Multiscale PCA based Quality Controlled Denoising of Multichannel ECG Signals

L. N. Sharma, S. Danadapat, and A. Mahanta

Abstract—**Multiscale Principal Component Analysis (MSPCA) is applied for quality controlled denoising of Multichannel Electrocardiogram (MECG) signals. Wavelet transform of MECG signals disseminates clinical information content into different wavelet subbands or scales. Collecting wavelet coefficients of all ECG channels at a wavelet scale multivariate data matrices are formed. Principal Component Analysis (PCA) is performed on these matrices for signal denoising. The desired quality of processed signals is achieved by selecting the principal components (PC) based on energy features in selected wavelet subband matrices. To control the quality of denoised signals, the number of PC selection is based on cumulative percentage of total variation of variances. The choice of multiscale matrices and selection of eigenvalues preserve the desired energy in the processed signals. Quantitative performance is measured using input and output Signal-to-Noise Ratio (SNR). Signal distortion metrics are evaluated using Percentage Root Mean Square Difference (PRD) and Wavelet Energy based Diagnostic Distortion (WEDD) measures. SNR improvement of 31.12 dB has been found with better denoising effect using database of CSE Multilead Measurement Library.**

Index Terms—**Denoising, ECG, MSPCA, PCA, PRD, WEDD.**

I. Introduction

Pathological information in physiological signals is most important and essential for a physician. The diagnostic information in the signals should not be disturbed by signal processing methods, irrespective of its nature whether it is normal or pathology. Electrocardiogram signals may carry important pathological information. Clinically, standard 12-lead ECG recorded in different leads: I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5 and V6, are in practice world-wide. The heart potential distribution, recorded in different leads, gives vital cardiac information. The clinically essential diagnostic information present in the signals must be preserved during signal denoising process. This requires a quality control measure. Signal processing by Principal Components Analysis (PCA) [1], [2], [3] is extensively used as a classical multivariate signal processing tool. PCA has been applied in different fields of science and engineering to better utilize its ability [4], [5], [6]. For biomedical signals like ECG, a robust extension of classical PCA by analyzing shorter signal segments is suggested [7]. It may be used in data reduction, beat detection, classification, signal separation and feature extraction [8], [9].

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In this article, it is suggested to apply Multiscale PCA to multichannel ECG signals, for quality controlled denoising. PCA is applied at wavelet scales after forming multivariate data matrices. The quality controlled denoising is a two steps process, (a) selection of multivariate matrices at wavelet scale for PCA based dimension reduction and (b) the choice of number of Principal Component (PC) at each wavelet matrices. The selection of effective PCs is normally based on the cumulative percentage of total variation shown by eigenvalues. For conventional PCA, it is taken 70% to 99% [3]. The diagnostic quality of denoised signal is qualitatively compared with the original signal. The quantitative distortion measures like PRD and WEDD are evaluated [10], [12], [13]. The enhanced multichannel signals contain all the clinical components with required 'PQRST' morphologies of ECG signals while reducing the noise.

II. Method

Multiscale Wavelet decomposition of, 'L' levels, for each channel signal from multichannel ECG data set results in 'L+1' subbands. Due to the nature of multiresolution decomposition, these subbands contain different diagnostic components [10]. Diagnostic information lies in higher order subbands [10], [11]. High frequency information and noise appears in lower order subbands. In Fig.1, energy contribution efficiency (ECE) [10], [11], [12] of wavelet subbands for multichannel ECG signals are shown. The multichannel ECG data is taken from CSE Multilead Measurement Library database. For six level wavelet decomposition the approximation subband is denoted as cA6 and details subbands are denoted as cD6, cD5, cD4, cD3, cD2 and cD1.

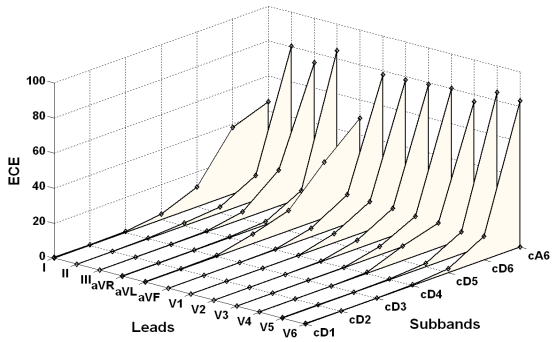

Fig. 1. ECE of wavelet subbands for multichannel ECG signals

Most of the signals energy is remain in cA6, cD6, cD5 and cD4 subbands. The diagnostic components and its clinical important is higher. The lower order subbands are less

significant in terms of diagnostic important. If subband matrices are formed arranging wavelet coefficients of the same scales of all the channels of multichannel ECG data set, we may apply PCA selectively to avoid losing 'PQRST' morphologies of original data set.

Wavelet transform (WT) gives k^{th} wavelet coefficient at $j^{th.}$ level as $w_{j,k}$. Thus, we find an approximation subband at level ' L ' and detail subbands at level ' j ', where j=1,2,...L . Wavelet coefficients are equal in numbers at a particular wavelet scale provided a same transformation criterion is applied with same mother wavelet. There is 'n' number of ECG channels. So, wavelet coefficients obtained by WT of MECG signals can be arranged in ' L+1 ' subband matrices. In these multiscale matrices rows represent wavelet coefficients and columns represent ECG leads or channels. So, this forms multivariate data matrix at a wavelet scale. At approximation level, the matrix is denoted as A_L and at details, matrices are written as D_j . PCA analysis by covariance method is applied in these multiscale matrices. To find the Principal Components (PCs) following operation are required

- Finding out the covariance matrices for A_L and D_j
- Eigen-decomposition of covariance matrices
- Finding out the eigen-vector and eigenvalues
- Arranging eigenvectors and eigenvalues in descending order
- Selection of eigenvalues to decide number of PC

Let, eigenvalues for A_L and D_j are written as

$$\lambda_{A_L}^{i} = \lambda_{A_L}^{1}, \lambda_{A_L}^{2}, ..., \lambda_{A_L}^{n} \quad (1)$$

$$\lambda_{D_j}^{i} = \lambda_{D_j}^{1}, \lambda_{D_j}^{2}, ..., \lambda_{D_j}^{n} \quad (2)$$

where ' L ', is wavelet decomposition level, ' j ', is the wavelet scale and 'n' is the number of ECG channels. This gives the number of eigenvalues and hence the number of principal components. For dimension reduction or denoising, the selection of eigenvalues which decides the principal components is an important step. The number of PC selected for PCA based processing decides the denoising effect. There may be the loss of signal and it may affect the signal quality. Higher number of PC selected for processing captures more signal energy.

Based on analysis of energy contribution efficiency of wavelet subbands (Fig.1) of multichannel ECG signals and eigenvalues due to eigen-decomposition, quality controlled denoising is proposed as

1) Select wavelet matrices from A_L and D_j based on ECE values.
2) Select the number of PC based on cumulative percentage of total variation of variances.

The first operation results in minimum loss of diagnostic components. In the second operation, cumulative energy may be varied between 60% to 99% to achieve quality denoising. Matrices at different wavelet scale do have different parts of 'PQRST' morphologies which are due to wavelet decomposition. These clinical components carry diagnostic information in the signal. To retain clinical information in the denoised signal, multiscale matrices should be handled carefully. It is seen that only few numbers of higher order multiscale matrices can be processed with reduced set of PCs. For lower order matrices all the PCs are kept for further processing. If higher order wavelet subband matrices are treated with lower number of PCs, we may loss the diagnostic Components. For denoising operation, selected principal components plays important role. There are many method suggested in literature. Most common method is to compare the cumulative percentage of total variation [3] shown by selected eigenvalues. If 'm' numbers of eigenvalues are considered from total 'n' numbers of eigenvalues for denoising, then cumulative percentage of total variation can be expresses as

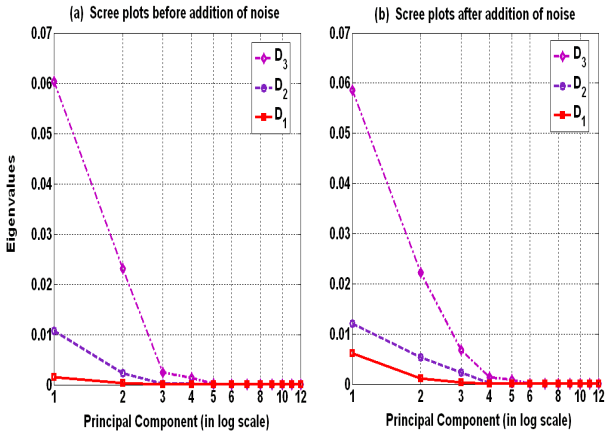

Fig. 2. Scree plots for D_1, D_2 and D_3. In panel (a) scree plots before addition of noise and in (b) scree plots after addition of zero mean, unity variance Gaussian noise

TABLE I: NUMBER OF PC FOR D_1, D_2 and D_3

Number of PC varying with T for D_1, D_2 and D_3			
T	D_1	D_2	D_3
60	1	1	1
80	1	2	2
95	2	2	3
99	3	4	5

$$T = \frac{\sum_{i=1}^{m} \lambda^{i}}{\sum_{i=1}^{n} \lambda^{i}} \times 100 \quad (3)$$

where λ^i is the i^{th} eigenvalue and T is the threshold set which gives cumulative percentage of total variation explained by number of PCs selected. The denoised signal quality depends on the energy captured by eigenvalues. Quality of the signal may be controlled if T is selected suitably. This minimizes the loss of diagnostic components with optimized denoising. In present work, the value of T is made variable from 60% to 99% as per required quality of signal with proper denoising effect.

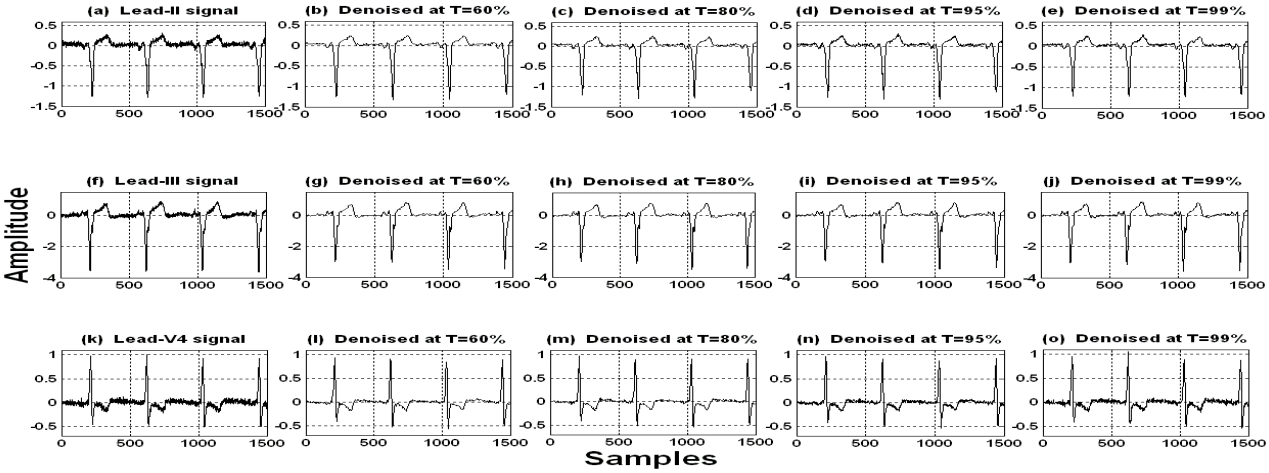

Fig. 3.Original signals with addition of gaussian noise, (a) lead-II (input SNR= 11.1), (f) lead-III (input SNR=29.37) and (k) lead-V4 (input SNR=3.10). the corresponding quality controlled denoised signals for T= 60%, 80%, 95% and 99% are shown in panels (b), (c), (d), (e); (g), (h), (i), (j) and (l), (m), (n), (o); respectively. CSE multilead measurement library, data set-m01-040 is used.

TABLE II: INPUT AND OUTPUT SNR (IN DB), CSE DATABASE, DATASET-M01-040

SNRs (in dB) at defferent leads												
Lead	**I**	**II**	**III**	**aVR**	**aVL**	**aVF**	**V1**	**V2**	**V3**	**V4**	**V5**	**V6**
Input SNR	-1.42	11.10	29.37	8.05	5.41	29.81	22.11	8.36	8.65	3.10	3.50	4.66
Output SNR	23.12	40.24	34.90	39.17	33.79	52.44	46.78	37.10	36.40	33.12	32.02	35.77
SNR Improvement	21.70	29.14	5.53	31.12	28.39	22.63	22.11	28.74	27.75	30.02	28.52	31.11

TABLE III: DISTORTION MEASURES: CSE MULTILEAD MEASUREMENT LIBRARY DATABASE, DATA SET-M01-040

Distortion metrics for proposed method												
Metric	**I**	**II**	**III**	**aVR**	**aVL**	**aVF**	**V1**	**V2**	**V3**	**V4**	**V5**	**V6**
PRD(T=60%)	29.95	13.24	17.16	13.98	18.10	7.24	9.59	15.45	15.95	18.74	19.71	16.47
PRD(T=80%)	30.88	15.95	15.59	14.93	20.46	5.87	7.12	16.37	17.87	15.26	19.72	16.62
PRD(T=95%)	30.15	17.48	15.14	12.17	18.64	3.97	6.24	14.29	5.08	15.82	19.48	15.99
PRD(T=99%)	27.08	12.94	15.24	9.28	17.35	4.88	9.67	17.05	4.23	16.93	20.51	17.31
WEDD(T=60 %)	12.63	3.41	5.97	3.45	5.87	3.34	4.20	6.26	5.05	5.08	5.78	4.26
WEDD(T=80 %)	12.88	3.73	5.62	4.17	6.28	3.17	3.79	6.23	6.29	5.05	6.15	5.02
WEDD(T=95 %)	12.38	4.14	5.42	2.37	6.06	2.93	3.64	5.73	3.31	4.49	6.30	4.73
WEDD(T=99 %)	10.88	3.09	5.48	2.61	5.83	3.03	4.46	7.06	2.96	4.98	6.55	4.91

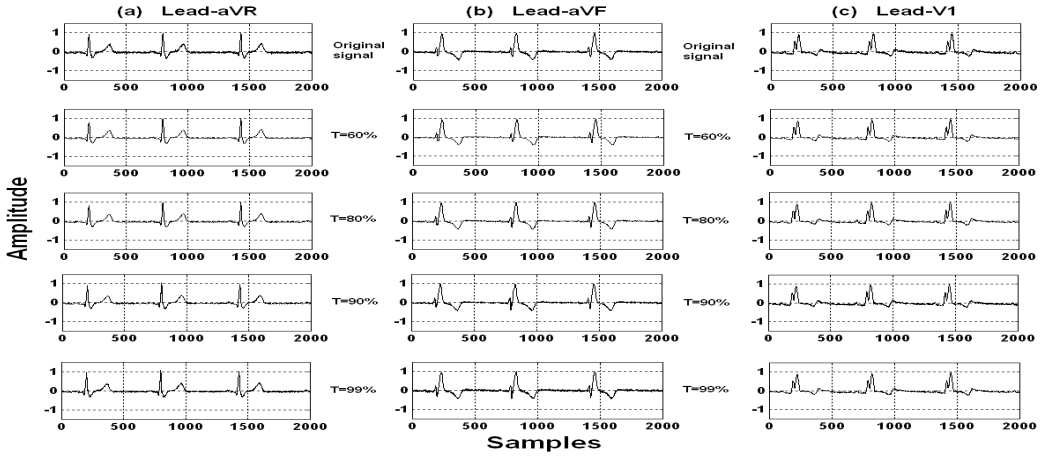

Fig. 4. Original signals with Gaussian noise at lead-aVR (I/P SNR=9.95), lead-aVF(I/P SNR=15.97) & lead-V1(I/P SNR=13.88) and respective quality controlled denoised signal for T= 60%, 80%, 90% and 99% using proposed MSPCA based denoising method. In (a) lead-aVR signal with denoised signals, (b) lead-aVF signal with denoised signals and (c) lead-V1 signal with denoised signals. CSE multilead measurement library, data set-M01-014 is used

III. Results and Discussion

Multichannel ECG signals are extracted from standard clinical data base, CSE Multilead Measurement Library [14]. Data set 3 of CSE multilead measurement library is used. The data set 3 has 125 original ECG data sets with almost equal numbers of normal and various pathological cases. The sampling frequency is 500 Hz. It has 10 bits resolution with maximal 5 mV quantization. Multivariate data matrix, S, is formed taking 4096 samples from each channel. This gives S as $[4096 \times 12]$ matrix. Signals extracted from data set-M01-040, are subjected to mean removal and amplitude Normalization. Six level wavelet decomposition is performed on each channel signals. The choice of decomposition level, L, which satisfy the frequency range of the main features of an ECG, is based on sampling frequency, F_s, [10], [11]. Daubechies 9/7 biorthogonal wavelet is used for wavelet transform of each channel signal. This wavelet is commonly used by different authors [10, 11, 12, 13] for its linear phase and symmetry and better performance for ECG signal.

Across wavelet subbands at each scale the number of coefficients are equal. From subbands of same level, considering all the ECG channels, multivariate matrices are formed. At approximation, A_L matrix and at details, D_j, matrices are constructed. L is the level of decomposition and $j=1,2,3,...,L$. Based on relative subband energy in terms of ECE values, the important of multiscale matrices are decided to retain clinical information. To avoid loosing clinical fidelity of multichannel signals, three subband matrices, D_1,D_2 and D_3 are selected for denoising operation with reduced number of principal components.

Fig.2 shows scree plots for D_1,D_2 and D_3 matrices with and without addition of white Gaussian noise. In Fig.2 (a), scree plots for three multiscale matrices D_1,D_2 and D_3 before addition of Gaussian noise are shown. After addition of zero mean and unity variance Gaussian noise, scree plots for same set of matrices are shown in Fig. 2 (b). Comparing both the figures, changes in amplitude of eigenvalues with principal components are noticed. After addition of noise, the significant numbers of principal components required for larger variation of variances are increased.

Accordingly, PCA may be performed with selected set of PCs to reduce noise content. Hence, denoising effect can be controlled by varying the numbers of PCs in these matrices. The cumulative percentage of total variation of variances decided by threshold, T, for D_1,D_2 and D_3 are varied from 60% to 99% to control the denoising performance. Number of principal components selected for denoising of multichannel signals, with varying T in different subband matrices, are recorded in Tab. 1. For more denoising effect, less numbers of PCs are selected. So, a lower percentage variation of, T, the loss is higher. Similarly, for higher percentage of variation, higher numbers of PCs are selected. This gives less denoising effect and lower loss in signal.
CSE database, Dataset-M01-040. In Fig.3(a) original lead-II signal (noise added) with corresponding denoised signals in Fig. 3(b), (c), (d) and (e) at T=60%, 80%, 95% and 99% are shown. Similarly, for signals of lead-III and lead-V4 results are shown in Fig. 3(f), (g), (h), (i), (j) and Fig. 3(k), (l), (m), (n) and (o) respectively. The denoising effect is better at T=60% and is lesser at T=99%. This shows the denoising may be controlled by varying threshold, T. It is essential to preserve clinical components of MECG signals during denoising process. The proposed multivariate denoising based on MSPCA helps retain diagnostic components of the signals of lead-I, II, III, aVR, aVL, aVF, V1, V2, V5 and V6.

The ECG signals of different leads are subjected to additive Gaussian noise to process with proposed denoising method. To quantify the denoising effect of the proposed method, the input and output SNR (in dB) are measured at T=60% and shown in Tab.2. All the channels show significant improvements in SNR (in dB). Higher SNR indicates improvement in signal quality. Higher SNR improvements are observed for the signals at lead-aVR, lead-V6 and lead-V4 with 31.12 dB, 31.11 dB and 30.02 dB respectively. Lowest SNR improvement of 5.53 is observed for lead-III. Higher SNR value at the input itself may be the reason for low improvement.

In Fig. 4, another data set, M01-014 is from CSE Multilead Measurement Library is tested at threshold T=60%, 80%, 90% and 99% of cumulative variance and variances. Results for aVR, aVF and V1 are produced. Input SNRs for lead-aVR, aVF and V1 are 9.95, 15.97 and 13.88 respectively. The output SNRs are found 39.72, 45.59 and 40.24 respectively for above leads. The controlled denoising of above signal show all the clinical information present in the filtered signals. This shows the ability of proposed method to clean the signal with different SNR values with different data sets.

It is required to evaluate the signal distortion due to denoising process. For physiological signals, a few existing error measures are considered in this work. The signal distortion metric, Percentage Root Mean Square Difference (PRD) and Wavelet Energy based Diagnostic Distortion measure (WEDD) [10], [12], [13] are evaluated.

In Table III, PRD and WEDD are evaluated at T=60%, 80%, 95% and 99% for Data set-M01-040. The lowest PRD at T=60%, 80% , 95% and 99% are 7.24 (aVF), 5.87 (aVF), 3.97 (aVF) and 4.23 (V3) respectively. The lower WEDD values at T=60%, 80%, 90% and 99% are 3.34 (aVF), 3.17 (aVF), 2.37 (aVR) and 2.61 (aVR) respectively. These value falls under excellent category signals [13]. This shows the proposed quality control denoising method preserve all the diagnostic components with required fidelity in 'PQRST' morphologies.

IV. Conclusion

In this paper, quality controlled denoising method using multiscale PCA is introduced. The proposed method exploits the property of wavelet transform and PCA. The method is evaluated using multichannel ECG signals from CSE multilead measurement library data sets. The cumulative percentage of total variation of variances given by eigenvalues decides the energy retain in the processed signal. Higher the threshold value, T, selected lower is the signal loss and less denoising effect. In contrary, lower the

threshold value, T, higher is the signal loss with more denoising effect. So, there is an optimum choice of PCs for quality controlled denoising effect. Thus, the target quality can be decided. It is suggested here that the cumulative percentage of total variation of variances given by eigenvalues may vary from 60% to 99%. The PC selection method can be improved by some other suitable critaria. The performance of this method is found satisfactory. The presented results show the preservation of clinically essential diagnostic components.

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