REMOVAL OF BASELINE WANDERING IN ECG SIGNALS USING SINGULAR VALUE DECOMPOSITION

T DHANARAJ
M.Tech Student, Department of EEE
Sri Venkateswara University College of Engineering,
Tirupati-517502

G UMAMAHESWARA REDDY
Associate Professor, Department of ECE,
Sri Venkateswara University College of Engineering,
Tirupati -517502

***Abstract**:*
The electrocardiogram (ECG) is an important tool for primary diagnosis of heart diseases. In the course of collecting ECG signal data, baseline drift, electromyography interference, and 50 /60 Hz power line interference will be introduced inevitably. These artifacts severely limit the utility of recorded ECG and thus need to be removal of these noises, for better clinical evaluation. Among these artifacts, the baseline drift is a typical low-frequency noise that distorts the susceptible ST segment. To remove baseline drift from the ECG signals, the Singular Value Decomposition (SVD) method is proposed. With the principle of SVD, by modification of singular values, noise can be removed from the signal.

Key Words: *ECG, baseline drift, SVD.*

I. INTRODUCTION

Heart diseases are the most common cause of death in the world, and the ECG is a standard tool in identifying abnormal rhythms of the heart. Generally, difficulties in ECG analysis may be caused by baseline drift, power line interference, and white noise [1-3].

Base line drift can change the change the shape of P-QRS-T waveforms and influence the accurate diagnosis of heart diseases, such as ischemia and arrhythmia [4]. Detection of ischemia can be achieved by analyzing the ST segment of the ECG and it can be influenced by slow baseline drift and noise [5]. Baseline removal is also needed in body potential mapping for the localization of ventricular arrhythmias [6] and the reconstruction of activation time imaging [7]. Sources of baseline drift in ECG recordings include respiration, muscle contraction, and electrode impedance changes [2, 4].

Baseline drift can be removed by filtering the signal with a high-pass linear phase filter. Non-linear phase filters are avoided because they can introduce distortions to the filtered ECG signal that can cause misdiagnosis. The operations to remove baseline drift can be computationally intense and also include frequency estimation and least-squares line fitting [4]. An alternative approach to remove baseline drift is the use of short-time Fourier transform, as proposed in [8]. However, the approach in [8] is dependent on the appropriate choice of time window and it is specific for baseline drift removal [9].

Baseline wandering usually comes from respiration at frequencies wandering between 0.15 and 0.3 Hz, and it can be suppressed by a high-pass digital filter and eliminating the trend of the ECG signal. There are numerous problems associated with filtering: first, when the FIR structure is used, the number of coefficients is too high and therefore long impulse response; second, there is an overlap on the spectrums of the baseline and ECG, removing baseline spectrum will cause distortion on the ECG components. Third, the cut-off frequencies are not in keeping with the AHA recommendations for ECG which state the lower frequency limit must be 0.05 Hz and removing any frequencies above it will cause distortion in the ST segment as well as QRS complex [10].

Singular Value Decomposition (SVD) method has been proposed for de-noising of ECG signals. First a signal is converted to a matrix with the specified window length and overlapping. Then SVD is applied for that matrix. Thus obtained singular value matrix(S) contains signal component, noise component and signal noise component. S is modified such that noise component gets completely eliminated and signal noise is reduced to some extent by multiplying with a negative exponential. With the modified singular values the matrix is reconstructed. This is again converted to reconstructed signal. The result shows the noise was reduced effectively.

II. METHODS AND MATERIALS

A rigorous approach to data analysis must involve an up-front characterization of the structure of the data. In addition to a broader utility in analysis methods, singular value decomposition (SVD) can be valuable tool in obtaining such a characterization. A single experiment can generate measurements for thousands, or even tens of thousands of data, but can consist of hundreds data are currently rather noisy, and SVD can detect and extract small signals from noisy data. SVD was used to reduce the noise reduction kind of elements separation. When signal is highly correlated

and mixed with the one dimensional noise using SVD for mapping to the higher dimensions space, the data which is more correlated, means the data of main signal are aligned in one direction, it means that singular values related to the ECG are greater and the singular values of the noise are assigned smaller values as well. In this way, the great and small elements of the signal would be separated from each other by singular values. In this result, we can separate the noise signal from the main signal. Of course, the singular values of the signal and noise cannot be perfectly separated from each other, in this status; we can do the separating procedure as follows.

$$X = U\,S\,V^{T} = \left(U_m\, U_{m,n}\; U_n\right)\begin{pmatrix} S_m & 0 & 0 \\ 0 & S_{m,n} & 0 \\ 0 & 0 & S_n \end{pmatrix}\begin{pmatrix} V_m^T \\ V_{m,n}^T \\ V_n^T \end{pmatrix}$$

Here the 'm' indices for main signal and 'n' indices for the noise. As seen in the above matrix, the singular values of signal are added in the number of the matrix elements. In this work, we tried to use a method in filtering the singular values of the SVD mapping; new way is presented in order to omit noise from ECG signal. In this process, at first signal is transferred to the higher dimension space by using SVD mapping, therefore through an algorithm its singular values are optimized and via the reverse mapping to the initial space would be reconverted.

SVD method over ECG signal:

In this work in order to apply SVD on ECG (sampling rate 360 Hz), initially one segment of signal in length of 4000 samples is selected and then windowing with the length of 40 samples and overlapping of 44% upon this segment of signal is applied and by placing each window of signal in one column of a 2 dimensional matrix, the desirable matrix for applying the SVD is achieved. Using the overlapping is in order to omit the edge effects. Conclusively, we have:

$$x = \left(x_1, x_2, \ldots\ldots, x_n\right) \rightarrow \begin{pmatrix} x_1 & x_{w-\alpha} & x_{2w-2\alpha} \\ x_2 & x_{w+1-\alpha} & x_{2w+1-2\alpha} \\ x_w & x_{2w-\alpha} & x_{3w-2\alpha} \end{pmatrix}$$

Here x is a segment of the main signal in the length of m, x_i is the samples of signal, w is the length of one window, and α is representing the overlapping. After applying the SVD upon the above matrix, through investigating the related singular values to the clean signals from the library of MIT-BIH and the noised signals, are observed that singular values of the clean signals under the effect of noise in comparison with the state of without noise, some changes upon each of it are happening. The idea is based on optimizing the singular values related to the noisy signal in order to reduce the effect of noise, these values to be multiplied into a function and remapped to the initial space by reverse transformation procedure.

III. EXPERIMENTAL RESULTS

The ECG signal is added with baseline wandering noise signal to test the proposed denoising of signals using SVD method. The results were obtained discussed based on the criteria of Maximum absolute error (MAE), Mean square error (MSE) and Signal to noise ratio of the output signal (SNR_O). The results are tabulated in the following tables for various noise signals respectively. Then output SNR is calculated for different values of input SNR to measure the performance SVD method based on SNR, MSE, and MAE as criteria.

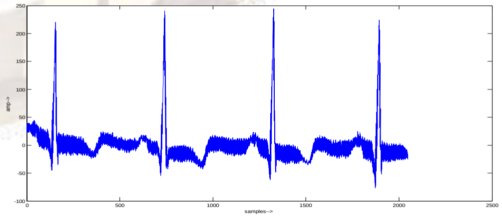

Fig 1 (a): Original Signal 100.dat

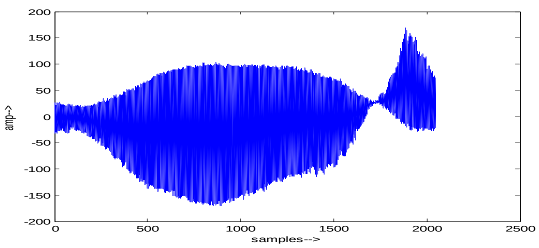

Fig 1 (b): Noise Signal bw.dat

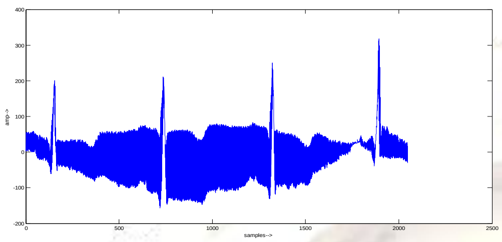

Fig 1 (c): Noisy ECG Signal

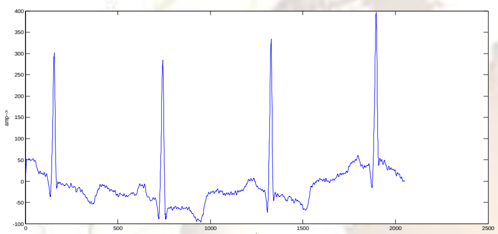

Fig. 1 (d) Reconstructed ECG Signal

Table1. SNRo, MAE and MSE values for denoising of the original signal corrupted by *bw.dat*

SIGNAL	SNRi: -1 dB			SNRi: 0 dB		
	MAE	MSE	SNRo	MAE	MSE	SNRo
100.dat	237.85	1053.3	0.2116	237.83	1053.3	0.2113
101.dat	275.37	741.39	0.0985	275.36	741.43	0.0983
103.dat	389.03	3234.7	0.2057	388.95	3234.4	0.206
114.dat	423.3	1953.4	0.0881	423.37	1953.3	0.0884
230.dat	298.06	3943.3	0.247	298	3944	0.2462
234.dat	336.19	176.17	0.1732	336.12	1761.3	0.1734

NOISE:bw.dat									
SIGNAL	SNRi: -7 dB			SNRi: -5dB			SNRi: -3 dB		
	MAE	MSE	SNRo	MAE	MSE	SNRO	MAE	MSE	SNRo
100.dat	238	1052.9	0.213	237.94	1053.6	0.2125	237.89	1053.9	0.212
101.dat	275.51	741.11	0.1001	275.54	741.2	0.0996	275.41	741.3	0.0991
103.dat	389.76	3238	0.2011	389.46	3236.5	0.2032	389.22	3235.5	0.2046
114.dat	423.96	1955.1	0.0844	423.74	1954.3	0.0861	423.57	1953.8	0.0872
230.dat	298.51	3937.3	0.2536	298.17	3939.6	0.251	297.99	3941.6	0.2488
234.dat	336.7	1766.3	0.1611	336.53	1764.3	0.1659	336.34	1762.9	0.1695

From the table, it is observed that even for the lower SNR values SVD method is performing well. From the plots, it is observed that some small fluctuations present in the input are getting smoothed out. From Visual inspection, it is observed that the denoised ECG signals features were retained in the signal effectively. It will be useful for easy diagnosis of ECG signal features.

IV. CONCLUSIONS

This method is based on enhancing and optimizing the Base line wandering Singular Values for omitting noise from ECG. Using different quantitative and qualitative parameters, the efficiency of this method is evaluated. Through using the stated parameters, it is indicated that this method can be utilized as one of the most powerful tools of denoising of ECG signal compared to the other methods. In addition of the quantitative and qualitative capability of the proposed method, fast running and applying this method. In this method the smaller values of SVD matrix are modified based on smaller values are containing noise. The around 20% of the first singular values are keeping intact. Around 60% of the next singular values are modified in exponential decay manner. The remaining singular values are nullified. Due to this the noise in the ECG signals is substantially eliminated.

V. FUTURE SCOPE

In this method SVD is applied every time on a signal which is circularly shifted version of the original signal. Assume a value for n for $N=2^n$, where n = 0, 1, 2…..n-1. Each time the signal is shifted by an amount N, and then SVD is applied. The output of SVD is shifted back same amount of shift. To obtain the reconstructed signal an average of all n signals is taken. All those signals are averaged on sample wise. Then the resulting signal may be much better than any of the other reconstructed signals. Another technique is by using principal component analysis; it can reduce the noise associated with the original ECG signal. This Translation invariant Singular Value Decomposition (TI-SVD) method can be more suitable for denoising of ECG signals with artifacts.

VI. REFERENCES

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