal is not stationary as well as many other medical signals, it changes its characteristic over time. Therefore, the removal of baseline signal does not give successful result for the entire signal with constant coefficient filters. Thus, filters whose coefficients are adapted to suit the time-varying properties of the signal should be used. LMS is the easiest and well-known adaptive filtering algorithm. In this study, the baseline of the ECG signal will be determined with LMS algorithm and removed from the signal. To achieve this aim, the base signal in the present time will be modeled in two different ways as constant and linear. The tracking of the baseline signal will be carried out by utilizing the current value of the ECG signal. The linear (consist of two-variables) baseline model is the contribution of this study to the existing studies.

Traditional approach is as follows: Suppose that $d(n)$ is ECG signal, $a(n)$ is filter output (the baseline signal): In this case, the algorithm is:

$$e(n) = d(n) - a(n) \tag{3.1}$$

$$a(n+1) = a(n) + \mu e(n) \tag{3.2}$$

This is classical approach. An alternative method is proposed in this study. In this second model, the baseline signal is expressed as a time-varying line: $a(n) + m \cdot b(n)$. The LMS algorithm for this model takes the following form:

$$e(n) = d(n) - a(n) - m \cdot b(n) \tag{3.3}$$

$$a(n+1) = a(n) + \mu e(n) \tag{3.4}$$

$$b(n+1) = b(n) + \mu e(n) \cdot m \tag{3.5}$$

Here, the baseline signal is represented by $a(n) + \left(t - \frac{n}{F_s} + m\right) \cdot b(n)$ line in the time interval of $\left[\frac{n}{F_s} - m, \frac{n}{F_s}\right]$. Here, F_s is the sampling rate.

3.3. Convergence analysis

In this section convergence of the trend estimation with the proposed LMS approach is presented. For this purpose set

$$\underline{w}(n+1) = [a(n+1),\ b(n+1)]^T\ , \tag{3.6}$$

$$\underline{v} = [1,\ m]^T\ , \tag{3.7}$$

where T denotes transposition operator. Notice that in case of classical approach

$$\underline{w}(n+1) = a(n+1)\ , \tag{3.8}$$

$$\underline{v} = 1\ . \tag{3.9}$$

The coefficient update equation then is written as

$$\begin{aligned} \underline{w}(n+1) &= \underline{w}(n) + \mu\underline{v}e(n) & (3.10) \\ &= \underline{w}(n) + \mu\underline{v} \cdot \left[d(n) - \underline{v}^T\underline{w}(n)\right]. & (3.11) \end{aligned}$$

Now, compute difference of coefficient vector. This difference is expected to vanish while n increases if the algorithm is convergent.

$$\begin{aligned} \underline{w}(n) &= \underline{w}(n-1) + \mu\underline{v} \cdot \left[d(n-1) - \underline{v}^T\underline{w}(n-1)\right] & (3.12) \\ \underline{w}(n+1) - \underline{w}(n) &= \underline{w}(n) - \underline{w}(n-1) + & (3.13) \\ & \quad \mu\underline{v} \cdot \left[d(n) - d(n-1) - \underline{v}^T\left(\underline{w}(n) - \underline{w}(n-1)\right)\right]. \end{aligned}$$

Letting $\Delta\underline{w}(n+1) = \underline{w}(n+1) - \underline{w}(n)$, and assuming $d(n) \approx d(n-1)$, we have

$$\begin{aligned} \Delta\underline{w}(n+1) &= \Delta\underline{w}(n) - \mu\underline{v}\underline{v}^T\Delta\underline{w}(n) & (3.14) \\ &= \left[I - \mu\underline{v}\underline{v}^T\right]\Delta\underline{w}(n), & (3.15) \end{aligned}$$

where *I* is a *2x2* identity matrix. The above equation can be revised as in the following using it's iterative characteristic by accepting that iteration start from $n = 0$.

$$\Delta\underline{w}(n+1) = \left[I - \mu\underline{v}\underline{v}^T\right]^{n+1}\Delta\underline{w}(0). \qquad (3.16)$$

We need to focus on the term $\underline{vv^T}$. In case of custom method

$$\begin{aligned} \underline{vv^T} &= 1, & (3.17) \\ I - \mu\underline{vv^T} &= 1 - \mu. & (3.18) \end{aligned}$$

To ensure convergence, or in other words to get $\Delta \underline{w}(n)$ vanishing as $n \to \infty$, we should have $-1 < 1 - \mu < 1$. This condition yields $0 < \mu < 2$. Now, let us switch to the proposed technique. Then

$$\underline{v}\underline{v}^T = \begin{bmatrix} 1 & m \\ m & m^2 \end{bmatrix}, \tag{3.19}$$

$$I - \mu \underline{v}\underline{v}^T = \begin{bmatrix} 1-\mu & -\mu m \\ -\mu m & 1-\mu m^2 \end{bmatrix}. \quad (3.20$$

The rank of matrix $\underline{v}\underline{v}^T$ is one, which is less than its row or column size. The Eigen-value decomposition of this matrix as follows.

$$\underline{v}\underline{v}^T = \frac{1}{\sqrt{1+m^2}} \begin{bmatrix} 1 & m \\ m & -1 \end{bmatrix} . \begin{bmatrix} 1+m^2 & 0 \\ 0 & 0 \end{bmatrix} . \begin{bmatrix} 1 & m \\ m & -1 \end{bmatrix} \frac{1}{\sqrt{1+m^2}} \tag{3.21}$$

The diagonal matrix in the middle of the right side of equation hold Eigen-values along its diagonal. The highest Eigen-value is $1 + m^2$, therefore according to the convergence requirement, the step parameter μ should be kept in the following limits to maintain convergence.

$$0 < \mu < \frac{2}{1+m^2}.$$

In addition to this reasoning let us also obtain the Eigen-value decomposition of matrix $I - \mu \underline{v}\underline{v}^T$:

$$I - \mu \underline{v}\underline{v}^T = \frac{1}{\sqrt{1+m^2}} \begin{bmatrix} 1 & m \\ m & -1 \end{bmatrix} . \begin{bmatrix} 1-\mu \cdot (1+m^2) & 0 \\ 0 & 1 \end{bmatrix} . \begin{bmatrix} 1 & m \\ m & -1 \end{bmatrix} \frac{1}{\sqrt{1+m^2}} \tag{3.22}$$

The diagonal matrix in the center of the right side of the above equation containing Eigen-values in its diagonal. Suppose that the name of this diagonal matrix is D. Then, it is observed that D^n becomes

$$\begin{bmatrix} \left(1-\mu\cdot(1+m^2)\right)^n & 0 \\ 0 & 1 \end{bmatrix} \approx \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \tag{3.23}$$

when n is large and μ is in the range given above. Therefore

$$\left[I-\mu\underline{v}\underline{v}^T\right]^{n+1} \approx \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \tag{3.24}$$

$$\Delta\underline{w}(n+1) \approx \Delta\underline{w}(0)\,. \tag{3.25}$$

That is

$$\Delta a\,(n+1) \approx 0\,, \tag{3.26}$$

$$\Delta b\,(n+1) \approx \Delta b\,(0)\,, \tag{3.27}$$

if n is large enough. From this investigation it can be concluded that the parameter $a\,(n)$ converges to its optimal value and, however $b(n)$ is about $\Delta b\,(0)$ far from the best value. The $\Delta b\,(0)$ is the divergence or change of $b\,(n)$ at initial step. If magnitude of $\Delta b\,(0)$ is not too large, the algorithm can be still interpreted as convergent because $b\,(n)$ is not far from the optimal value.

3.4. The synthetically generated test signal

The two algorithms were tested and experimented on a synthetic signal and then a real ECG signal. The artificial signal is described in this subsection.

A signal resembling an ECG with a known base component was generated as follows. For this purpose, let us choose the original and the baseline shifted signal as in the following;

$$s_1(t) = \begin{cases} \frac{250}{3}\left(e^{-30t} - e^{-31t}\right), & t > 0, \\ 0, & t < 0 \end{cases} \tag{3.28}$$

$$s(t) = \sum_{n=-\infty}^{\infty} s_1(t-n) + 0.25\, sin\left(\frac{\pi t}{10}\right) \tag{3.29}$$

In the above equations $s(t)$ stands for noisy ECG and the term $0.25\, sin\left(\frac{\pi t}{10}\right)$ is the baseline wander. This synthetic signal will be employed for understanding function of the two techniques.

4. RESULTS AND DISCUSSION

Baseline wander noise makes it difficult for ECG data to output correctly. This noise must be cleared for proper analysis and display of the ECG signal. LMS algorithm, one of the adaptive filter algorithms, was used to eliminate this noise. Baseline wander was carried out in two ways constant and linear for noise suppression. To examine the effects of stress on the electrical activity of the heart, the signal must be filtered and monitored simultaneously during real-time processing and visualization. In this study, MATLAB tool was used to design reduced noise electrocardiograms. Synthetic signal is produced and results are shown. It was also compared with the data of the real patient from the MIH-BIH database.

The results obtained with synthetic signal: The peak of $s_1(t)$ is 1. The synthetic signal was sampled at a rate of 500 Hz. Here, the parameter μ was selected as 0.1 for the first model and 0.01 for the second model. The constant m was chosen to be 0.2. The original signal and filter outputs are given in figures 3.1 to 3.4. From these figures and μ values used for two cases, it is observed that the second model adapts more rapid than the first and captures the baseline signal.

The outcomes of the real ECG data: The approaches have been also investigated and tested on the ECG-ID data set of a patient in the MIH-BIH data base contain ECG signal data. For this data sampling rate is $F_s = 500$ Hz. The parameters of the LMS algorithms for this ECG signal have been kept same as for the synthetic signal. The results for both approaches are sketched in figures 3.5 to 3.8. As in the case of synthetic signal it is seen that the second model adapts more rapid than the first and captures the baseline signal.

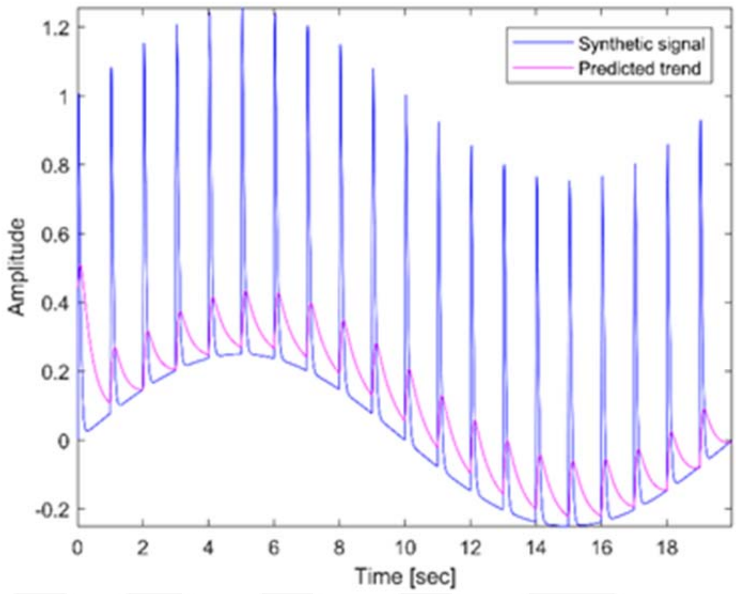

Figure 3.1. Synthetic signal with a trend and estimated trend by using zero-order polynomial model for trend.

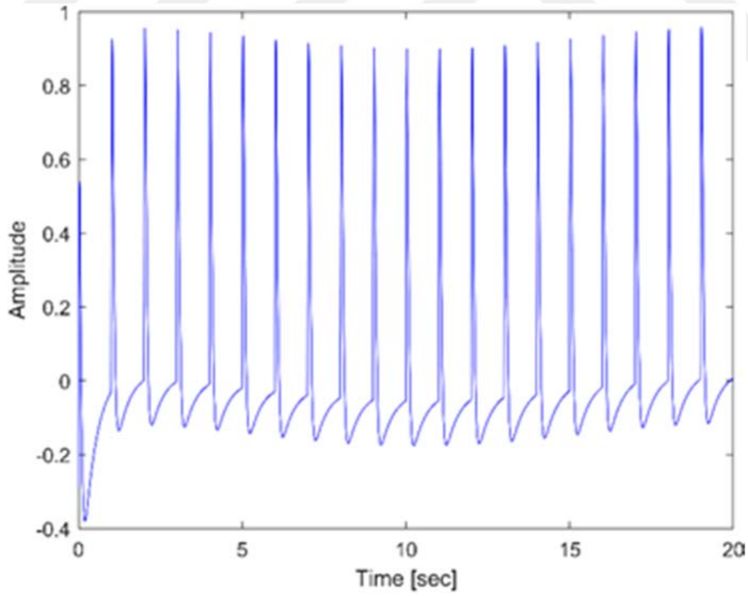

Figure 3.2. De- trended signal obtained by removing estimated base line signal from synyetic signal given in figure 3.1.

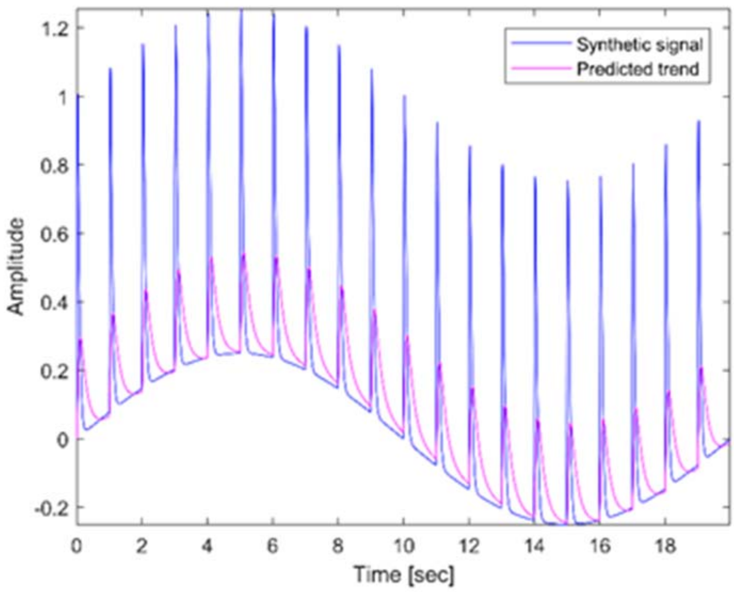

Figure 3.3. Synthetic signal with a trend and estimated trend by using first order polynomial model for trend.

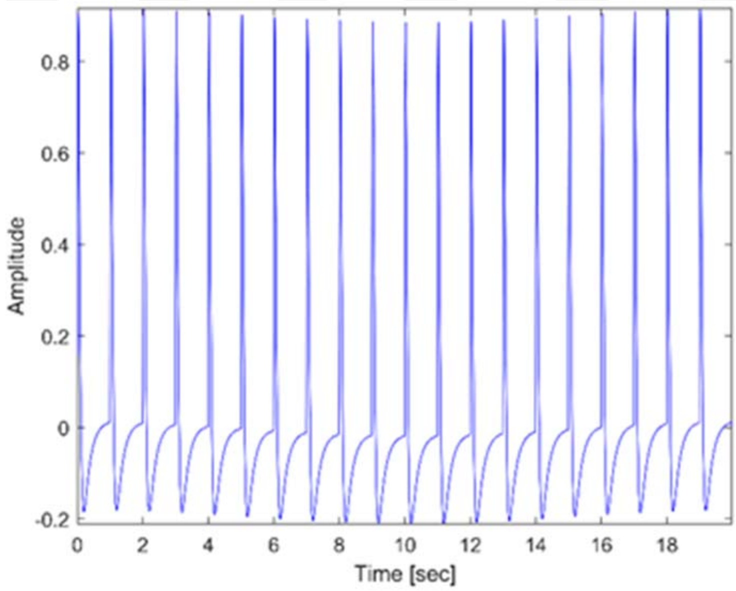

Figure 3.4. De-trended signal obtained by removing estimated baseline signal from synthetic signal given in figure 3.3.

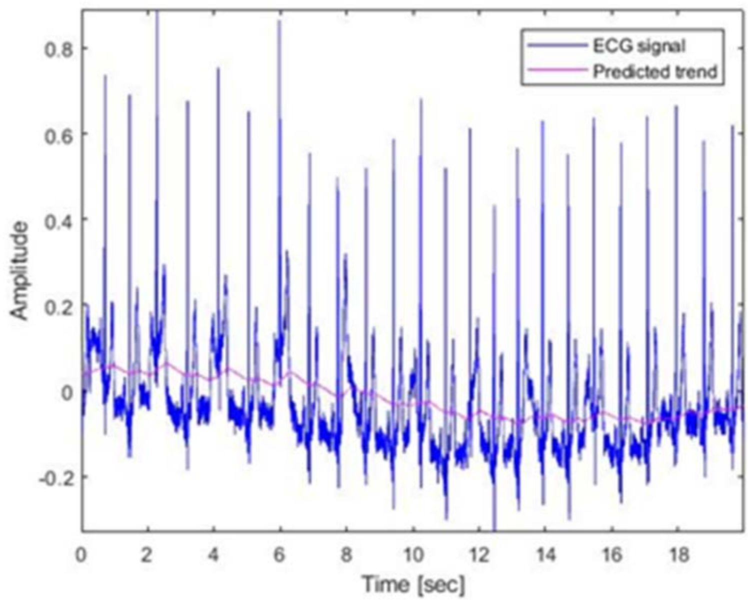

Figure 3.5. Real ECG signal and estimated trend by using zero-order polynomial model for trend.

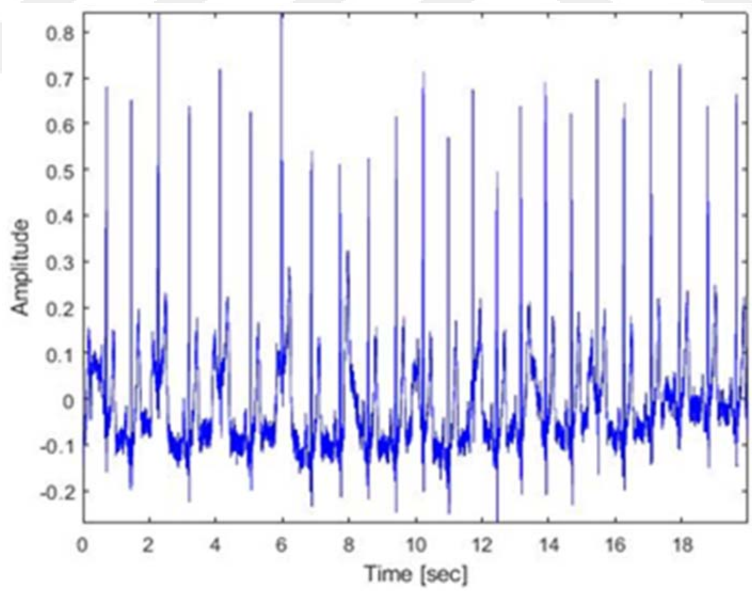

Figure 3.6. De-trended signal obtained by removing estimated baseline signal from ECG signal given in figure 3.5.

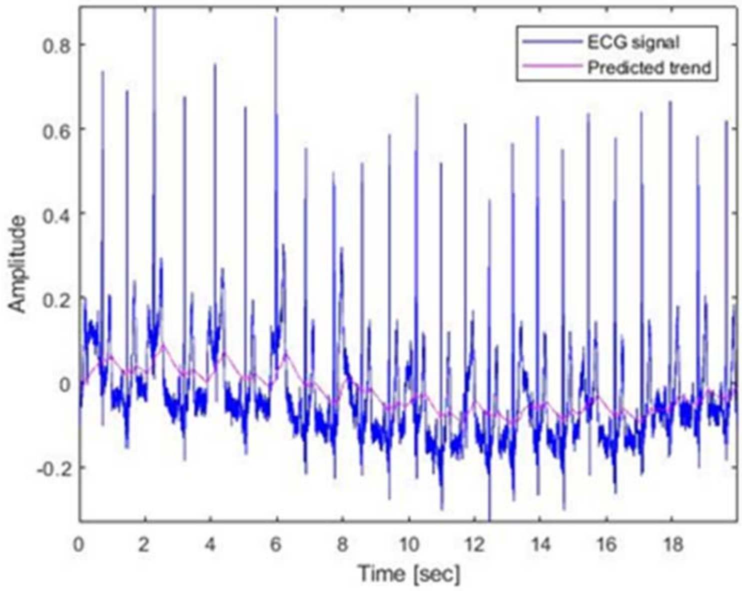

Figure 3.7. Real ECG signal and estimated trend by using first-order polynomial model for trend.

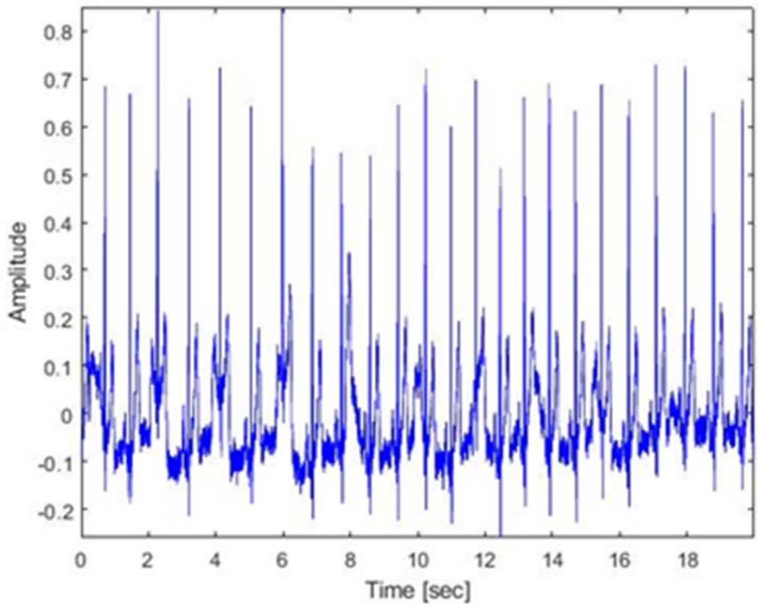

Figure 3.8. De-trended signal obtained by removing estimated baseline signal from ECG signal given in figure 3.7.

5. CONCLUSIONS

Biomedical signals play an important role in the diagnosis of patients. A new structure and algorithm has been proposed for the LMS adaptive filter because the signal can be mixed in various ways with noise over time, depending on the environment and the patient's condition.

Baseline wander is one of the causes of dominant distortion in ECG signals. The adaptive filtering method can be used to remove the circulation of the baseline in ECG signals. Traditional method is easy to apply and calculate but the alternative method applied allows the signal to be captured and thrown faster. In this study, an alternative method was applied outside the traditional method to eliminate baseline wander. In the traditional method, synthetic ECG signals have been tested on synthetic signals. Alternative method has been applied on ecg signals of an individual from the MIH-BIH database.

In this study, the instant value of the baseline signal of an ECG signal has been model as first order polynomial as an alternative to zero order polynomial (dc) which is a the most common approach. The coefficients of the model has been calculated via LMS algorithm and the estimated baseline has been removed from the ECG signal. It is observed that the suggested model can capture and track the base signal and adapt faster than the classical approach. It is concluded that alternatively, a linear model of the instant value of the trend can be used in LMS algorithm to estimate and remove it from an ECG signal or to predict and discard the noise component in an ECG in real time.

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RESUME

Buse Bozok was born in İstanbul in 1993. She received BSc. Degree in Electronics Engineering Department from Toros University, Mersin in 2016. Now she has been working as an Electronics Engineer at company for 2 years.

APPENDIX

APPENDIX- THE ALGORITHMS USED IN THE THESIS WORK

This the algorithm of the study using synthetic signal.

```
% addpath(genpath('F:\mcode'))
% SIGNAL
N = 10000;
n = 0:N - 1;
Fs = 500;
[y, x, trend] = syntecg;
M = 0.2*Fs;
% x: ECG
% trend : trend
% y = EXG + trend
% LMS (fits constant)
% mu = 0.005;
mu = 0.1;
a = zeros(1, N + 1);
e = zeros(1, N + 1);
a(1) = sum(y(1:M)) / M;
for k = 1:N
e(k) = y(k) - a(k);
a(k + 1) = a(k) + mu*e(k);
end
a = a(2:N + 1);
e = e(2:N + 1);
figure(1)
p = plot(n, y, 'b', n, a, 'm'); axistight
figure(2)
```

```
plot(n, e, 'b');
% LMS (fitsline)
mu = 0.01;
m = (M - 1)/Fs;
a = zeros(1, N + 1);
b = zeros(1, N + 1);
e = zeros(1, N + 1);
trnd = zeros(1, N + 1);
for k = 1:N
e(k) = y(k) - a(k) - b(k)*m;
a(k + 1) = a(k) + mu*e(k);
b(k + 1) = b(k) + mu*e(k)*m;
trnd(k + 1) = a(k + 1) + b(k + 1)*m;
end
a = a(2:N + 1);
b = b(2:N + 1);
e = e(2:N + 1);
trnd = trnd(2: N + 1);
disp('a = ');  disp(a);
disp('b = ');  disp(b);
disp('e = ');  disp(e);
figure(3)
plot(n, y, 'b', n, trnd, 'm'); axistight
figure(4)
plot(n, e, 'b'); axistight
```

This the algorithm of the study using real patient from the MIH-BIH database.

```
% addpath(genpath('F:\mcode'))
% SIGNAL
[sig, Fs, tm] = rdsamp ('/ecgiddb/Person_01/rec_1', 1);
N = length(sig);
% M = 0.1*Fs;
% M = 0.5*Fs;
M = 2*Fs; % K*Fs K
if is column(sig)
sig = sig';
end
y = sig;
n = 0:N - 1;
% LMS (fits constant)
% mu = 0.005;
mu = 0.001;
a = zeros(1, N + 1);
e = zeros(1, N + 1);
a(1) = sum(y(1:M)) / M;
for k = 1:N
e(k) = y(k) - a(k);
a(k + 1) = a(k) + mu*e(k);
end
a = a(2:N + 1);
e = e(2:N + 1);
figure(1)
p = plot(n/Fs, y, 'b', n/Fs, a, 'm'); axis tight
xlabel('Time [sec]');
```

```
ylabel('Amplitude');
figure(2)
plot(n/Fs, e, 'b');
axis tight
xlabel('Time [sec]');
ylabel('Amplitude');
% LMS (fits line)
mu = 0.0005;
m = (M - 1)/Fs;
a = zeros(1, N + 1);
b = zeros(1, N + 1);
e = zeros(1, N + 1);
trnd = zeros(1, N + 1);
for k = 1:N
e(k) = y(k) - a(k) - b(k)*m;
a(k + 1) = a(k) + mu*e(k);
b(k + 1) = b(k) + mu*e(k)*m;
trnd(k + 1) = a(k + 1) + b(k + 1)*m;
end
a = a(2:N + 1);
b = b(2:N + 1);
e = e(2:N + 1);
trnd = trnd(2: N + 1);
disp('a = ');  disp(a);
disp('b = ');  disp(b);
disp('e = ');  disp(e);
figure(3)
plot(n/Fs, y, 'b', n/Fs, trnd, 'm'); axis tight
xlabel('Time [sec]');
```

```
ylabel('Amplitude'); figure(4)
plot(n/Fs, e, 'b'); axis tight
xlabel('Time [sec]');
ylabel('Amplitude');
```