Trend Removal of ECG Signal with LMS Algorithm

Buse BOZOK
Electrical and Electronics Engineering Dep
Çukurova University
Adana, Türkiye
bbozok@oyakliman.com

Sami ARICA
Electrical and Electronics Engineering Dep.
Çukurova University
Adana, Türkiye
arica@cu.edu.tr

Abstract— **In this study, the LMS algorithm was employed to detect and track baseline wanders introduced during the acquisition of electrocardiogram signals. The baseline wander was removed from the signal and ECG is corrected. For this purpose, the baseline signal was modeled as a constant and a line in the LMS algorithm. The two approaches were applied to the signals received from MIH-BIH database records and the results were reported and compared. When the experimental results are investigated it is observed that the line model adapts faster and tracks baseline wander.**

Keywords — LMS algorithm; ECG; baseline signal suppression; adaptive filter.

I. INTRODUCTION

Medical signals are generally low-intensity signals at the micro and milli 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 numerous methods to suppress the baseline signal in the literature [1]. These methods can be 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. The Savitzky-Golay filter [2], [3] is the most common one and a gold standard among these. On the other hand, least mean square (LMS) [4], recursive least squares (RLS), and Kalman adaptive filter/algorithm are causal techniques which are also utilized to remove baseline signal [5]. In these approaches, mainly, the baseline signal is expressed as a constant and adapted or changed over time (varying with time) regarding the signal. [5]. These approaches can be used in real-time applications.

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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 [6].

II. METOD

In this section, the process of tracking and removing the base signal using two different models with LMS is explained. In the first model, suppose that $d(n)$ is ECG signal, $a(n)$ is filter output (the baseline signal): In this case, the algorithm is:

$$e(n) = d(n) - a(n) \quad (1)$$

$$a(n+1) = a(n) + \mu e(n) \quad (2)$$

In the 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:

$$e(n) = d(n) - a(n) - m \cdot b(n) \quad (3)$$

$$a(n+1) = a(n) + \mu e(n) \quad (4)$$

$$b(n+1) = b(n) + \mu e(n) \cdot m \quad (5)$$

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. [7]

III. FINDINGS & DICCUSION

The methods mentioned in the second section have been applied to a synthetic signal and a real ECG signal.

An artificial signal with a known base component can be generated to analyze and interpret the two approaches. It resembles an ECG signal. For this purpose, let us choose the original and the base line shifted signal as follows.

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

$$s(t) = \sum_{n=-\infty}^{\infty} s_1(t-n) + 0.25\, sin\left(\frac{\pi t}{10}\right) \qquad (6)$$

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 0.005 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 1-4. 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 approaches have been also investigated and tested on the ECG-ID dataset of a patient in the MIH-BIH database containing rich 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 5-8. 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.

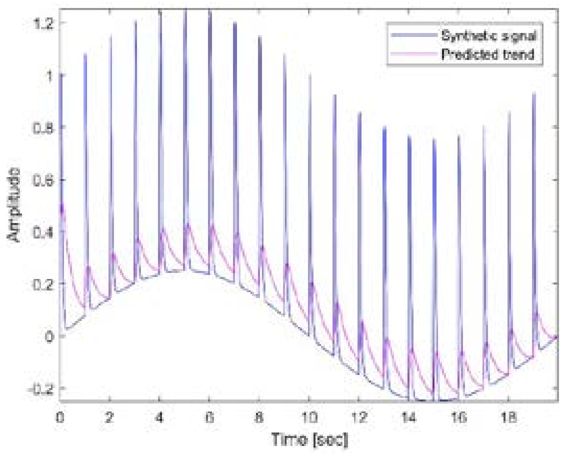

Figure 1. Synthetic signal with a trend and estimated trend by using zero-order polynomial model for trend.

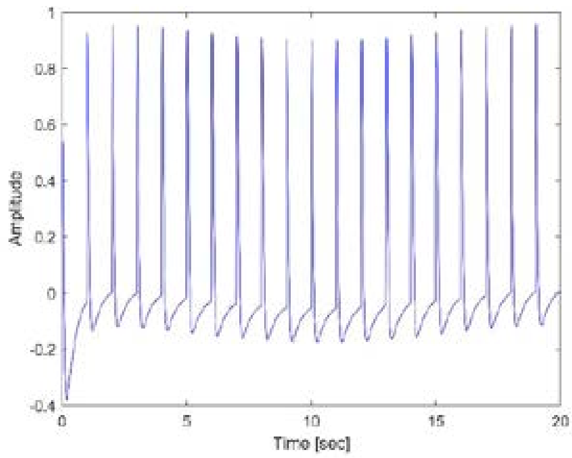

Figure 2. De-trended signal obtained by removing estimated baseline signal from synyetic signal given in figure 1.

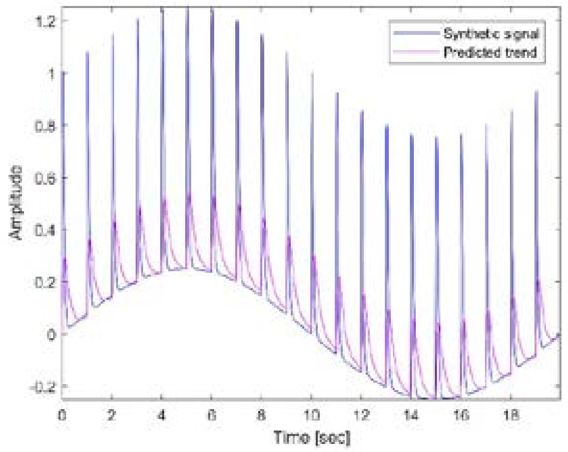

Figure 3. Synthetic signal with a trend and estimated trend by using first order polynomial model for trend.

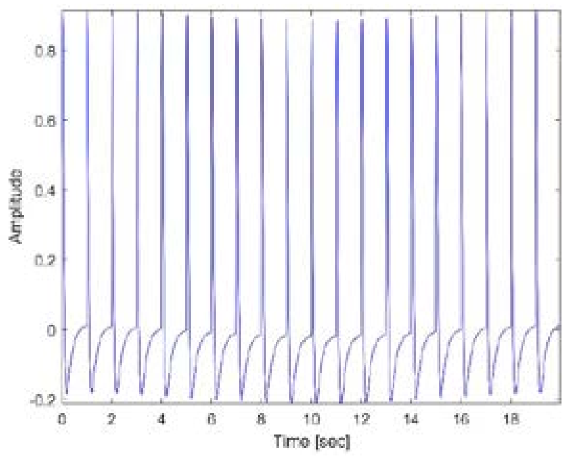

Figure 4. De-trended signal obtained by removing estimated baseline signal from synyetic signal given in figure 3.

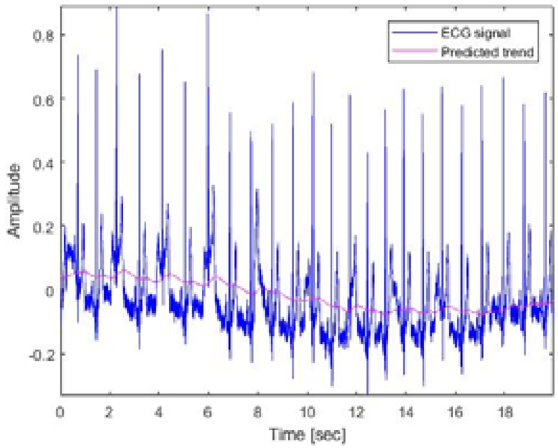

Figure 5. Real ECG signal and estimated trend by using zero-order polynomial model for trend.

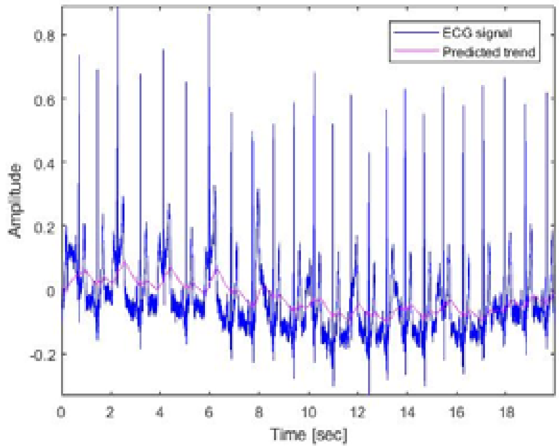

Figure 7. Real ECG signal and estimated trend by using first-order polynomial model for trend.

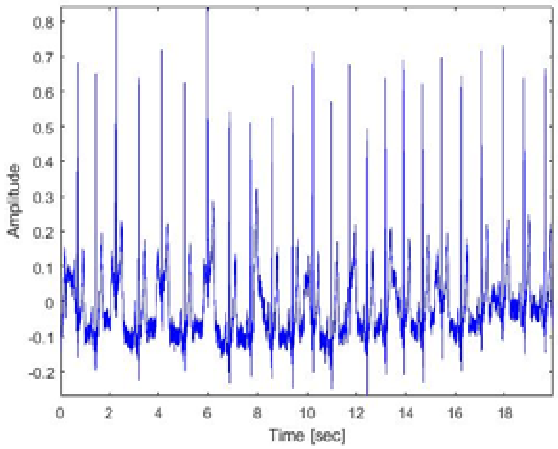

Figure 6. De-trended signal obtained by removing estimated baseline signal from ECG signal given in figure 5.

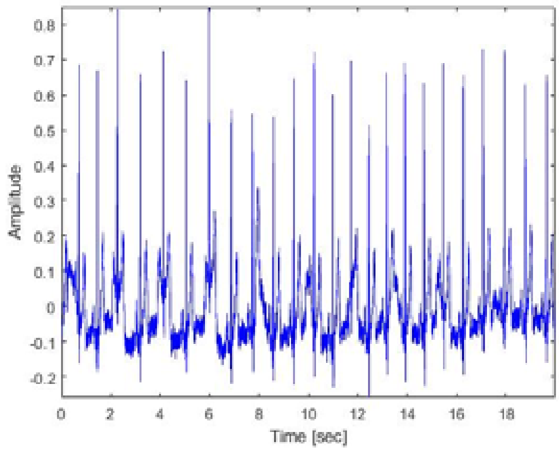

Figure 8. De-trended signal obtained by removing estimated baseline signal from ECG signal given in figure 7.

IV. CONCLUSIONS AND DISCUSSION

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.

V. REFERENCES

[1] Ouali, M. A., Ghanai, M., & Chafaa, K. (2018). Upper envelope detection of ECG signals for baseline wander correction: A pilot study. Turkish Journal of Electrical Engineering and Computer Sciences, 26(2), 803–816

[2] Savitzky A., and Golay, M.J.E. 1964, Analytical Chemistry, vol. 36, pp. 1627–1639.

[3] S. J. Orfanidis, Introduction to Signal processing, vol. 15, no. 1. 1998. OK.

[4] Radhika, P. Ashwin, M., & Simha, C. V. M. N. (2014). Performance Analysis of Different LMS Algorithms for Health Monitoring ECG Sensor. 1376–1382.

[5] A. Schlogl, J. Fortin, W. Habenbacher and M. Akay, "Adaptive mean and trend removal of heart rate variability using Kalman filtering," 2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Istanbul, Turkey, 2001, pp. 571-573 vol.1. doi: 10.1109/IEMBS.2001.1018997.

[6] Laguna.P, Jane. R, Caminal. P, ―Adaptive Filtering Of ECG Baseline Wander‖, Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp: 508-509,1992.

[7] Haykin, S. Adaptive Filter Theory, 4th ed. Englewood Cliffs, NJ, USA: Prentice-Hall, 2002.