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A Simplistic and Novel Technique for ECG Signal Pre-Processing

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ABSTRACT

Automated recognition of patterns in an ECG signal quintessentially requires removal of noises, such as Baseline wander (BLW), breathing activity, poor quality of electrodes and current flowing in the cables of the acquisition system, during its pre-processing for improving the signal quality to enable the identification of various physiological and pathological phenomena from it. In the literature, it has been well established that statistical domain technique *viz.* ICA (independent component analysis) surpasses the performance of even higher order filters in removing interferences by calculating independent components with much less computational/mathematical complexity and loss of information. Thus, it will result in higher signal-to-noise-ratios (SNRs) mitigating masking effects of various interferences. On the other hand, LDA (linear discriminant analysis) minimizes the variance and maximizes the distance between any two data-classes while detecting/classifying them resulting in very less false detections. Therefore in this paper, ICA and LDA are proposed to be used combinedly for pre-processing and classification of an ECG signal, respectively. Hence, important latent attributes of the ECG signal are retained with maximally statistically independent criteria using ICA and effective classification/detection is accomplished by cutting down the dimensional costs using LDA. The performance of ICA in ECG signal pre-processing is further compared with that obtained using ANF (adaptive notch filter) to further demonstrate its superiority. The proposed technique is able to achieve sensitivity (Se), detection error rate (DER) and output SNR of 99.92%, 0.122% and 37.77dB, respectively on Massachusetts Institute of Technology- Beth Israel Hospital Arrhythmia database (MB ARR DB).

KEYWORDS
Adaptive notch filter (ANF); BLW; ECG; Independent component analysis (ICA); MATLAB@2015a; SNR

ABBREVIATIONS

SNR	Signal-to-Noise Ratio
CAMD	Computer-aided medical diagnosis
Se	Sensitivity
DR	Detection Rate
KNN	K-Nearest Neighbour
SVM	Support vector machines
MB ARR DB	MIT-BIH arrhythmia database
FoM	Figure-of-Merit
WT	Wavelet Transform
MIT-BIH	Massachusetts Institute of Technology-Beth Israel Hospital
PP	Positive Predictivity
SP	Specificity
STFT	Short Time Fourier Transform
ECG	Electrocardiogram
BLW	Baseline Wander
PLI	Power Line Interference
HoFs	Higher Order Filters

1. INTRODUCTION

The heart is an essential organ of the human body, which pumps blood throughout the body [1]. Still, timely detection of the ever-increasing incidences of heart disease is a massive challenge both in rural and urban areas. A large number of patients suffering from various heart diseases such as cardiovascular diseases (CVD) [2], atrial fibrillation (AF) [3], premature ventricular contraction (PVC) [4], coronary artery disease (CAD) [5], myocardial infarction (MI) [5], atrial tachycardia (AT) [6], and premature atrial contractions (PAC) [6] are being reported from rural areas nowadays. The increasing number and widespread occurrences of such incidences motivated the present authors to develop a more effective and simplistic Electrocardiogram (ECG) signal pre-processing methodology. ECG signal is interfered by various noises such as Baseline wander (BLW), breathing activity, poor quality of electrodes, current flowing in the system-cables, *etc.* during its acquisition hiding the use-

This article has been corrected with minor changes. These changes do not impact the academic content of the article.

ful information that is required for accurate diagnosis of cardiac diseases like R-peak detection.

Pre-processing of the ECG signal plays an important role in achieving satisfactory signal-to-noise-ratio (SNR), which may further enable their applications in telemedicine for monitoring of a variety of heart diseases. This way health status of the heart of the patients can be assessed well in time than that possible with the use of widely reported and used conventional tools such as filters (analog and digital), stockwell transform (S-transform), short-time Fourier transform (STFT), *etc.* [7].

An ECG represents an electrical activity of the heart produced by its myocardial contraction [8,9], which is recorded by placing the surface electrodes on the human body at the correct positions [10]. The inappropriate placements of precordial leads and electrodes may lead to invalid ECG recordings that are popularly known as artifacts.

The recorded ECG generally consists of three waves; P-wave, QRS complex, and T-wave due to depolarization of the atrium, depolarization of the ventricle, and the repolarization of the ventricle, respectively [11] as shown in Figure 1. The accurate interpretation of heart diseases from P-QRS-T waves is a very tedious and complex task even for medical practitioners when inspected manually. This is more critical, especially for borderline cases like the instance when the patient has a disease but has been diagnosed healthy to the contrary due to the fact that these waves have high variability *i.e.* they may vary for the same patient at different observation instants or can be similar for different patients.

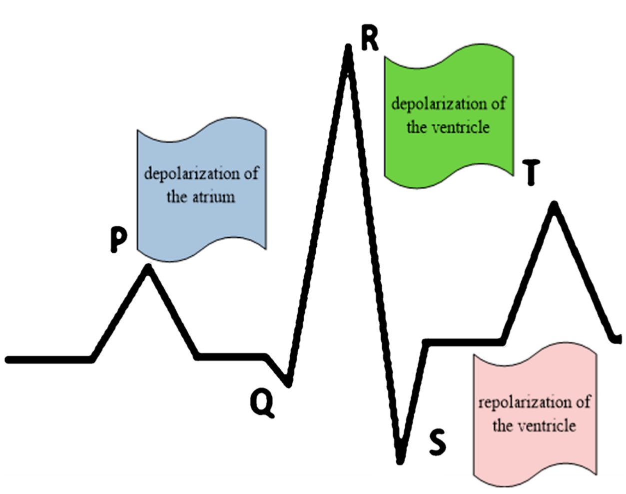


Figure 1: Constituent waves of ECG signal

Therefore, efficient signal processing techniques are required at the pre-processing stage itself for removing different types of distortions [12,13] such as baseline wander (BLW), low and high frequency components (muscle and movement artifacts), *etc.* [14] and to increase overall effective and accurate diagnosis. BLW is caused due to variable electrode-skin impedance, electrosurgical noise [13], patient body movement [15], cardio surgical equipment [16], bad electrodes, electronic noise introduced by amplifiers [17,18] and improper electrode placement and respiration [19]. It changes the baseline of the ECG signal and extends its frequency spectrum from fractions of Hertz to a few tens of Hertz (35 Hz for muscle related noises) [18]. Generally, different types of noise are removed on the basis of their frequency contents [20]. Unfortunately, there is no specific filtering technique for diagnosing a particular heart disease using the above [21].

Digital signal processing (DSP) improves ECG filtering to assist cardiologists in accurately and timely diagnosing heart related problems [22,23]. The primary goal is to preserve the essential clinical information of the ECG signals after performing the filtering operation [24,25]. Signal quality is measured by estimating the SNR of the sampled signals [26]. In the existing literature, fixed notch filter [27], low-pass, high-pass, band-pass and median filter [19], re-sampling, residual error signal, and principal component analysis (PCA) [28,29], adaptive filtering (AF) method, neural network (NN) [30–32], neighboring coefficients (NCs) [33], and wavelet transform (WT) [34–36] are some of the popular and widely used techniques that have been used for removing the undesired non-stationary trends from the ECG signals. Also, wavelet transforms have been used for various denoising and analysis related to responses of the complex systems to arbitrary inputs [37,38]. But all these methods did not get wide acceptance due to the time varying characteristics of an ECG signal. In some cases, they even failed to analyze micro potentials due to their overlap with the power line interference (PLI). Therefore in this paper, independent component analysis (ICA) and linear discriminant analysis (LDA) are proposed to be used combinedly for pre-processing and classification of an ECG signal, respectively. ICA is selected because it outperforms seven higher order filters (both analog and digital) with much less computational/ mathematical complexity and loss of information. It removes interferences by calculating independent components (ICs). LDA is selected to minimize the variance and maximize the distance between any two data-classes which results in a very less number of false detections. The performance of ICA is also compared with another benchmark technique for such purposes *viz.* ANF (adaptive notch filter). ANF has been selected due to its adaptive nature and the fact that it eliminates the need for higher filter-orders unlike that required in ordinary analog and digital filters. The performance of the proposed technique is assessed on the basis of sensitivity (Se) and detection error rate (DER) along with SNR [39].

The paper is organized as: Section 2 presents an overview of the related works, Section 3 details about used materials & methods, Section 4 includes results & discussion, followed by Section 5 concludes the paper.

2. RELATED WORK

In [40], Gupta and Mittal utilized a digital bandpass filter (DBPF) for removing BLW & PLI. But the performance of DBPF suffers due to the time-varying nature of the ECG signal. In [41], Mehta and Lingayat proposed SVM for detecting QRS complexes in an ECG signal. There, two distinct methods were utilized for pre-processing the acquired ECG signals *viz.* digital filtering for removing BLW & PLI and entropy criterion for feature generation. Further, SVM was considered for classifying the QRS and non-QRS regions. However, the performance of the digital filtering relies on the accurate selection of appropriate both low and high cut-off 3 dB frequencies, respectively for low- and high-pass filtering sections, which becomes very cumbersome due to time-varying nature of the ECG signal. In [42], Sheetal *et al.* attempted QRS complex detection using a hybrid filter consisting of a derivative and maximum-mean-minimum (MaMeMi) filter. The performance of that algorithm was evaluated using confusion matrix parameters viz. true positives (TPs), false positives (FPs), and false negatives (FNs). Other parameters *viz.* sensitivity (Se), positive predictivity (PP), and detection error rate (DER) were also computed. The performance of MaMeMi filter depends on the tuning between filter coefficients and sampling frequency. Also, it needs at least two registers to store the maximum and minimum values. In [39], Gupta and Mittal used fractional wavelet transform (FrWT) as a pre-processing technique and compared its performance with other existing state-of-the-art techniques based on either wavelet transform (WT) or fractional Fourier transform (FrFT). The proposed FrWT technique obtained promising results over other existing techniques due to its multiresolution analysis capability and signal representation in the fractional domain. Unfortunately, the efficacy of FrWT is highly dependent on the selection of appropriate values of both the rotation angle and basis function. In [43], Sharma, and Sunkaria proposed MI detection using stationary wavelet transform after decomposing the ECG signal. They extracted various features *viz.* energy, slope, and entropy for specific wavelet bands and classified them using KNN. The performance was compared on the basis of specificity (Sp), Se, accuracy (Acc), PP, and area under the receiver operating characteristics curve (AUC). But, SWT efficacy is limited due to the absence of phase information. In [44], Gu *et al.* proposed a simple basic algorithm *i.e.* ISC algorithm for improved R peak detection in wearable devices. To minimize the false detection, the reported technique was elaborated on the basis of an updated slope comparison threshold, updated amplitude selection threshold, and RR interval judgement. However, ISC needs processing of a large number of variables. In [45], Kora and Krishna proposed the detection of heart diseases on the basis of the similarity between the two waveforms as determined using wavelet coherence technique (WCT). They used the extracted parameters for analysing the ECG signal and Bat algorithm was used for further optimization. Levenberg Marquardt neural network classifier was used for classifying these features. The approach of WCT leads to a natural, local, and multiscale estimate of non-stationary dependencies. Unfortunately, coherence is very sensitive to fluctuations of linearity in phase. In [46], Lin *et al.* proposed a novel fetal R-peak enhancement technique because the fetal cardiovascular system might have hidden peaks. The proposed technique statistically generated the weighting mask to highlight the hidden peaks. They used simulations to validate their research work based on noise contamination and R-peak interval changing rate. However, it was able to obtain only limited accuracy. In [47], Cleetus *et al.* attempted to investigate the directional interaction changes based on the Granger causality technique during postural change that occurs in the cardio-respiratory system during the procedures. Further, it was also used in the frequency domain to investigate the directional interaction changes between cardiac and respiratory signals. But, this technique can test cause–effect relations with only constant conjunctions.

3. MATERIALS AND METHODS

A variety of ECG records/datasets are generally required for accurate analysis of the status of the heart of a patient. These records contain all the timing and amplitude information of the key features that are to be detected for diagnosing any possible heart abnormality. Also, any change in the morphology of an ECG signal needs to be investigated in respect of the type of arrhythmia, posture, lead placements, *etc*. But, this information is generally masked by several errors and artifacts known as noncardiac components challenging the detection of cardiac components

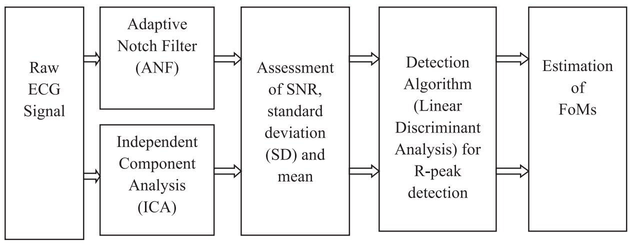


Figure 2: Proposed technique

of an ECG signal [48,49]. Moreover, the removal of such errors and artifacts usually takes more time which is very crucial during emergencies. Thus, exploration for more efficient and effective computational algorithms evolved using different permutations and combinations of existing algorithms from different domains is much needed.

Therefore in this paper, ICA and LDA are proposed to be used combinedly for pre-processing and classification of an ECG signal, respectively. The performance of ICA is also compared with another benchmark technique *i.e.* ANF which also has a time varying filter coefficients. Figure 2 shows the proposed methodology in this paper.

3.1 ECG Signal Acquisition

ECG data was acquired using a lab set-up based on MP35/MP100 version of BIOPAC which is regarded as a highly recommended biomedical hardware/ instrument among the biomedical research community. The data were acquired at room temperature under the supervision of a well trained technician at NIT Jalandhar, Punjab, India. ECG recordings of a group of people belonging to different age groups and cadres *viz.* college guards, old age persons, outsiders, residents, and students, who volunteered by giving their written willingness for the purpose, were obtained. A total of 132 recordings were acquired in six days from different subjects *i.e.* 22 recordings at a sampling rate of 360 Hz on each day both in sitting and lying postures. All these data sets were got verified by various experts/cardiologists. Further, validation is done by comparing the results obtained using the entire standard Massachusetts Institute of Technology-Beth Israel Hospital Arrhythmia database (MB ARR DB) as per the practice followed in the existing literature *e.g.* in [50]. Figure 2 shows a schematic of the methodology proposed in this paper.

3.2 Pre-Processing Methods

Pre-processing has become more crucial in the present era of increasing use of Computer-aided medical diagnosis (CAMD) system for effective diagnosis of heart diseases. Nowadays there exist a plethora of different datasets from various cardiology labs/hospitals posing a huge challenge to cardiologists and doctors to analyze and manually interpret them accurately [51,52]. Therefore, it is increasingly becoming essential to use CAMD that further underlines the need for appropriate and efficient pre-processing methodologies. The present paper is a step in that direction. For the effective interpretation of such datasets, robust pre-processing techniques are required. Therefore, in this paper, ICA + LDA has been proposed to be used combinedly alongwith suitable comparison with other benchmark techniques *viz.* ANF at the pre-processing stage to validate the efficacy of the proposed approach. Here, ANF has been considered for comparison since it is reported to be a benchmark technique in the literature due to its two features *viz.* adaptive nature and the fact that it obviates the need for higher-orders of the filters unlike that required in ordinary analog and digital filters. MATLAB@2015a was used for carrying out all the simulations.

3.2.1 Adaptive Notch Filter (ANF)

A notch filter is capable of removing PLI of the stationary signal. However, sometimes the signal is non-stationary in nature. In such cases, an adaptive notch filter is often used to provide effective tracking of the frequency variations in the input signal [53]. The adaptive process is accomplished using both FIR (finite impulse response) and IIR (infinite impulse response) filters. This process can be resumed using the most recent coefficients at any time. The filter structure consists of a cascade of second order sections [54]. The adaptive notch filter transfer function is given in [54] as:

$$T(z) = \frac{1}{2}\left(1 + \frac{\xi + pz^{-1} + z^{-2}}{1 + pz^{-1} + \xi z^{-2}}\right) \tag{1}$$

where ξ decides the rejection bandwidth.

3.2.2 Independent Component Analysis (ICA)

ICA is a nonlinear approach [35,55,56] for dimensionality reduction of the records in a database. It considers the observed signal as constituting a linear mixture of source components that are statistically-independent [57]. Also, ICA involves very less computational/ mathematical complexity and loss of information resulting in higher SNRs.

In this technique, a corrupted signal is decomposed into different independent sources based on their mutual independence that is equal in numbers to the number of observed mixtures in it. This technique works as a blind source separation technique for linear mixtures that decomposes such a multivariate signal into additive subcomponents [35,56]. As ECG signal is generated due to atrial and ventricular activities that are independent of each other, therefore, ICA has always been a better choice for such applications as reported in the literature [58–61]. Additionally, it has emerged as a substitute to the higher order digital filters for achieving enhanced SNRs in noisy cardiac signals. Mathematical details of ICA are reproduced next for ready reference.

The basic linear ICA model for a set of N measured signals $x = [x_1, \dots, x_N]^T$ is represented as a linear combination of the unknown sources $s = [s_1, \dots \dots \dots, s_N]^T$ as:

$$x = As \tag{2}$$

where A is N × N mixing matrix (N-dimensional vectors s and x denotesingle observations of the source and measured signals, respectively). The weighting and source matrices are expressed as:

$$W = A^{-1} \tag{3}$$

$$s = Wx \tag{4}$$

3.3 Signal-to-Noise-Ratio (SNR) (Input and Output), Standard Deviation, and Mean

The SNR (dB) at input stage is expressed as [1,62],

$$\mathrm{SNR_{dB}} = 10\log_{10}\frac{[x(t)_{\mathrm{neat}}]^2}{(x(t)_{\mathrm{noisy}} - x(t)_{\mathrm{neat}})^2} \tag{5}$$

The SNR (dB) at output stage is expressed as [1,62],

$$\mathrm{SNR_{dB}} = 10\log_{10}\frac{[x(t)_{\mathrm{neat}}]^2}{(x(t)_{\mathrm{filtered}} - x(t)_{\mathrm{neat}})^2} \tag{6}$$

where $x(t)$ is the ECG signal.

3.4 Classification/Detection Algorithm

LDA (linear discriminant analysis) minimizes the variance and maximizes the distance between any two data-classes while detecting/classifying them resulting in very less false detections. This fact motivated the authors to propose the use of LDA alongwith ICA in this paper for classifying the features of an ECG signal. It is a widely used technique for detection purposes. It detects patterns in the underlying application using a dimensionality reduction approach, which is very famous in machine learning (ML) and pattern classification applications [63–65]. In this paper, LDA is applied to different datasets to investigate its effects on the eigenvectors. Afterwards, the dimensionality reduction step is performed for transforming a higher dimensional space into a space with lower dimensions. In the end, the process is terminated based on the "*supremum of eigen values*".

The mathematical expression to obtain the mean for the class matrix is expressed as:

$$M_c = \sum_{i=1}^{c} n_i(m_i - m)(m_i - m)^T \tag{7}$$

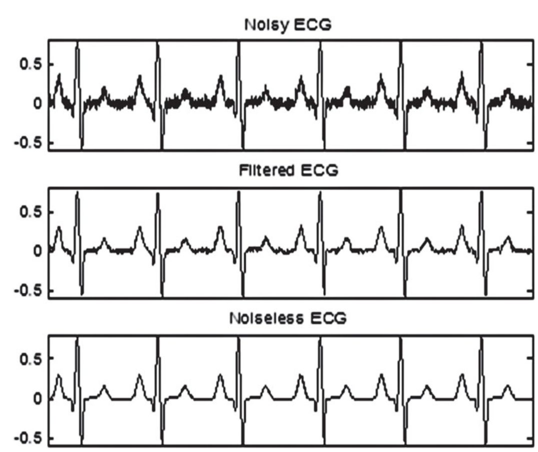
The mathematical expression to obtain within-class matrix is expressed as:

$$M_w = \sum_{i=1}^{c}\sum_{j=1}^{n_i}(a_{ji} - m_i)(a_{ji} - m_i)^T \tag{8}$$

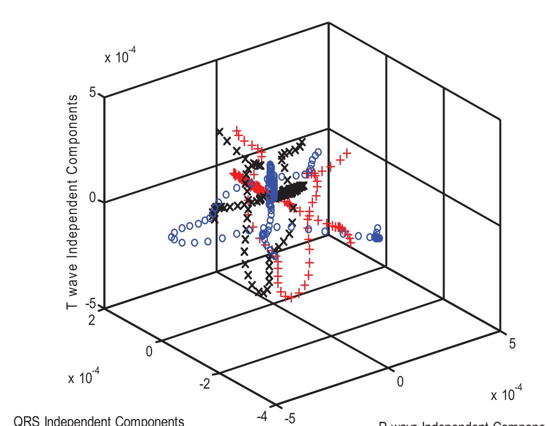
where a_{ji} shows the j^{th} sample in the i^{th} class.

Matrix W_X gives the generalized eigenvalues, expressed as:

$$W_X = {M_W}^{-1}M_c \tag{9}$$



(a)



(b)

Figure 3: (a) Adaptive notch filtering of ECG signals and (b) ICA of ECG signal

In this paper, ICA and LDA are proposed to be used combinedly for pre-processing and classification of an ECG signal, respectively. For evaluating the performance, different figures-of-merit (FoM)are considered as explained next.

3.5 Figures of Merit (FoM)

For evaluating the performance of the proposed technique, two important performance parameters or FoMs *viz.* sensitivity (Se) and detection rate (DR) are considered in this paper. They have been defined in [66,67] as.

Mathematically, they are defined in [21,25] as:

$$\text{Sensitivity (Se)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{10}$$

$$\text{Detection Error Rate(DER)} = \frac{\text{Total False Rate(FN + FP)}}{\text{Total Actual Peaks}} \tag{11}$$

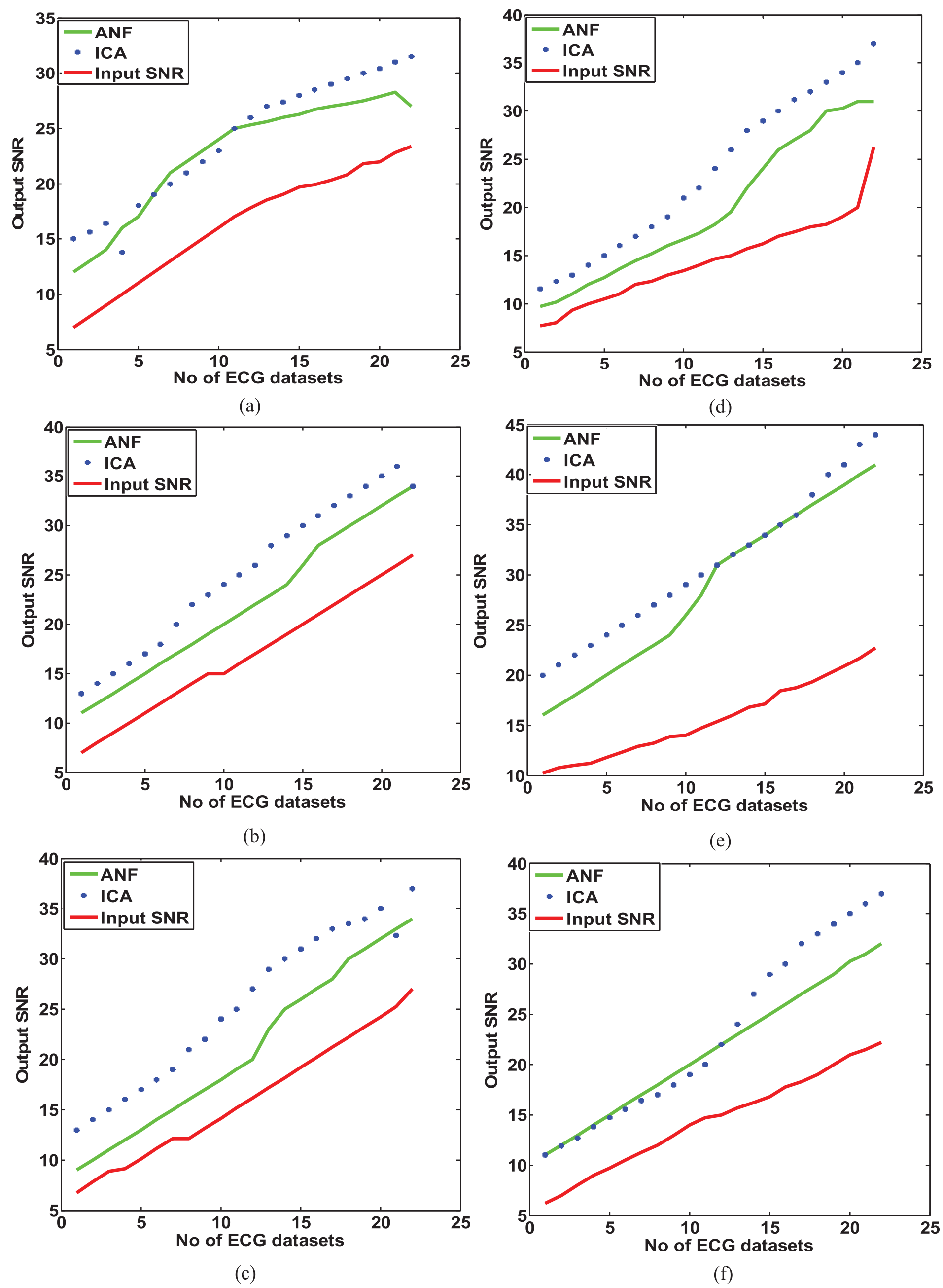


Figure 4: Comparison of output SNR using proposed methodology and existing ANF *vis-à-vis* input SNR for each of the 22 data records arranged in the ascending order for(a) first day (b) second day (c) third day (d) fourth day (e) fifth day (f) sixth day

where TP, FP, and FN are true positives, false positives, and false negatives, respectively.

4. RESULTS AND DISCUSSION

Mixing matrices& independent components were computed using ICA by implementing it in MATLAB through seventy iterations (*i.e.* forty-eight for MB ARR DB and twenty-two for real time ECG recordings). The obtained matrices had 2×2 and 3×3 dimensions for MB ARR DB and real time ECG recordings, respectively. On the other hand, a total of seventy seven iterations were performed for ANF out of which seven iterations were for selecting an appropriate rejection bandwidth and seventy iterations were for their processing. In MB ARR DB, ECG signal from only channel 1 has been considered for all the simulations.

The main obstacle in biomedical signal processing is low SNR of the signal due to the existence of various types of noise, especially those that have amplitudes comparable to that of the signal itself. In the case of an ECG signal, various noises can have amplitudes up to 300 mV, which can mask the vital information contained in it's R-peaks that have an amplitude of 1.6 mV. ICA has been proposed to be used for removing such noises in this paper alongwith a comparison of its efficacy with that obtained using ANF. The obtained results are shown in Figure 3(a,b), respectively. The performance of the proposed technique is assessed by computing the SNR of the reconstructed signal. The estimated mean value and standard deviation of the signal are 0.4 mvolt and 0.765, respectively. Figure 4 shows that the proposed ICA + LDA technique outperforms ANF + LDA at the pre-processing stage since the higher improvement in SNR is obtained *vis-à-vis* the input SNR for each of the 22 data records acquired on each day from a different set of subjects belonging to various age groups in different weather conditions. In Figure 4, x-axis shows the calculated output SNR for all 22 data records that were acquired on each day totalling to 132 data records in six days from a different set of volunteers belonging to different age groups. It shows the output SNR as achieved using the proposed ICA based approach and existing ANF *vis-à-vis* the input SNR for each of the 22 data records on a day.

However, it can be observed from the Figure 4(a,e,f) that for some ECG datasets, ANF achieves higher improvement in output SNR as compared to the proposed technique but still it's higher for the majority of 22 real time ECG datasets using the proposed technique.

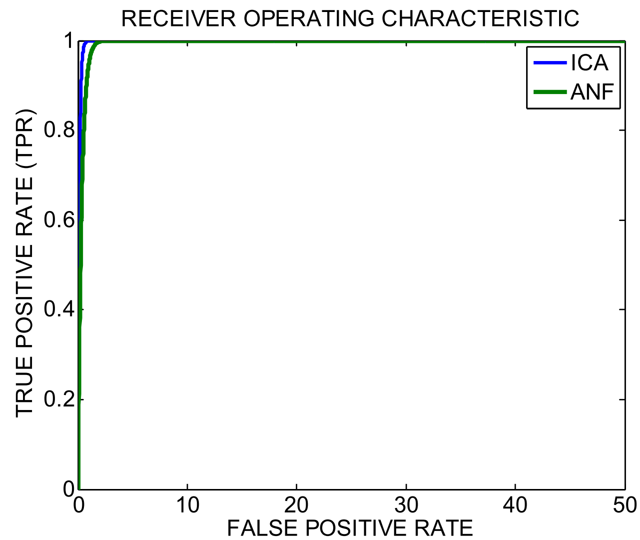


Figure 5: ROC curve

The proposed technique attains zero false detection (FN + FP)for various datasets of MB ARR DB *viz.* 100, 103, 118, 202, 207, 209, 212, 220, 221, 223, 230,231,233, and 234. The proposed technique achieved a total detected beats of 110097, TPs of 110108, total FNs of 83, and FPs of 52. The considered FoMs with proposed technique *viz.* DR of 0.122% and Se of 99.92% are obtained.

"Receiver Operating Characteristic (ROC)" is also used in this paper for examining the discriminative power of the proposed methodology. Figure 5 shows the ROC curve which reveals that the false positive rate is very less and the true positive rate is very high (above 90%) simultaneously using the proposed approach *viz.* ICA + LDA. On the contrary, the false positive rate is higher using the existing ANF + LDA technique.

Table 1 showcases the merits and demerits of the proposed technique *vis-à-vis* other existing techniques. It can be observed that the proposed technique outperforms the existing techniques at all levels *viz.* extraction of important features, SNR, removal of artifacts & noises, and a non-linear dimensionality reduction. The superior performance of the proposed methodology amply demonstrates its practicality in getting a quick and precise analysis making it suitable for emergency situations.

Table 2 shows the comparison of the proposed technique with other existing techniques. In the literature, Se of 82.75%, 99.7%, 99.97%, 98.84%, 95.60% was reported in Narina *et al.* [75], Acharya *et al.* [5], Kora [76], Kaya *et al.* [73], and Ripoll *et al.* [77], respectively.

Table 1: Merits and demerits of the proposed technique *vis-a-vis* other existing techniques

S.No.	Technique	Merits	Demerits	Ref.
1	ANF	Can have varying filter coefficients	Does not provide the actual ECG signal.	[68,69]
2	ICA	ICA is better technique to extract features.	Cannot work effectively when cardiac dynamics are affected by body movements.	[70,71]
		ICA enhances SNR and represents all characteristics of the actual ECG recorded dataset.	Cannot segregate the signals if signals were having Gaussian amplitude distribution.	
		It provides good result for neglecting artifacts and noises.	Estimation of energies and their order are not possible of extracted independent components.	
		It can works as a non-linear dimensionality reduction technique as well as provides result like higher order digital filter.		
3	Wavelet transform	It has muti-resolution capability which signifies its further applications for low SNR signals (also for Electro-Encephalo-Gram, EEG).	Proper selection of basis function with scale is extreme important.	[9,36]
4	Digital Bandpass filter (DBPF)	DBPF operation is invariance of temperature and drift unlike of analog filters.	It requires proper selection of cut-off frequencies of low pass and high pass filter.	[72]
5	MaMeMi filter	It can remove BLW with minimum resources	It requires a larger filter order to achieve ideal characteristic.	[42]
6	Fractional Fourier transform	Represent different views of the given signal at different rotation angles.	Unable to filter out the motion artifacts.	[39]
7	Principal Component Analysis (PCA)	Reduces overfitting and improves visualization	It needs data in standardized format.	[73]
8	Directed Coherence	It is useful in multivariate stochastic systems	It suffers due to normalization strategy which needs exhaustive steps.	[47]
9	SavitzkyGolay Digital Filtering	It preserves all essential clinical attributes after its processing.	Sometimes higher filter order are required which increases the computational complexity due to weighting matrix.	[74]
10	Local adaptive wiener filter	It can be implemented for most of the real time applications. And able to minimize the mean squared error (MSE).	It only showcase point estimates.	[33]

Table 2: Comparison of the proposed approach with other existing approaches

Ref	Technique	Se (in %)	DER (in%)	Output SNR (in dB)
Prop	**ICA + LDA**	**99.92**	**0.122%**	**37.77dB**
[75]	Wavelet and SVM classifier	82.75	–	–
[5]	DCT, DWT, EMD, LPP, KNN	99.7	–	–
[76]	HF + FFPSP	99.97	–	–
[73]	KNN + GA	98.84	–	–
[77]	Shallow networks	95.60	–	–

On the other hand, the proposed technique yields Se of 99.92%, DR of 0.122%, and output SNR of 37.77 dB. These values are much better as compared to other state-of-the-art techniques.

Additionally, the proposed technique is also compatible with new programming languages such as Python, R-language, *etc*., and is able to achieve higher values of performance evaluating parameters.

5. CONCLUSION

Accurate analysis of an ECG signal is very challenging due to its nonlinear characteristics. The proposed technique *viz.* ICA + LDA has been successfully implemented to enhance the quality of an ECG signal leading to the feasibility of its automated analysis. This has been established through the obtained values of the considered FoMs *i.e.* DR of 0.122%, Se of 99.92%, and output SNR of 37.77 dB. Therefore, it is concluded that the obtained performance is similar to that obtained using higher order filters but with much less computational complexity enabling the accurate recovery of the original ECG signal. This has not been possible with other existing approaches till date as demonstrated by suitable comparisons with one of the benchmark techniques *viz.* ANF as reported in the literature.

However, the proposed approach has certain limitations which can be taken up in future. For example, ICA here fails to detect the correct number (order) and scaling (with sign) of the source signals and LDA is sensitive to overfitting. Therefore in future, elephant herding optimization (EHO) along with support vector machine (SVM) may also be incorporated to minimize this ambiguity.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

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