# Uni-channel PCA for noise reduction from ECG signals

R.Palaniappan, Tan Eng Khoon
Biomedical Engineering Research Centre, Nanyang Technological University, Singapore

*Abstract* — **In this paper, we propose a method that utilizes single channel principal component analysis (PCA) to reduce impulsive noise from electrocardiogram (ECG) signals. The novelty of the method lies in the use of PCA from a single channel, instead of multi-channels (or multi-signals) as in the conventional PCA. This is very useful in most cases where only the lead II ECG signals are available, in addition to being cost effective and computationally faster. The proposed method works by adaptively segmenting the single ECG signal, where the R peaks are used as approximate points to segment the ECG signals. This is important for proper alignment of the segmented ECG signals. The segmented signals are now treated as multi-channel ECG signals to be applied with PCA. Because the ECG part is more correlated as compared to noise, PCA will be able to separate noise from ECG using only a few selected principal components. The method is applied to reduce impulsive noise that is added to known ECG signals. In addition, the method is also applied to ECG signals from Massachusetts General Hospital/Marquette Foundation database. The results indicate that few segmentations are enough to increase the signal to noise ratio (SNR). The method could also be adapted for noise reduction from other biomedical signals.**

*Keywords*— **ECG, PCA, Impulsive Noise**

## I. INTRODUCTION

An artifact that corrupts biomedical signals like electrocardiogram (ECG) signals is impulsive noise, which could be caused by muscle activities. Removal or reduction of this noise is important in ECG analysis because the proper detection of QRS complex becomes difficult with noise. This is especially true for automatic diagnosis of cardiac states using ECG signals. Principal Component Analysis (PCA) is a common technique that has been used to reduce noise from biomedical signals [2-6]. However, all these methods use multi-channel or multi-trial signals or both. Here, a novel method of applying PCA to single channel ECG recording is proposed.

The method is applied to reduce noise from uni-channel, (i.e. single) ECG signal. This becomes important when one wishes to use PCA to reduce noise from single ECG signal. Using a single ECG signal will be computationally faster and also cost effective. The single ECG signal is segmented adaptively using the approximate location of R peaks. This is important for proper alignment of the segmented ECG signals. The segmented signals are then formed into an array to be used with PCA. Because the signal parts of the ECG signal are more correlated from one another as compared to noise, it will be possible to use PCA to reduce noise. The first few principal components (PC) will account for the signal parts and only these will be used to reconstruct the denoised ECG.

In the experimental study, the proposed method has been applied to a normal and an abnormal (sinus tachycardia) ECG signals contaminated with different noise factors. In addition, the method was also applied to three ECG signals from Massachusetts General Hospital/Marquette Foundation database.

## II. METHODOLOGY

Two clean ECG signals, one a normal sinus rhythm and another, an abnormal sinus tachycardia rhythm have been used in the experimental study. These signals were obtained from [7].

Impulsive noise created following the approach given in [8] is added with different factors to these ECG signals. Noise is modeled by a mixture of Gaussian noise, which has a probability distribution function of

$$N(n) = (1-\varepsilon)G_1\left(\frac{n}{\sigma_1}\right) + \varepsilon G_2\left(\frac{n}{\sigma_2}\right) \tag{1}$$

where $G_1$ and $G_2$ are probability distribution functions of Gaussian random variable. $\sigma_1$ and $\sigma_2$ are standard deviations of $G_1$ and $G_2$, with $\sigma_2$ much larger than $\sigma_1$. Here, we use $\sigma_1$ as 0.1 and $\sigma_2$ as 1.0.

The noisy ECG signal could now be represented as

$$y(n) = x(n)_{ECG} + Ag(n)_{noise} \tag{2}$$

where $y(n)$ is the noisy ECG signal and $A$ is the varying noise factor.

The proposed algorithm is as below:

Step 1: Detect $R$ peaks. $R$ peaks are detected using QRS complex detected from Pan and Tompkins method [9].

Step 2: Compute *R-R* interval (*Rint*). The *R-R* intervals between all the *R* points are computed and the mean *R-R* interval is computed.

Step 3: Adaptive segmentation of a single ECG signal. ECG signals are segmented with the *R* peak locations as the centers with the range of $\pm Rint$. Note that some data redundancy may occur between the different segments but this is not really a problem because the redundant data are normally isoelectric lines, which carry no significant information.

Step 4: Each of the segmented signals is now combined into a matrix, **y**.

Step 5: Covariance computation. The covariance of matrix **y** is computed using:

$$\mathbf{R} = E\left(yy^{T}\right). \tag{3}$$

Step 6: Next, matrices $\mathbf{E}$ and $\mathbf{D}$, are computed where $\mathbf{E}$ is the orthogonal matrix of eigenvectors of $\mathbf{R}$ and $\mathbf{D}$ is the diagonal matrix of its eigenvalues, $\mathbf{D} = diag(d_1, ...., d_n)$.

Step 7: The PCs can now be computed using

$$\mathbf{P} = \mathbf{E}^{\mathbf{T}} \mathbf{y}^{\mathbf{T}}. \tag{4}$$

Step 8: Retain first few PCs. In this work, Kaiser's rule [9] is used to give the number of required PCs. Using this method, PCs that have eigenvalues more than 1.0 are assumed to be part of the signal while the rest are assumed to be part of the noise.

Step 9: The signal part of the ECG (without noise) can now be reconstructed from the selected PCs using

$$\tilde{\mathbf{x}} = \hat{\mathbf{E}}\hat{P}, \tag{5}$$

where $\hat{\mathbf{E}}$ and $\hat{P}$ are the eigenvectors and PCs, respectively.

Step 10. All the signals in matrix $\hat{x}$ are combined to give one ECG signal, $\hat{\hat{x}}$.

Step 11. Construct the final ECG signal without noise using $\hat{\hat{x}}$. Use the *R* peak locations, *Rint* and $\hat{\hat{x}}$ from Step 10 to reconstruct the final single ECG signal without noise.

## III. Results

Figures 1 to 3 shows the results for the normal sinus rhythm ECG signal contaminated with noise with factors: 0.2, 0.1 and 0.05, respectively. Figures 4 to 6 shows the results for the arrhythmic sinus tachycardia rhythm ECG signal contaminated with noise with factors: 0.2, 0.1 and 0.05, respectively. Each of the signals was 5 seconds in length and with a sampling frequency of 200 Hz, the signals consisted of 1000 data points. Note the signal to noise (SNR) improvement after using the proposed method in each of figure.

Figures 7, 8 and 9 show the results of applying the proposed method to three ECG signals from MGH/MF database. The signals were obtained from tapes mgh002 and mgh004 in the database. Each of the signals used here was for 5 seconds. Since the MGH/MF database sampling frequency is 360 Hz, these signals consisted of 1800 data points.

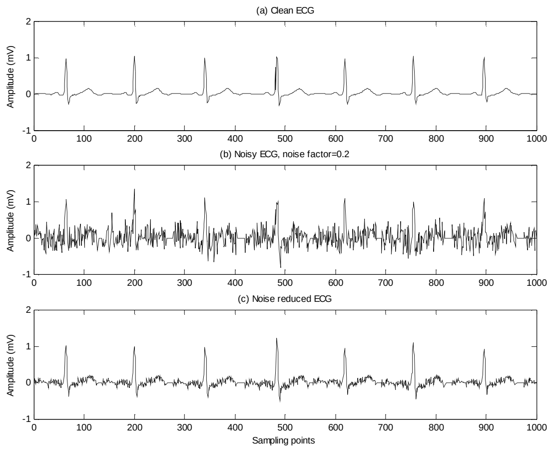


Fig. 1. (a) Clean ECG (b) Noise ECG with noise factor=0.2, SNR=-1.40 dB (c) Noise reduced ECG, SNR=7.58 dB.

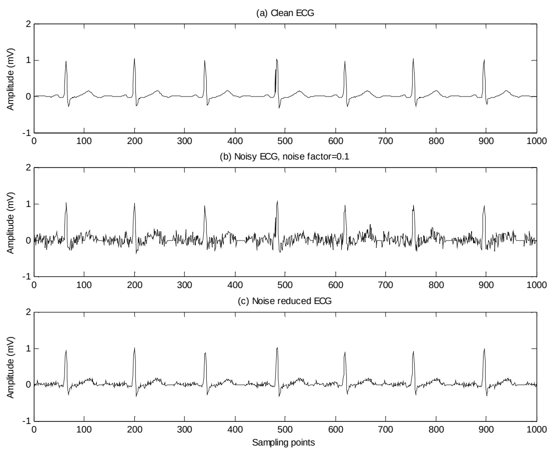


Fig. 2. (a) Clean ECG (b) Noise ECG with noise factor=0.1, SNR=4.48 dB (c) Noise reduced ECG, SNR=11.59 dB.

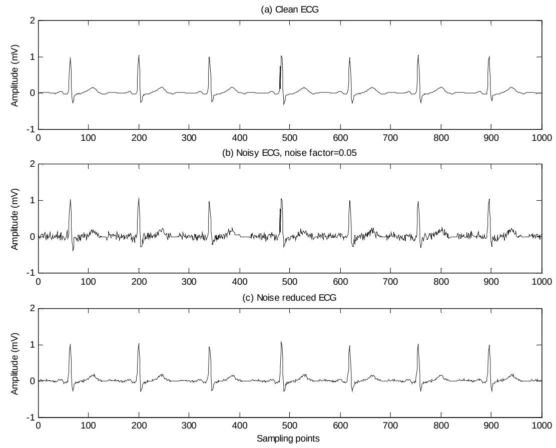


Fig. 3. (a) Clean ECG (b) Noise ECG with noise factor=0.05, SNR=10.53 dB (c) Noise reduced ECG, SNR=13.45 dB.

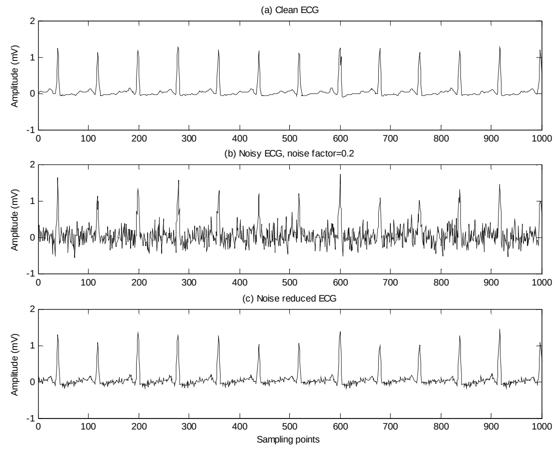


Fig. 4. (a) Clean abnormal ECG (b) Noisy ECG with noise factor=0.2, SNR=1.91 dB (c) Noise reduced ECG, SNR=12.52 dB.

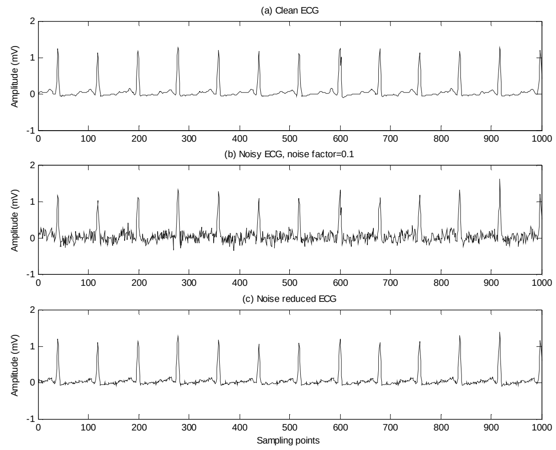


Fig. 5. (a) Clean abnormal ECG (b) Noisy ECG with noise factor=0.1, SNR=7.63 dB (c) Noise reduced ECG, SNR=15.09 dB.

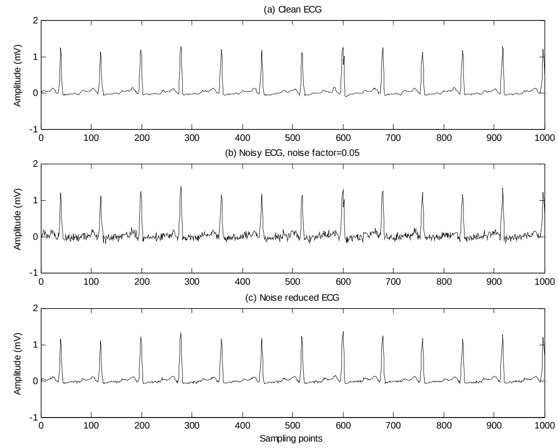


Fig. 6. (a) Clean abnormal ECG (b) Noisy ECG with noise factor=0.05, SNR=13.31 dB (c) Noise reduced ECG, SNR=16.82 dB.

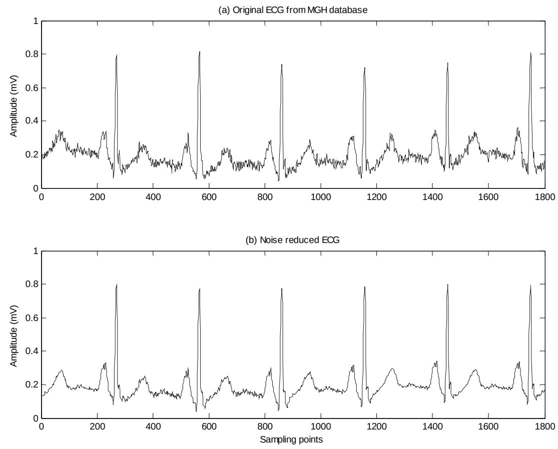


Fig. 7. (a) ECG from MGH/MF database – example from tape mgh002 (b) noise reduced ECG.

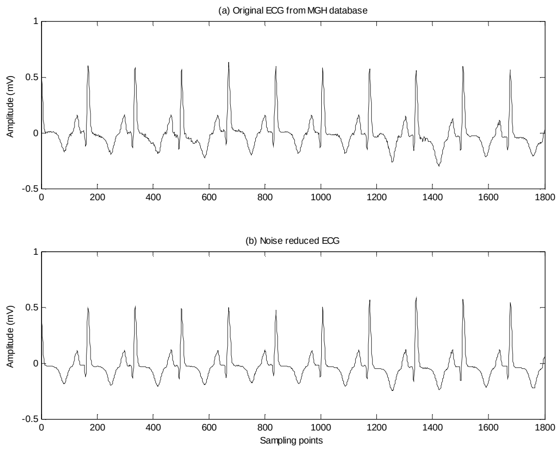


Fig. 8. (a) ECG from MGH/MF database – example from tape mgh004 (b) noise reduced ECG.

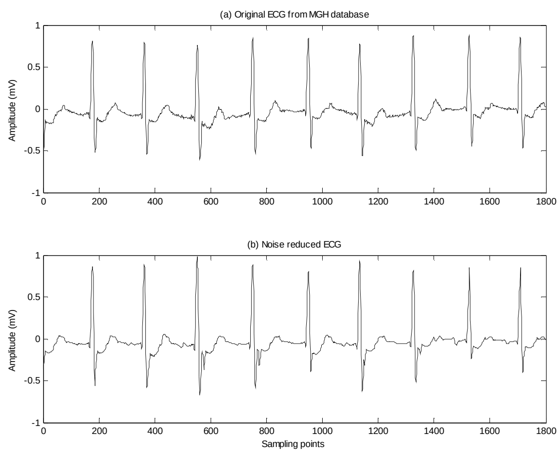


Fig. 8. (a) ECG from MGH/MF database – example from tape mgh010 (b) noise reduced ECG.

## IV. DISCUSSION

As could be seen from Figures 1 to 6, the proposed method has reduced most of the noise from the ECG signals. This is true for both the normal and arrhythmic cases.

Because there is correlation from one part to another in the ECG signals, the PCs with higher eigenvalues will consist more of ECG and less of noise. Noise is uncorrelated (or less correlated), so the PCs with lower eigenvalues will consist mostly of noise. Therefore, by retaining only the higher eigenvalue PCs for reconstruction, it is possible to reduce most of the noise. With more segmentation, it would be possible to obtain better noise reduction.

A higher increase in SNR (i.e. more noise reduction) could be seen for ECG signals corrupted with heavier noise. For example, an SNR improvement from -1.40 dB to 7.48 dB was obtained for the ECG signal with noise factor=0.2 (shown in Figure 1), while the improvement for noise factor=0.05 was smaller (from 10.53 dB to 13.45 dB). This is as expected because the PCs representing the noise for the earlier case will have larger amplitudes and when these are discarded during reconstruction, more noise will be discarded and thus the higher increase in SNR as compared to the latter case.

Figures 7, 8 and 9 show the results of applying the proposed method to the MGH/MF database ECG signals. It could be seen that the method has reduced noise from these ECG signals. The important point to note is here is that the improvement in the quality of the signal is achieved without distorting the original signal.

The method will produce good results for continuous type of ECG signals, whether arrhythmic or normal. However, the method may not work for ECG signals which contains single QRS arrhythmic beat like that exhibited by premature ventricular contraction. Baseline wanderings may also distort the output from the proposed method. But these problems are also existent in conventional multi-channel and multi-signal PCA noise reduction techniques and pose a future challenge.

## V. CONCLUSION

In this paper, we have proposed a method of using PCA to reduce noise from single channels of ECG signals. The method's novelty lies in the fact that most PCA related work use multi-channel or multi-trial ECG signals, unlike the single channel ECG used here. Using a single channel ECG signal results in lower cost and design complexity. The method works by adaptively segmenting the ECG signals using the R peaks. The segmented signals are now used by PCA to reduce noise. The experimental results show the validity of the method in reducing impulsive type of noise from single ECG signals. The method could also be adapted to reduce noise from other biomedical signals like electroencephalogram.

## REFERENCES

[1] Tjoa, M.P., Dutt, D.N., Lim, Y.T., Yau, B.W., Kugean, R.C., Krishnan, S.M., and Chan, K.L., "Artificial neural networks for the classification of cardiac patient states using ECG and blood pressure data," *Seventh Australian and New Zealand Intelligent Information Systems Conference*, Australia, pp. 323-327, 18-21 Nov. 2001.

[1] Celka, P., Mesbah, M., Keir, M., Boashash, B., and Colditz, P., "Time-varying Dimension Analysis of EEG Using Principal Component Analysis and Model Selection", *Proceedings of IEEE EMBS International Conference*, pp. 1404-1407, 2000.

[2] Panerai, R.B., Ferreira, A.L.A.S., and Brum, O.F., "Principal component analysis of multiple non-invasive blood flow derived signals," *IEEE Transactions on Biomedical Engineering*, pp. 533-537, vol. 35, no. 7, 1988.

[3] Sadasivan, P.K., and Dutt, D.N., "SVD based technique for noise reduction in electroencephalographic signals," *Signal Processing*, pp. 179-189, vol. 55, 1996.

[4] Palaniappan, R., Anandan, S. and Raveendran, P., "Two Level PCA to Reduce Noise and EEG From Evoked Potential Signals," *Proceedings of 7th International Conference on Control, Automation, Robotics and Vision*, Singapore, pp. 1688-1693, December 2-5 2002.

[5] Lange, D.H., and Inbar, G.F., "Variable Single-Trial Evoked Potential Estimation Via Principal Component Identification," *Proceedings of IEEE EMBS International Conference*, pp. 954-955, 1996.

[6] Brenda M. Beasley, *Understanding EKGs: A Practical Approach*, Prentice Hall, 2003.

[7] Chu, C.H., and Delp, E.J., "Impulsive Noise Suppression and Background Normalization of Electrocardiogram Signals Using Morphological Operators," *IEEE Transactions on Biomedical Engineering*, vol. 36, no. 2, pp. 262-272, February 1989.

[8] Pan, J., and Tompkins, W.J., "A Real-Time QRS Detection Algorithm," *IEEE Transactions on Biomedical Engineering*, vol. 32, no. 3, pp. 230-236, March 1985.

[9] Jolliffe, I.T., *Principal Component Analysis*, Springer-Verlag, 1986.