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Research Article

DENOISING OF ECG SIGNAL USING ADAPTIVE INDEPENDENT COMPONENT ANALYSIS

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ABSTRACT
It has been observed that denoising of ECG is done in stationary condition i.e. when the patient under scanner is lying on bed or in rest condition. This is very common case and the noise added in this condition can be removed by many different methodologies like FFT, wavelet, ICA etc. However, when the ECG is monitored in dynamic condition e.g., on tread mill testing, the noise inserted due to motion artifact is of entirely of different nature as compared to that of the static condition. In the presented work, the focus is on denoising of ECG signal corrupted by motion artifact conditions.

Keywords*: *ICA, ECG, SVD

INTRODUCTION
Electrocardiograms (ECGs) are signals that originate from the action of the human heart. The ECG is the graphical representation of the potential difference between two points on the body surface, versus time. Each heartbeat is a complex of distinct cardio logical events, represented by distinct features in the ECG waveform.

During the acquisition of ECG signal it gets corrupted due to different types of artifacts and interferences that may hide important diagnostic information. Independent Component Analysis (ICA) is a blind source separation technique that can be used for the removal of such noises and artifacts. In this paper, different ICA schemes such as JADE algorithm and Fast ICA are discussed and applied for ECG denoising. The database used is MIT-BIH database.

ECG recordings are examined by a physician who visually checks features of the signal and estimates the most important parameters of the signal. Using this expertise the physician judges the status of a patient. Therefore the recognition and analysis of the ECG signals is a very important task. The standard parameters of the ECG waveform are the P wave, the QRS complex and the T wave. But most of the information lies around the R peak. Additionally a small U wave (with an uncertain origin) is occasionally present.

Related Works

In this paper a combination of Extended Kalman Filter (EKF) and a dynamic model of a synthetic electrocardiogram (ECG) for ECG denoising is proposed. Experimental results show that the proposed algorithm is very efficient for the extraction of the ECG signals from noisy data measurements (Ouali *et al.*, 2013).

In this paper an efficient filtering procedure based on the singular Value Decomposition (SVD) has been proposed. SVD, a high resolution spectrum estimation tools, is used to decompose the ECG data matrix into orthogonal subspaces. Due to the energy-preserving orthogonal transformation in the SVD, these subspaces correspond to the signal and noise components contained in the ECG data. Projection of the data onto the desired subspace eliminates the noise and the unwanted signal components (Ouali and Chafaa, 2013).

Noise always degrades the quality of ECG signal. ECG noise removal is complicated due to time varying nature of ECG signal. As the ECG signal is used for the primary diagnosis and analysis of heart diseases, a good quality of ECG signal is necessary. A survey of various types of noises corrupting ECG signal and

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various approaches based on Wavelet Transform, Fuzzy logic, FIR filtering, Empirical Mode Decomposition used in denoising the signal effectively are presented in this paper. The result tables comparing the performances of various denoising techniques based on related parameters are included (Sarang *et al.*, 2013).

New improved methods for denoising Electrocardiogram (ECG) signal are proposed based on adaptive filter with Empirical mode Decomposition (El\'ID) and Ensemble Empirical mode Decomposition (El\'ID). El\'ID and EEMD methods are used to decompose the ECG signal into intrinsic mode functions (Il\1F). Performance of traditional El\'ID based denoising methods improved b)' adaptively processing the Il\1F components which are related to ECG noise. Convergence issue in Least Mean Square (Ll\1S) algorithm addressed by El\1D based adaptive algorithm. Block least mean square (BLMS) algorithm used with El\1D and EE!\JID to improve the computational efficiency of adaptive processing. Proposed methods are applied on white Gaussian noise added ECG signal and real time ECG signals obtained from physionet MIT-BIH arrhythmia data base. Signal to Noise Ratio (SNR), correlation co-efficient and Mean Square Error (l\1SE) are used to measure and compare the performance of proposed methods with traditional EMD based methods. All the experiments done with l\1ATLAB based coding. Results show that El\1D with BL!\JIS algorithm performs better than traditional El\1D based methods (Jenitta and Rajeswari, 2013).

The Electrocardiogram (ECG) signal is the electrical manifestation of the contractile activity of the heart and helps the physicians to interpret any physiological or pathological phenomena. The ECG recording is often deteriorated by several factors such as power line interference and baseline wander noise. These noises have to be removed for better clinical evaluation. The power line interference is cancelled by passing the first IMF of the Empirical mode decomposed (EMD) noisy signal through FIR low pass filter. In this paper a new strategy is proposed to remove baseline wander noise. The proposed method is evaluated over MIT-BIH ECG database in terms of visual inspection and qualitatively by root mean square error (RMSE). Finally the results are compared with the FIR filtering method (Anapagamini and Rajavel, 2013).

Significant diagnostic information in healthcare is obtained from Electrocardiogram (ECG) signals, so improvements in their analysis are also of growing importance. In the field of signal processing, the rapidly developing signal technology and flourishing variety of algorithms have proved successful targets for research in healthcare. During the acquisition of ECG signal it gets corrupted due to different types of artifacts and interferences that may hide important diagnostic information. Independent Component Analysis (ICA) is a blind source separation technique that can be used for the removal of such noises and artifacts. In this paper, different ICA schemes such as JADE algorithm and Fast ICA are discussed and applied for ECG denoising. Also made an attempt to apply constrained ICA (ICA) for ECG signal denoising which was used for fetal ECG extraction. The database used is MIT-BIH database (Mrinal and Mukherji, 2013).

The fetal ECG (fECG) is one of the most valuable tools for monitoring the health of the fetus throughout pregnancy. However, its clinical use has been limited by the difficulty in analyzing such non-invasive ECG recordings. The aim of this study was to develop a robust algorithm for the analysis of 4-channel abdominal ECG recordings and test its performance in the Computing in Cardiology Physionet Challenge 2013. Signals were pre-processed by a combination of frequency filtering and wavelet de-noising. Adaptive cancellation of the maternal ECG (ECG) was performed using maternal QRS time markers obtained from the principal component containing the largest ECG. Following further wavelet de-noising of the residuals, the fetal QRS time markers were computed with a local peak detection algorithm from the first principal component. The derived fetal HR (event 4) and fetal RR (event 5) time series were compared to the reference values obtained from a scalp electrode signal. This algorithm scored 223.23 for Challenge event 4 and 19.34 for Challenge event 5, outperforming the sample algorithm (Costanzo *et al.*,).

There are two main research topics about ECG signal proposed. One is the noise reduction, and the other is R peaks detection. Both of the two algorithms are based on discrete wavelet transform (DWT). DWT is efficient for analyzing nonstationary signals like ECG signal. The Simplest wavelets (sym5) and soft-thresholding are chosen as the wavelet function and thresholding method to do noise correction at the first denoising stage. The second stage is R wave detection. The MITBIH arrhythmia database is used to verify proposed algorithm. We reconstruct the decomposition level 3 to 5. Choosing the adaptive threshold and window size are the key points to reduce error rate. Applying two thresholds leads to better performance, compared to applying one threshold. At the last stage, we do noise correction again.With the information of R wave position, a novel method is proposed to eliminate the electromyogram (EMG) signal. The algorithm for R wave detection has a sensitivity of 99.70% and a positive predictivity of 99.65%. The error rate is 0.65% under all kinds of situation (0.37% if ignoring 3 worst cases). For noise correction, the SNR improvement is achieved at least 10dB at SNR 5dB, and most of the improvement SNR is better than other methods at least 1dB at different SNR. To apply presented algorithms for the portable ECG device, all R peaks can be detected no matter when people walk, run or move at the speed below 9km/hr (Lin *et al.*, 2013).

To judge whether the pulse rate variability can be used as a surrogate of heart rate variability, as well as investigate the quantitative relationship between them. Methods: Being simultaneously acquired, the pulse wave and ECG data were denoised, removed baseline drift. Then the pulse rate intervals and heart rate intervals were extracted. Finally, the relationship between the heart rate variability and pulse rate variability were studied in the time domain, frequency domain, and nonlinear analysis. Conclusion: By studying the pulse rate variability's and heart rate variability's of 30 healthy adolescents, we find that heart rate variability and pulse rate variability is correlated, but the difference is relatively small, in a resting condition, the difference of time domain is less than 3%, the Frequency domain is less than 9%, the nonlinear is less than 9%, which in a certain extent can replace each other. Furthermore, the influence from the neural regulation and respiration caused the delay of PRV in comparison with HRV, ranging from 6% to 20% of a heartbeat period. The breathing more greatly influences the PRV than HRV (Enze *et al.*, 2013).

Algorithm

In ICA, the measured signal should be linear combinations of independent source signals, and the independent signals should be non-gaussian in nature.

The noisy signal is given by:

$x = A.s + n$

Where, $x(t) = [x_1, x_2, x_3, \ldots. x_p]^T$

$s(t) = [s1, s2, s3, \ldots. Sq]^T$ where $q < p$ such that

$x(t) = A.s(t)$

When demixing matrix W is multiplied by vector x it can recover the original signals contained in s. So the major aim of ICA algorithm is to compute the demixing matrix W, such that: $s(t) = W.x(t)$

Thus, making $W = A^{-1}$.

Generally, ICA input signals are the observed signals, which may be measurement time series, such as sampled voltage values in time as in the case of ECGs, image pixel values, or basically any sets of values fulfilling the assumptions of ICA. In the sequel, the term 'measured signals' refers to a set of simultaneously measured digital discrete-time signals with constant interval between the measured signal samples. All signals are assumed to be sampled at the same time instances. ICA is realized by an iterative numerical algorithm, several of which exist.

RESULTS AND DISCUSSION

The proposed algorithm has been tested on the ECG data as obtained from the MITH web site. The ECG data are for normal and stressed person. Many arrhythmia cases are also available for testing purposes. The sample length is given against each ECG sample. Presently here, only case studies are given due to space limitations. However, the algorithm has been tested on more than 50 ECG samples for testing purposes. The results are fair enough in terms of noise removal.

Case-1

No. of Samples = 39237

ECG Features before Denoising

Mean = 0.638455
Standard Deviation = 0.230871
Energy = 0.000414
Power = 0.638455
Entropy = -0.000000
Variance = 0.006623
SNR before Denoising = 0.839585
MSE before Denoising = 0.341424

ECG Features after Denoising

Mean = 1.005916
Standard Deviation = 0.230707
Energy = 0.001018
Power = 1.005916
Entropy = -0.000000
Variance = 0.006612
SNR after Denoising = 4.844048
MSE after Denoising = 0.341324

Case-2

No. of Samples = 32144

ECG Features before Denoising

Mean = 0.643482
Standard Deviation = 0.239712
Energy = 0.000421
Power = 0.643482
Entropy = -0.000000
Variance = 0.006611
SNR before Denoising = 0.843213
MSE before Denoising = 0.346437

ECG Features after Denoising

Mean = 0.996367
Standard Deviation = 0.239706
Energy = 0.000999
Power = 0.996367
Entropy = 0.000000
Variance =0.006607
SNR after Denoising = 4.542810
MSE after Denoising = 0.319840

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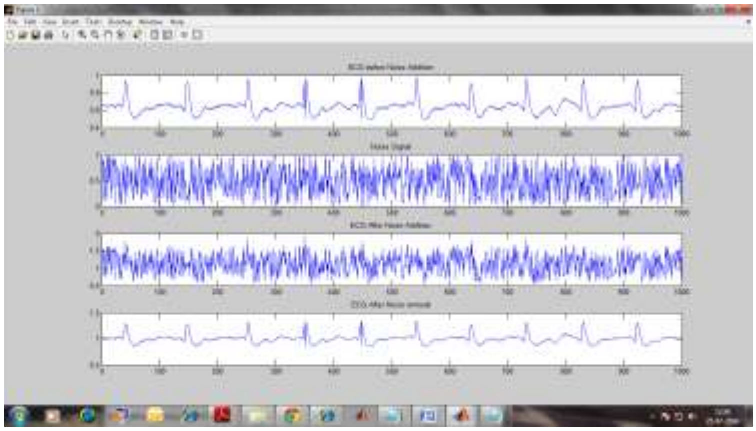
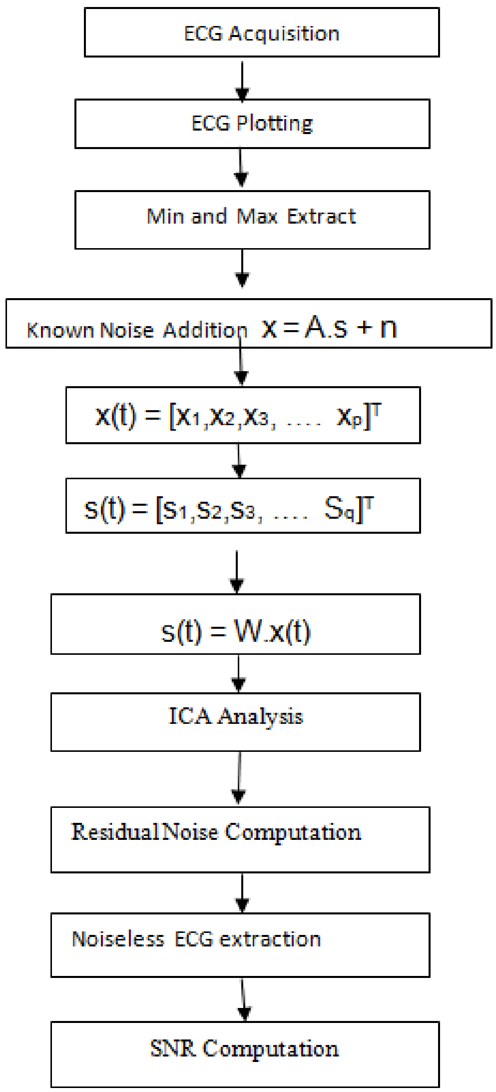


Figure 1: Original, Noisy and denoised ECG signal

Flow Chart



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