International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 02, 2021

Preprocessing of ECG Signals for Cardiovascular diseases

[1]Pratibha Chavan, [2]B. Sheela Rani, [3]M. Murugan, [4]Pallavi Kolapkar

[1]Research Scholar, Sathyabama Institute of Science and Technology (Deemed to be University), Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai - 600 119. Tamil Nadu, India.
Asst. Professor, Department of E&TC Engineering & Associate Dean – IR,
Trinity College of Engineering and Research, Pisoli, Pune-411048, MH, India.
[2]Director (Research) and Professor, Sathyabama Institute of Science and Technology (Deemed to be University), Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai - 600 119.Tamil Nadu, India.
[3]Vice-Principal and Professor of ECE Department, SRM Valliammai Engineering College, Kattankulathur - 603203, Chengalpet (Dist.) Tamil Nadu, India.
[4]PG student of Digital Electronics Engineering, Trinity College of Engineering and Research, Pisoli, Pune-411048, MH, India.

Email: [1]cpratibhapramod@gmail.com, [2]sheelarani@sathyabama.ac.in, [3]dr.murugan.m@gmail.com, [4]kolapkarpallavi306@gmail.com

Abstract: CVD (Cardiovascular) Diseases is leading cause of human deaths globally. The increasing threats of CVD can be early detected with various medical tests, including electrocardiogram (ECG), and also 2D Echo, Stress Test. As ECG is non-invasive, clinical therapeutic agent, so with the help of an ECG signal, early detection of CVD is possible and proper medication can be provided for human life. All these signals from different equipment can, however, be non-stationary and repetitive, which takes more time to process and exhausting for physical examination. Moreover, Heart Signal from ECG machine is not a stationary indicator, the discrepancies might not be repeated and may demonstrate up at various periods, hence there is a need to adopt a computer aided model for fast and accurate prognosis of CVD's. Similarly, the pre-processing of ECG signals is crucial as ECG signals are generally consists of various types of drift called as noise as well as various types of artifacts. During the preprocessing step, our main objective is to reduce or overcome on this noise so that we can able to get the proper de-noised signal which will help to decide the fiduciary points (P, Q, R, S, T), its event, non-event phenomenon such as P-wave, QRS-complex, T-wave, PQ-segment, ST- segment. Typical types of noise may have categories such as a power line intrusion, baseline wander, and noisy contact data of electrode, electrode motion artifacts, muscle contraction, and instrumentation noise. In this paper, we are focusing the preprocessing of the ECG signals through various filters accessible, so we can eliminate the undesirable noise through the original ECG data signal that will help us evaluate the clean signal which will contribute to predict the accurate result in classification.

Keywords: CVD, ECG, Pre-Processing, Notch Filter, Butterworth Filter, Bandpass Filter, HRV, PQRS Complex
Keywords: We would like to encourage you to list your keywords in this section

1. INTRODUCTION

CVD is one of the main causes that contribute to a worldwide rise in death rates [1]. From the data available from the World Health Organization reports, 17.5 million people were affected by CVDs death-wise which eventually increased medical expenditure [2]. The expenses need to bear globally cause of this medical calamity because of these Heart Diseases was valued at US$863 billion in 2010[1] [2]. Also, it is predicted that these expenses will continue to increase and will touch US$30 trillion by 2030. Popular cardiovascular diseases include myocardial infarction (MI); followed by a heart attack, heart disease, cardiac myopathy, rheumatic heart disease, heart defects and cardiac arrhythmia [1], [2], [3]. So proposed methodology studies two types of cardiomyopathy i.e. MI, DCM and HCM which are seen as distinct myocardial anomalies. HCM causes because of enlargement in heart muscles that affect the coronary arteries and inter-ventricular septum (IVS) Have the harden. While DCM causes due to expansion in the left ventricle (LV) because of the squeezing and receding of the myocardium [2]. This, therefore, has a dangerous influence LV diastolic function which results in heart failure or arrhythmias. Myocardial infarction is a complication of coronary heart disease (CAD) that results in myocardial mortality due to excessive disruption in the oxygenated supply of the blood [2].

This condition, thus contributes to a decrease in cardiac after load, and the degree of effect relies on both the magnitude of the region affected. In the electrocardiogram (ECG) impulses, the formation of CVDs such as (LVH) because of HCM has mirrored as higher R signals and skewed T ripples in the left pericardial and on the side forward leads, i.e. lead V5-6, and I and VL, correspondingly. DCM also includes large R waves. The MI state is characterized by a Heart Rate Signals with ST sections Depending on the scale of both ends, is enlarged or diminished by flat T signals. Medically both of these changes in ECG parameters are analyzed objectively and presented systematically to determine the Requires CVDs. Nevertheless, the anti-stationary presence of the ECG signal suggests, CVD indications can appear spontaneously within the timing. Besides, some critical diagnostic data are not noticeable with physical inspection and can lead to perception discrepancies [3]. Moreover, computer-aided methods could be more suitable and practical for correct diagnosis to address these shortcomings during much of the human evaluation. Hence, in this review, we concentrated on characterizing triple CVDs (HCM, DCM, and MI) by obtaining comparative non-linear wavelet characteristics from ECG impulses.
The initial part of the ECG Signal is very raw. It contains many noise signals attached to it while recording the patients' ECG pattern. So in this paper, we are focusing on the preprocessing part of the raw ECG Signals by applying various filters on the signal thus reducing the noise.

2. REVIEW WORK

The adversarial approach of Para-noising the ECG signal was explored, i.e. extracting usable outputs of good quality through noisy ECG signals utilizing the adversarial process [5]. The investigation of writers is focused on the antagonistic process, which continually accumulates information about the data through the competition between the creator and the classifier. Next, they had drawn up a new understanding of the adversarial approach to explaining that it should be used to minimize noise. They suggested a new default feature that would serve as an additional effective solution to receiving strong-quality signals. They also suggested an antagonistic method of mal-noising ECG signals, allowing good use of the antagonistic

method's sweeping generalization capabilities. They also measured the SVM algorithm efficiency of signals.
In Automated Classification researches of a life-threatening cardiac condition, congestive heart failure (CHF) occurs if the heart's pump operation is smaller than those of natural condition [6]. This paper suggests a new method for developing a classifier-based framework for CHF's automatic recognition. Electrocardiogram pulses are obtained from a repository and then preprocessed using Butterworth high pass filter with such a 0.5HZ cut-off rate to eliminate interference. The filtered Heart Rate Singal is separated into frames with a length of 4 sec each [2] [6]. Depending upon it CHF is detected. A time-based analysis is done and data is transformed in various forms like Discrete Fourier Transform, M of spectral coefficient, Gaussian Matrix, and S transform. Entropy is extracted. Some authors study the ECG, its features and use [7]. A detailed study of ECG signals is done and its processing is also mentioned [4] [7].
In another research by Zerina Masetic, Abdulhamit Subasi Computer-controlled pulse detection system designed to diagnose congestive cardiac failure [8]. The BIDMC repository obtains ECG signals with heart failure and the MIT-BIH Arrhythmia repository obtains ECG symptoms with healthy heartbeats. Dataset function metrics are derived using the Burg autoregressive (AR) method. The data collection is gathered into 2800 Arrhythmia data segments of which 1500 refer to failure of heart rate pulses and the left over 1300 information pieces relate to regular heartbeats. The very same data sets have been used for 5 separate forms of classification, including the decision tree C4.5, k-NN, SVM, ANN, and RF. Who obtained high statistical measurements across all classifiers? Classification of coronary vein sickness with multilead Electrocardiogram and Deep CNN signals [4] [8] [9]. From this article a deep CNN model that automatically recognizes the Myocardial Infection on 12-lead Heart Rate signals. With planned CNN model, indicators are defined by continuous definition with no further abstraction of the handmade function. In this article, 12-lead traces were collected from the PTB clinical ECG repository of -related forms of MI. Deep learning strategy to recognition of heartbeat based on Electrocardiogram for diagnosis of arrhythmias by G.Sannino, G.DePietro Promotes that classification is among the Highly popular health and molecular biology topics, particularly for coronary artery disease, are pulse disruptions or rhythms that can occur occasionally in a person's daily life [10].

3. OBJECTS AND METHODS

3.1 OBJECTS.

This research work we are focusing on the MIT-BIH Arrhythmia dataset our source repository dataset.
The Total Sample ECG signal is forty-eighth recording which contains data from two sensors, i.e. MLII and V1 had recorded. The sampling frequency had kept as 360Hz per channel and 11-bit resolution had maintained over 10 mv Range. In particular, most frequent reference in this search is MLII where the signal ECG morphology is clearly visible. The MLII led and the normal sinus rhythm is allowed for evaluation. The virtual ECG impulses are based on the Principle of the parametric series. Here, varying amounts of Gaussian white noise distort the signal. We are trying to give a short description of ECG Signal properties in the following paragraphs.

3.1.1 ELECTROCARDIAM SIGNALS.

Heart rate anatomy is important for retrieving properties of Arrhythmia impulses that are quasi-regular as depicted in Figure 1. The stimulation to heartbeat can be represented with four simple features: P-wave (sluggish left excursion), QRS-complex (quick middle

excursion), and T-wave (Slow walk to the right) and U-wave (Low second correct outing). During the processing of ECG Signals, many issues are raised and one needs to solve that.
(1) While recording the signal data, it generally contains Gaussian and White noise signals
(2) The basic features displayed in Figure 1 must always be calculated with the utmost precision to prevent medical errors.
(3)The reference model is not optimally usable for tuning an estimator.

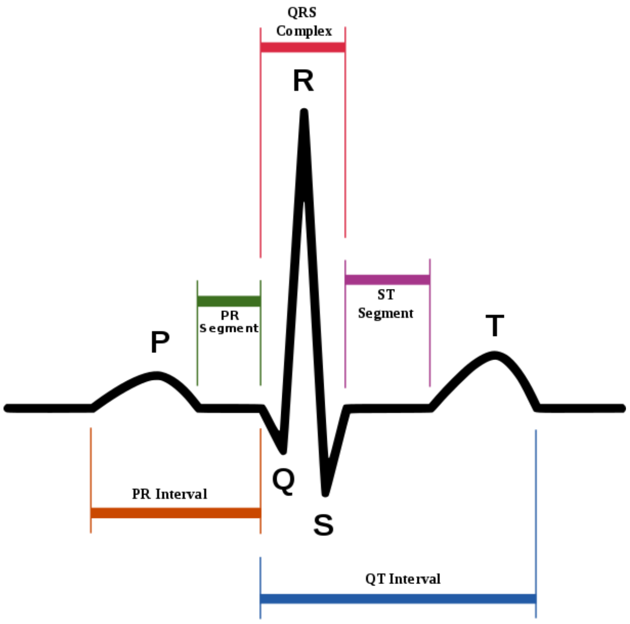


Figure 1: Standard ECG Heartbeat Pulse Model

4. TYPE OF ECG SIGNAL NOSE AND FILTER METHODS

4.1 BASE LINE WANDER

Baseline wandering or base drifting is the phenomenon where a signal's base axis (x-axis) tends to 'roll' or travel back and forth, instead of linear. That allows the whole pulse from its usual base to change. In the ECG signal, default wandering is caused by inadequate electrodes (electrode-skin impedance), person, activity, and respiratory rate (breathing). Fig 2 illustrates a normal Arrhythmia signal influenced by the wandering of the baseline.
0.5 Hz is set as range for the frequency content of the baseline wander. Yet higher body motion during the workout or stressful check increases the intensity value of baseline wandering. As the reference signal is also a lower volume signal, Finite Impulse Response (FIR) heavy-pass zero step forward-back processing with a finish rate of 0.5 Hz can also be used to measure and delete the threshold in the ECG signal.

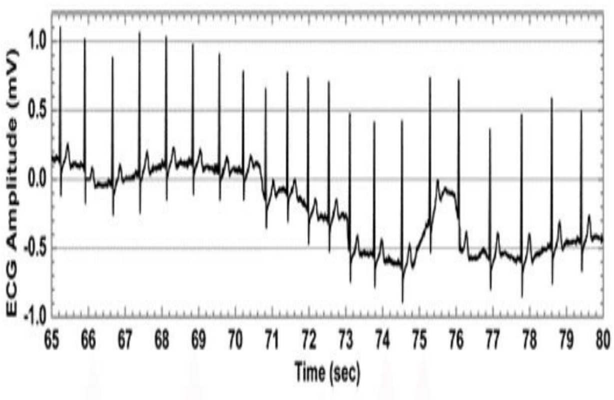


Figure 2: ECG signal with baseline wander

4.2 POWERLINE INTERFERENCE:

Power line-induced electric fields represent a common source of interference in the Electrocardiogram and any other neuronal signal derived from the ground layer. This disturbance is distinguished by sine wave intervention of 50 or 60 Hz, likely followed by multiple frequencies. This narrowband noise makes it harder to evaluate and understand the ECG, as limited-amplitude delineation of input and output is unreliable and invalid waveforms may be introduced. Disruption of the power line from ECG transmissions must be avoided, since it automatically resizes low-frequency Electrocardiogram signals such as P and T signals. (Fig 3) displays Heart Rate signal normally influenced with an interruption from the power line

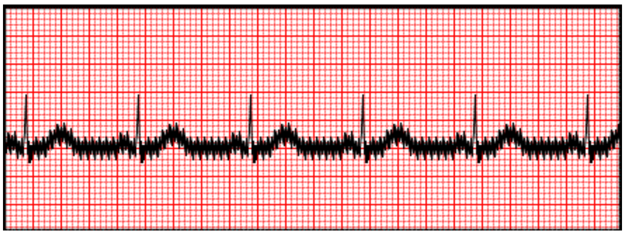
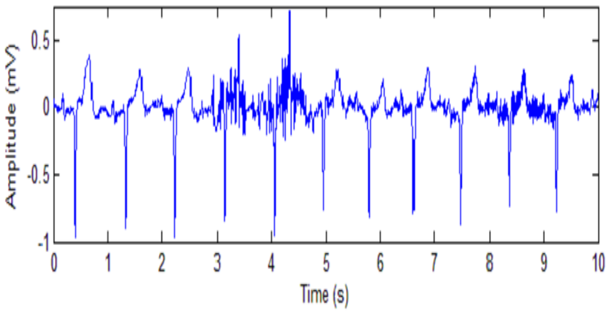


Figure 3: Power line Interference ECG Signal

4.3 EMG NOISE

The existence of muscular disruption in several ECG implementations poses a significant challenge, particularly in observations obtained throughout the workout, as low amplitude waveforms can become fully obscured. Muscle distortion is not eliminated by narrowband filtering, as compared to baseline wandering and 50/60 Hz intervention, but poses a much more complicated filtration issue, as the spectrum quality of muscle contraction greatly crosses that of dynamic PQRST. Because the Electrocardiogram is a repetitive signal, a method may be used to reduce muscle interference which is comparable to the study of potential. Productive disturbance removal by combining the ensemble is therefore limited to specific QRS morphology at a time and needs many beats to be possible. Data acquisition strategies are also required which can reduce the effect of muscular interference. The following diagram indicates an Arrhythmia pulse that has been messed with as an EMG signal.

Figure 4: ECG signal with EMG noise



4.4 METHODS TO REMOVE BASELINE WANDERS

An ideal way to select the best possible available filter is selecting high-pass filter as a start point for filtering out the noise from ECG Signal.

$$H(e^{jw}) = \begin{cases} 0, 0 < |\omega| < \omega_c \\ 1, \omega_c < |\omega| < \Pi \end{cases}$$

Where, $2\pi f_C = 2\pi f_C$ and $\frac{F}{F_S} = \frac{fs}{fs}$ Thus, if $f_S = 0.5Hz$ and $f_S = 250Hz$ Otherwise the standardized cut-off frequency relating $(fs) = 0.002$.

4.5 METHODS TO REMOVE POWERLINE INTERFERENCE

A rather modern approach to Power line interference elimination is to define a filter represented by a complicated set of zeros.

The transformation function of Notch Filter (2nd Order) is described as follows.

$$\begin{aligned} H(z) &= (1 - z_1 z^{-1})(1 - z_2 z^{-1}) \\ &= 1 - 2\cos(\omega_0) z^{-1} + z^{-2} \end{aligned} \qquad (2)$$

Because this filter does have a notch by means of a fairly huge throughput, it can modulate power line pressure and also Electrocardiogram bandwidth filters with wavelengths of almost 0. Therefore, the filter has to be adjusted such that the knot is more efficient.

The range of the notch is identified and decided by the polar radius r and decreased as the group size approach r. Practical result of this observation is that a residual current produces a ringing artefact in the out signal in the transmitter. These filtering may occur after the transient for functional filtering, this imitates the small-amplitude cardiovascular activity that often exists in the intermediate section of the QRS system, i.e. the delayed ability.

4.6 MINIMIZING EMG NOISE METHODS

Higher frequency distortion is the EMG disturbance; thus, an n-point rolling normal (MA) filter could be used to get rid of or at best reduce EMG interference starting the Electrocardiogram transmissions. For equations the MA filter has the following form.

$$p(t) = \sum_{b=0}^{c} \mathrm{Uk}\, q(t - x) \quad (3)$$

Where q and p are filter entry and exit, both. The Uk quantities are filter parameters, or press values, b=0, 1, 2. t, where t is filter order. The consequence of dividing by the sample size used (t+1) is reflected in the sums of the filter parameters

5. RESULTS AND DISCUSSION

We had used the MIT-BIH Arrthymia dataset. It consists of around 43 dataset files. In this Initial work we are focusing on pre-processing part of the ECG Signals. We’ll be looking at how to analysis a particularly noisy ECG signals using HeartPy python library.

For the purpose of this analysis we are using four of the files in .csv data format for ease of use. All files are recorded at 360 Hz

We'll be using these files with varying signal-to-noise (SNR) ratios:

118e24 : SNR: 24dB

118e12 : SNR = 12dB

118e06 : SNR = 6dB

118e00 : SNR = 0dB

These files have noisy and non-noisy sections. To keep download size low we have extracted a two-minute section of the noisy segment to work with.

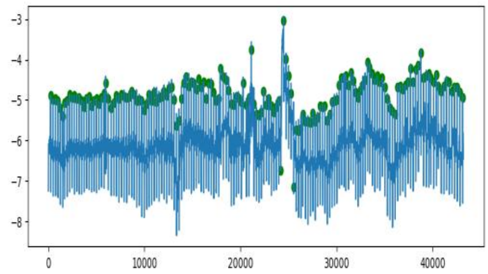


Figure 5 Raw ECG Signal

Figure 5 shows the unprocessed Electrocardiogram Signal with noise added. Signal is not clear and we need to implement the filters on it.

Note that the annotations supplied with the dataset have small errors. This is because of how these are usually annotated: peaks are automatically marked and manually corrected where necessary. Due to the immense amount of work (1 hour of ECG will contain on average 3600 peaks already!) small errors are generally deemed acceptable and remain. Only peaks at strange positions are corrected.

In figure 6, base line wander had been removed on original ECG Signal.

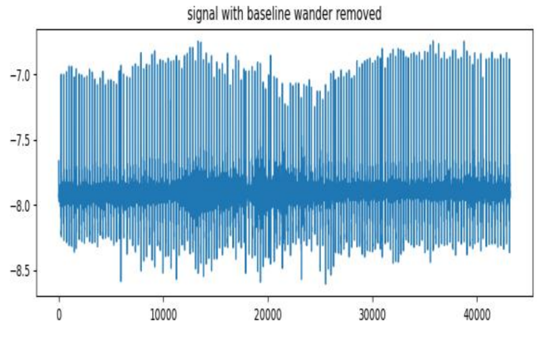


Figure 6: Base Line Wander Removed Signal

Now we are scaling the data after filtering using hp.scale_data() to standardize amplitude. This is a linear operation and so doesn't affect temporal position of data. The figure 7 represents the same.

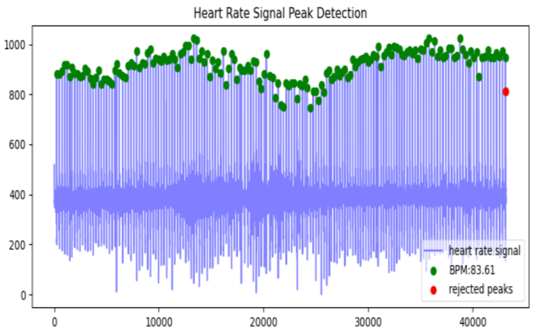


Figure 7: HR Detection after scaling the data

In Next Step, ECG Signals generally has very narrow peaks. Filtering usually keeps the maximum at the same place but can narrow the waveform further, causing issues. Because HeartPy was designed for much wider PPG waveforms, up sampling generally does the trick as it gives more data points per peak. It doesn't move or change relative peak positions.

6. CONCLUSION

Based on the pre-processing results after applying the filters, it is observed that 60Hz Power line interference is embedded in the ECG signal can be filtered out with the help of a filtering mechanism based on digital signal processing.

By taking the implementation details of various digital signal processing methods, we had tried to implement several filters with linear-phase. They are band pass low and high filters, notch filters, etc. The notch filter has an issue with a significantly increased magnitude that can obscure the ECG signal, but also has the benefit of a lower filtering level. When the equiripple notch filter is in the lower order we cannot neglect the ripple effect of the pass band.

Our future work will represent an analysis of the QRS Complex using a different algorithm and feature extraction of filtered ECG signals for further processing.

7. REFERENCES

[1] Muhammad Adam, Oh Shu Lih, Vidya K Sudarshan, Joel EW Koh, Yuki Hagiwara, Tan Jen Hong, Tan Ru San, U Rajendra Acharya. "Automated Characterization of Cardiovascular Diseases Using Relative Wavelet Nonlinear Features Extracted from ECG Signals", Computer Methods and Programs in Biomedicine, 2018, Computer Methods and Programs in Biomedicine 161 (2018) 133–143

[2] U.R. Acharya, H. Fujita, A. Muhammad, S.L. Oh, V.K. Sudarshan, J.E.W. Koh, Y. Hagiwara, K.C. Chua, K.P. Chua, R.S. Tan, Automated characterization and classification of coronary artery disease and myocardial infarction by decomposition of ECG signals: a comparative study, Inf. Sci. 377 (2017) 17–29.

[3] J.E. Tarride, M. Lim M, M. DesMeules M, et al. , A review of the cost of cardiovascular disease, Can. J. Cardiol. 25 (2009) e195–e202 .

[4] WorldHealth Organization, in Global Health estimates: Deaths By cause, Age, Sex and Country, WHO, Geneva, 2014, pp. 20 0 0–2012

[5] Jilong Wang, Renfa Li, Rui Li, Keqin Li, Haibo Zeng, Guoqi Xie, Li Liu. "Adversarial de-noising of electrocardiogram", Neurocomputing, 2019
[6] R.K. Tripathy, Mario R.A. Paternina, Juan G. Arrieta, Alejandro Zamora-Méndez, Ganesh R. Naik. "Automated detection of congestive heart failure from electrocardiogram signal using Stockwell transform and hybrid classification scheme", Computer Methods and Programs in
[7] Biomedicine, 2019
[8] A survey on ECG analysis elan Kaplan Berkaya, Alper Kursat Uysal, Efnan Sora Gunal, Semih Erginc, Serkan Gunal, M. Bilginer Gulmezoglu. https://doi.org/10.1016/j.bspc. 2018.03.003 1746-8094/2018 Elsevier Ltd
[9] Zerina Masetic, Abdulhamit Subasi. "Congestive heart failure detection using random forest classifier", Computer Methods and Programs in Biomedicine, 2016
[10] Ulas Baran Baloglu, Muhammed Talo, Ozal Yildirim, Ru San Tan, U Rajendra Acharya. "Classification of Myocardial Infarction with
[11] Multi-Lead ECG Signals and Deep CNN", Pattern Recognition Letters, 2019
[12] G. Sannino, G. De Pietro. "A deep learning approach for ECG-based heartbeat classification for arrhythmia detection", Future Generation Computer Systems, 2018
[13] Cheng-Hung Tsai. "Adjustable 60Hz noise reduction by a notch filter for ECG signals", Proceedings of the 21st IEEE Instrumentation
[14] and Measurement Technology Conference (IEEE Cat No 04CH37510) IMTC-04, 2004
[15] L SORNMO. "ECG signal processing", Bioelectrical Signal Processing in Cardiac and Neurological Applications, 2005
[16] Available from: https://www.researchgate.net/publication/302631407_Low-Power_Wearable_ECG_Monitor ing_System_for_Multiple-Patient_Remote_Monitoring/ figures?lo=1
[17] Available from: https://www.researchgate.net/publica-tion/224326734_Estimation_of_noise_in_ECG_signals_using_wavelets/figures?lo=1
A. Jayant, T. Singh and M. Kaur (2013): Different Techniques to Remove Baseline Wander from ECG Signal, Int. J. of Emerging Research in Management & Technology, 2.
[18] Leif Sornmo and Pablo Laguna. (2005) Bioelectric Signal Processing in Cardiac and Neurological Processing. 1st Ed., Elsevier Academic Press, ISBN: 9780124375529.
[19] Rangraj M. Rangayyan. (2002) Biomedical Signal Analysis: A case study approach. John Wiley & Sons, Inc., ISBN: 0-471- 20811-6.
[20] J. L. Talmon, J. A. Kors, and J. H. van Bemmel (1986): Adaptive Gaussian filtering in routine ECG/VCG analysis, IEEE Trans. Acoust. Speech Sig. Proc. 34: 527-534.
[21] E. K. Hodson, D. R. Thayer, and C. Frankli (1981): Adaptive Gaussian filtering and local frequency estimates using local curvature analysis, IEEE Trans. A coust. Speech Sig. Proc. 29, 854-859.
[22] V. de Pinto (1991): Filters for the reduction of baseline wander and muscle artifact in the ECG, J. Electro Cardiol. 25: 40- 48.
[23] Roman Kaszynski and Jacek Piskorowski (2007): Selected Structures of Filters with Time-Varying Parameters, IEEE Transactions on Instrumentation and Measurement, 6: 2338- 2345.
[24] M. Milanesi, N. Martini, N. Vanello, V. Positano, M. F. Santarelli, R. Paradiso, D. De Rossi, and L. Landini. (2006) Multichannel Techniques for Motion Artifacts Removal from Electrocardiographic Signals. In: Proceedings of the 28th IEEE EMBS Annual International Conference New York City, USA. 3391-3394