© May 2019 | IJIRT | Volume 5 Issue 12 | ISSN: 2349-6002

Image Processing in Frequency Domain Using Matlab

C.Kokilavani [1], G.Sandra Karunya[2], A.Mathan Gopi[3], D.Rajinigirinath[4]
[1]PGStudent, Sri Muthukumaran Institute of Technology, Chennai, Tamil Nadu, India
[2,3]Assistant Professor Sri Muthukumaran Institute of Technology, Chennai, Tamil Nadu, India
[4]Head of the Department Sri Muthukumaran Institute of Technology, Chennai, Tamil Nadu, India

***Abstract*- Objective: image processing in frequency and classification of noises can play a vital role in the development of robust unsu-pervised electrocardiogram (ECG) analysis systems. This paper proposes a novel unified framework for automatic detection, localization and classification of single and combined ECG noises. Methods: The proposed framework consists of the modified ensemble empirical mode decomposition (CEEMD), the short-term temporal feature extraction, and the decision rules based noise detection and classification. In the proposed framework, ECG signals are first decomposed using the modified CEEMD algorithm for discriminating the ECG components from the noises and artifacts. Then, the short-term temporal features such as maximum absolute amplitude, number of zerocrossings, and local maximum peak amplitude of the autocorrelation function are computed from the extracted high-frequency (HF) and low-frequency (LF) signals. Finally, a decision rule-based algorithm is presented for detecting the presence of noises and classifying the processed ECG signals into six signal groups: noise-free ECG, ECG+BW, ECG+MA, ECG+PLI, ECG+BW+PLI, and ECG+BW+MA. Results: The proposed framework is rigorously evaluated on five benchmark ECG databases and the real-time ECG signals. The proposed framework achieves an average sensitivity of 99.12%, specificity of 98.56%, and overall accuracy of 98.90% in detecting the presence of noises. Classification results show that the framework achieves an average sensitivity, positive predicticvity, and classification accuracy of 98.93%, 98.39% and 97.38%, respectively. Conclusion: The proposed framework not only achieves better noise detection and classification rates than the current state-of-the-art methods but also accurately localizes short bursts of noises with low endpoint delineation errors. Significance: Extensive studies on benchmark databases demonstrate that the proposed framework is more suitable for reducing false alarm rates and selecting appropriate noise-specific denoising techniques in automated ECG analysis applications.**

Index Terms- ECG signal quality assessment, ECG noise detection and classification, muscle artifacts, baseline wander, ECG denoising

I. INTRODUCTION

Electrocardiogram (ECG) signals are often corrupted with different types of noises and artifacts, such as baseline wan-der and drift (electrode contact noise and electrode motion artifacts), powerline interference (PLI), and muscle artifacts, making it almost impossible to perform a morphological to handle relatively noise-free ECG signals [1]. In such sce-narios, existing systems render the inaccurate and unreliable measurements which lead to produce high false alarm rates for the noisy ECG signals [3]. Consequently, frequent false alarms are not only most annoying and disturbing both the clinicians and the patients but also lead to misdiagnosis of cardiac arrhythmias [3]- [7]. The issue of high false arrhythmia event alarm and heart-rate alarm rates highly impacts the usability of real-time ECG monitors because of the two main reasons: (i) noises and artifacts in the isoelectric line of the ECG signal are falsely detected as normal beats or abnormal beats; and (ii) severely contaminated ECG beats are misclassified due to the inaccurate measurements of essential ECG feature parameters [4]- [7]. Therefore, noisy ECG signals must either be discarded or filtered prior to the extraction of feature parameters.

A. Related Works and Motivation

Various strategies have been adopted to handle the problem of high false alarm rate due to the noises and artifacts [2]- [7]: (i) ECG denoising based approach to suppress the noises and artifacts in the ECG recordings and (ii) signal quality indices (SQI) based approach to assess the clinical acceptability of the recorded ECG signals.

1) ECG Denoising Based Strategy: To reduce the false alarm rates, various ECG denoising methods have been presented based on the moving average and median filters, frequency selective filters, adaptive filters, Wiener filters, polynomial filters, singular value decomposition (SVD), discrete cosine transform (DCT), discrete wavelet transform (DWT), switching Kalman filters, empirical mode decomposition (EMD), nonlinear Bayesian filter (NBF), mathematical morphological (MM) operators, principal component analy-sis (PCA), independent component analysis (ICA), nonlocal means (NLM) method, variational mode decomposition (VMD), and EMD-wavelet method for removal of single and combined ECG noise sources [2], [8], [9]. Most existing de-noising methods are highly capable of suppressing noises and artifacts that are very different from those of ECG morphology. Evaluation results show that the baseline wander removal methods may distort the ST-segment due to the attenuation of the low-frequency components of ECG signal [8]. Results further show that simple filters are not adequate to remove severe EMG noise without distorting the amplitude, duration, interval and shape features of the ECG signal [9]. The EMD based denoising method introduces significant distortion at the beginning and end of QRS complexes that may cause widening of the QRS complex [9]. Thus, the denoising methods significantly alter the ECG local waves due to the impossibility

B. Objective and Key Contributions

Literature studies show that a single signal processing technique is not adequate to remove different kinds of noises and artifacts in the ECG signals. Moreover, the denoising results show that each of the filtering techniques may introduce different kinds of waveform distortion. Thus, it is very important to identify the nature of noises in the ECG recordings and to choose appropriate signal processing techniques suited to the noise types. Further, in some ECG recording scenarios, the noises and artifacts can occur partially in the 10 s duration ECG signal. Therefore, it is important to determine boundaries of the localized noisy ECG portions either to mark as an unreliable measurements or to discard the noisy ECG segments from the feature extraction. To the best of our knowledge, there is no systematic framework which can perform automatic detection, localization and classification of noises and artifacts present in the ECG signal. These issues are very important design consideration for real-time ECG signal analysis and diagnosis systems under resting, ambulatory and exercise ECG recording conditions.

2)This paper proposes a novel unified framework for automatic detection, localization and classification of noises and artifacts present in the ECG signal. The present study has four major goals: (i) Unlike past SQA studies, we aim to propose an unified ECG noise detection, localization and classification frame-work, which has great potential in reducing the number of false alarm rates and selecting noise-specific signal processing (or noise models) technique(s) for effective removal of noises from ECG signal. (ii) We intend to reduce computational load of the commonly used CEEMD algorithm by introducing new stop-ping criteria such as number of zerocrossings (NZC) and maximum absolute amplitude (MAA) in the iteration process. Signal Quality Assessment Based Strategy: Besides the noise reduction strategy, signal quality assessment (SQA) strategy has been employed to tackle the false alarm problem. Most methods were presented for classifying the recorded ECG signals into acceptable or unacceptable[5]-[7]. This section briefly describes the feature extraction for assessing the ECG signal quality. D. Tobon Vallejo et al. proposed a modulation spectrum-based ECG quality index based on the spectral signal representation and correlation. C. Orphanidou et al. proposed signal quality indices based on the heart rates, RR interval features and template matching. E. Morgado, et al. proposed an ECG quality estimation method based on the cross-correlation among leads, decision-tree and SVM classifier. J. Behar et al. investigated the ECG signal quality using seven SQIs, such as the kurtosis SQI (kSQI), the skewness SQI (sSQI), the relative power in the QRS complex (pSQI), the relative power in the baseline (basSQI), the fraction of beats detected by wqrs that matched with beats detected by eplimited (bSQI), the ratio of the number of beats detected by eplimited and wqrs (rSQI), and the ratio comprising of the sum of the eigenvalues associated with the five principal com-ponents over the sum of all eigenvalues obtained by principal component analysis of the time-aligned ECG cycles (pcaSQI), and the SVM classifier. P. X. Quesnel et al.

proposed an ECG signal quality analysis based on the ensemble averaging of detected PQRST complexes and average PQRST complex subtraction from each of the PQRST complexes of ECG signal. G. D. Clifford et al. investigated seven signal quality indices (iSQI, bSQI, fSQI, sSQI, kSQI, pSQI, and basSQI) with multi-layer perceptron (MLP) and SVM classifiers for determining clinical acceptability of ECG signals. L. Johannesen and L. Galeotti proposed an automatic ECG quality scoring methodology based on the QRS feature extraction and rule-set. Li et al. performed ECG signal quality assessment based on the spectral distribution signal quality index (sdSQI), the comparison of multiple QRS detectors on a single lead (bSQI), the degree of agreement between beat detection on different leads (iSQI), and the kurtosis of the ECG (kSQI). J. Lee et al. presented an automatic motion and noise artifact detection using empirical mode decomposition, three statistical measures such as the Shannon entropy, mean, and variance of the first IMF, and feature thresholding rules. D. Hayn et al. presented a QRS detection based ECG quality assessment using the QRS

II. PROPOSED ECG NOISE DETECTION, LOCALIZATION AND CLASSIFICATION FRAMEWORK

This section first presents a modified complete ensemble empirical mode decomposition (CEEMD) algorithm with new stopping criteria and discusses advantages of the proposed stopping criteria in reducing the computational load significantly as compared to that of the conventional CEEMD algorithm. Then, we describe the major components of the proposed framework, including (i) the ECG signal and noise separation; (ii) the short-term temporal feature extraction; and (iii) the decision rules based noise detection and classification.

A. Modified CEEMD Algorithm

There are several techniques to decompose an ECG signal into several subsignals. Empirical mode decomposition (EMD), which is a self-adaptive time-frequency analysis technique, is widely used for decomposing complex, multicomponent signal into several fast and slow oscillations called intrinsic mode functions (IMFs). The complete ensemble EMD technique has been proposed to overcome the drawbacks of the basic EMD and ensemble EMD (EEMD), such as mode mixing problem of the basic EMD, where different oscillations exist in the same IMF, or similar oscillations exist in different IMFs; producing varying number of IMFs; and reconstructed signals contain residual noise after decomposition when signal to noise ratio (SNR) is low. Torres et al. proposed the CEEMD algorithm that adds different realizations of Gaussian noise to the residual signal after extracting subsequent intrinsic mode functions [29]. It has been proven that the CEEMD algorithm provides an exact reconstruction of the original signal and an improved spectral partition of the modes, with a lower computational cost by requiring less than half the sifting iterations that for the EEMD algorithm [29]. By applying the CEEMD algorithm, a signal is adaptively decomposed into a finite set of intrinsic mode functions (or oscillation modes) and a residue, wherein the decomposition procedureis continued until the obtained residue is no longer feasible to be decomposed (a constant or a monotonic slope, or with only one extremum) or until a predetermined threshold is achieved. The lower-order IMFs capture fast oscillation modes of the high-frequency noises caused by muscle artifacts, power line interferences, and recording instrument noises while higher-order IMFs typically capture slow oscillation modes of base-line wanders. The final residue represents the trend component of the signal. In this study, we intend to explore the number of zerocrossings and magnitude of the slow oscillation mode of the residue obtained at the IMF extraction process in order to reduce the computational load of the conventional CEEMD algorithm.

In the modified CEEMD algorithm, the decomposition process is terminated when any following stopping criterion is satisfied, namely, the magnitude of the current residue is less than the predefined threshold, or the number of zerocrossings (NZC) of the current residue is less than the predefined NZC value. The result of the modified CEEMD algorithm produces a finite set of IMFs and a residue of baseline wander. The predefined threshold values for the stopping criteria are chosen based on the temporal parameters such as maximum absolute amplitude and number of zerocrossings of the slow oscillation of the baseline wanders. By considering the baseline wanders with frequency less than 1 Hz and the magnitude of severe baseline wanders, the NZC of 10 and MAA of 0.1 mV are chosen to discriminate the baseline wanders from the ECG components and the MA and PLI noises.

For a given input ECG signal x[n], the modified CEEMD algorithm with new stopping criteria can be summarized as:

B. Signal and Noise Separation

The decomposition results of the modified CEEMD algorithm are shown in Fig. 3. Results show that lower-order IMFs and higher-order IMFs capture the fine scales (or high-frequency (HF) components) and coarse scales (or low-frequency (LF) components) of the ECG signals, respectively. For the noise-free ECG signals, lower-order IMFs, or modes M1 and M2 in Fig. 3(a), capture fast varying components of QRS complexes and higher-order IMFs, or modes M8 and M9 in Fig. 3(a), capture very LF components of the local waves.

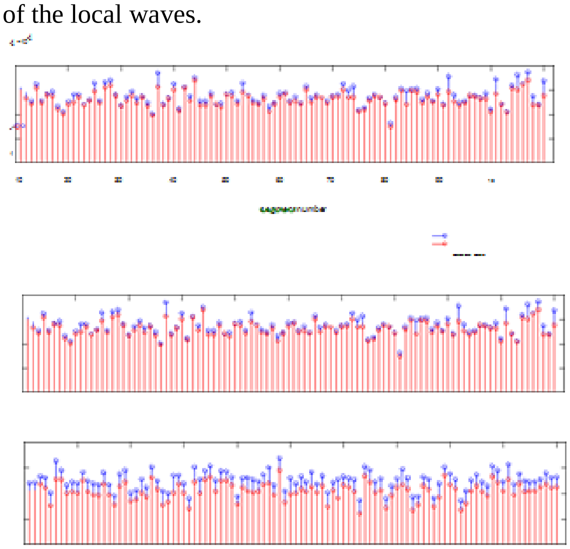

Fig. 2. Computational loads of the modified CEEMD and conventional CEEMD algorithms, in terms of sifting operations for (a) Noise-free ECG signals (b) ECG signals corrupted with baseline wanders.

For the noisy ECG signals, lower-order IMFs capture the HF components of the MA, PLI noises and the HF components of QRS complexes. For both cases, the final residue includes the components of the baseline wanders.

For characterization of different kinds of ECG noises, we first construct three subsignals such as (i) high-frequency signal h[n] obtained by adding the first three IMFs, which may include the components of the MA, PLI and instrument noises and the HF components of QRS complexes; (ii) low-frequency signal b[n] including baseline wander, which is the final residue; and (iii) the ECG signal c[n] obtained by adding remaining IMFs, which include the major components of P-wave, QRS-complex and T-wave. The preliminary evaluation results of the signal and noise separation process are shown in Fig. 4. The results in Fig. 4(a2) and (b2) show that the HF signals adequately capture the MA and PLI noises

C. Short-term Temporal Feature Extraction

The ECG noises and artifacts are typically characterized by their peak-to-peak amplitude, frequency content and duration

In this study, we intend to explore the temporal features such as maximum absolute amplitude (MAA), number of zerocrossings (NZC) and autocorrelation function (ACF) that are computed from the extracted HF and LF signals h[n] and b[n] for detection and classification of different kinds of noises.

Maximum Absolute Amplitude: The presence and severity of each of the noises and artifacts can be defined based on the peak-to-peak amplitudes of the extracted HF and LF noise signals h[n] and b[n]. Thus, the MAA feature is extracted from the final residual signal b[n] for detecting the presence of BW noises. Based on the amplitude ranges of the local waves such as P-wave, q-wave, QRS-complex, and T-wave, the maximum absolute amplitude threshold of 0.1 mV is chosen in this study. The severity of the HF noises can be defined based on the MAA of the HF signal h[n]. The maximum absolute amplitude threshold of 0.05 mV is chosen for detecting the presence of the muscle artifacts and PLI noises. However, the predefined thresholds can be set based on the acceptable maximum noise level of the application-specific ECG analysis system.

Number of Zerocrossings (NZC) Envelope: The decom-position results show that the extracted HF signal may include HF noises or/and HF components of the QRS complexes. For noise-free ECG signals, the extracted HF signal h[n] includes localized HF components of the QRS complexes and very small amplitude noise components in the non-QRS complex.

In practice, amplitudes of the QRS complex portions in the HF signal are unpredictable under different kinds of normal and abnormal ECG signals. Thus, a simple maximum amplitude thresholding rule cannot be suitable for detecting the presence of HF noises in the ECG signal. Therefore, this study explores distinctive noise-specific features such as short-term zerocrossing and autocorrelation features for detection and classification of HF noises. The extracted HF signal h[n] is first divided into overlapping frames with a frame shift of one sample. The overlapping process is implemented as

hk[n] = h[k + n]; n = 0; 1; 2; N 1: (5)

where k = 0; 1 L M 1. h_k[n] is the k^{th} frame and M denotes the frame size. Then, the NZC is computed for each of the frames of a HF signal h[n]. The NZC feature envelope is computed as

Compute NZC :

if max(h [n]) > 0:05

NZC(k) =0 : Otherwise: j k j (6)

For the clean and noisy ECG signals, the NZC envelopes extracted from the HF signal h[n] are shown in Figs. 5(a3) and (b3) and 6(a3) and (b3). Results in Fig. 5(a3) and (b3) show that the NZC envelope is composed of localized short-duration pulses at the QRS complex portions and zero values in the small-amplitude noise portions for the case of noise-free and baseline wandered ECG signals. For the noisy ECG signal corrupted with MA, the extracted NZC envelope in Fig. 6(a3) contains wider pulses with spurious peaks. For detecting the presence of the HF noises, the gate signal is computed as

1; NCZ[n] > 1

g[n] = 0; Otherwise: (7)

III. RESULTS AND DISCUSSION

This section first briefly describes the different benchmark ECG databases and performance metrics used for evaluating the performance of the proposed framework. Then, we present the evaluation results of the proposed framework for detection, localization and classification of single and composite noises.

A. Test ECG Databases and Performance Metrics

In this study, we evaluate performance of the proposed framework using different kinds of noise-free and noisy ECG signals taken from a wide variety of benchmark ECG databases, including the MIT-BIH Arrhythmia (MIT-BIHA) database [34], the MIT-BIH ST Change (MIT-BIHSTC) database [35], the PTB Diagnostic ECG (PTBDECG) database [36], the Fantasia database [37] and the PhysioNet/Computing in Cardiology Challenge 2011 (PCICC2011) database [38]. The MIT-BIHA database contains 48 two lead ambulatory ECG recordings of half hour each, obtained from 47 subjects. The recordings were digitized at 360 samples per second with 11-bit resolution. The beats, heartbeat type and signal quality were labeled by expert annotators. The MIT-BIHA database contains 15 different types of heartbeats, good quality of ECG signals, signal loss, and different kinds of noises such as baseline wanders and muscle artifacts [34]. The PCICC2011 database contains 2000 twelve-lead ECG recordings (I, II, II, aVR, aVL,aVF, V1, V2, V3, V4, V5, and V6) with standard diagnostic bandwidth (0.05-100 Hz). The leads were recorded simultaneously for a minimum of 10 seconds and were dig-itized at 500 samples per second with 16-bit resolution. The ECG signals show different noises and artifacts due to the misplaced electrodes, external interference, poor skin-electrode contact, and artifact resulting from patient motion. The ECG signals were labeled as ‘acceptable’ or ‘unacceptable’ by expert annotators [38]. The PTBDECG database contains 549 high-resolution records from 290 subjects. Each record consists of 15-leads, including the 12-leads and the 3 Frank lead ECGs (vx, vy, vz). The signals were digitized at 1000 samples per second with 16 bit resolution [36]. The MIT-BIHSTC database includes 28 two-leads ECG recordings of varying lengths, which were recorded during exercise stress tests [35]. The Fantasia database contains 120 minutes of continuous supine resting ECG signals obtained from 20 young and 20 elderly subjects. Each signal was digitized at 250 Hz with 12/16-bit resolution. The ECG signals show significant baseline wander and rapid motion artifact noise.

In this study, the performance of the proposed framework is also evaluated using the real-time recorded ECG signals using Allengers Virgo multi-lead ECG/EEG data acquisition system. The ECG signals were recorded from 50 normal subjects for 10 minutes each (5 minutes resting and 5 minutes extensive muscle activity conditions). The experimental set-up for this study is illustrated in Fig. 8. The real-time recorded ECG signals during sitting and extensive muscle activity conditions are shown in Fig. 9. For performance evaluation, different kinds of noisy ECG signals having time-varying noise levels and composite noise sources are generated using realistic ECG noises such as the baseline wander, muscle artifacts, and electrode movements [33]. Further, PLI noises are generated and then added to the ECG signals taken from the bench-mark databases. For some ECG databases, manual annotation of signal quality and noise type is not available. However, all the 10-second duration ECG signals were manually labeled the ‘acceptable’ or ‘unacceptable’ ECG signals and the noise classes, namely noise-free ECG, ECG+BW, ECG+MA, ECG+PLI, ECG+BW+PLI, and ECG+BW+MA.

The performance of the ECG noise detection and classification is evaluated using benchmark metrics, such as sensitivity (Se), positive predictivity (Pp), specificity (Sp), and overall accuracy (OA), which are computed from the number of true positives (TP), number of true negatives (TN), number of false positives (FP), and number of false negatives (FN)

(a) Resting ECG recording with sitting position (b) Extensive activity condition with standing position

Fig. 8. Experimental set-up for recording the ECG signals in real time using Allengers Virgo multilead ECG/EEG data acquisition system.

Obtained through a cross validation of the detection and classification results. The performance metrics are defined as:

Se =	TP / TP+FN	100, Pp =	TP / TP+FP	100, Sp =	TN / TN+FP	100,
OA =	TP+TN / TP+FN +FP+TN	100, and	CA =	TP / TP+FN+FP		100. In

this study, the noise detection performance is evaluated using the Se, Sp and OA metrics. The noise classification is evaluated using the Se, Pp and CA metrics.

In the first experiment, we evaluate the effectiveness of the proposed framework in detecting the presence of noises in the ECG signals. For comparison purpose, we implemented five methods, such as QRS complex features and template matching [5], the higher order statistics (HOS) features and QRS complex-based features followed by machine learning classifiers [14], moving average-based filter and low-level features [31],

correlation between PQRST morphologies of ECG beats [13], QRS-detection and RR-interval features and heuristics rules [18]. The test ECG signals include the sharp and tall P and T waves, small and wide QRS complexes, irregular ECG morphological patterns, ventricular tachycardia, ventricular fibrillation and flutter, atrial fibrillation and flutter, left bundle branch block, right bundle branch block, irregular heart rhythms, abrupt change due to device saturation, long pauses and various patterns of BW, MA and PLI noises. These test ECG signals are categorized into four groups: (i) Group-

A:clean and noisy ECG signals with normal sinus rhythm; (ii) Group-B: clean and noisy ECG signals with ventricular arrhythmias; (iii) Group-C: clean and noisy ECG signals with

IV. CONCLUSION

This paper proposes a novel unified framework for automatic detection, localization and classification of single and combined ECG noises. A modified CEEMD algorithm is presented with new stopping criteria for reducing the computational load. We have explored short-term temporal features, such as maximum absolute amplitude, number of zerocrossings, and local maximum peak of the autocorrelation function for discriminating the BW, MA and PLI noises. Based on the feature thresholding rules, the processed ECG segments are classified into six groups: noise-free ECG, ECG+BW, ECG+MA, ECG+PLI, ECG+BW+PLI, and ECG+BW+MA. The proposed method is validated on the large collections of single and multilead ECG signals taken from five standard ECG databases. The proposed method achieves an average Se of 99.12%, and Sp of 98.56%, and OA of 98.90% in detecting the noise-free and noisy ECG signals. Results show that the proposed method outperforms state-of-the-art methods for different groups of ECG signals in the presence of various types of noises and artifacts. The classification results show that the proposed method achieves an average Se of 98.93%, and Pp of 98.39%, and CA of 97.38% in classifying the ECG signals into six groups. Extensive evaluation results of the proposed method demonstrate the effectiveness and versatility of aforementioned temporal features with predefined thresholds used in this study. Unlike other existing methods, the proposed unified framework not only can achieve better ECG noise detection and classification rates but also accurately localize the short bursts of noises present in the ECG signals.

REFERENCES

[1] G. M. Friesen et al., “A comparison of the noise sensitivity of nine QRS detection algorithms,” IEEE Trans. Biomed. Eng., vol. 37, pp. 85-98, Jan. 1990.

[2] J. Oster et al., “Semisupervised ECG ventricular beat classification with novelty detection based on switching Kalman filters,” IEEE Trans. Biomed. Eng. vol. 62, no. 9, pp. 2125-2134, Sep. 2015.

[3] Q. Li and G. D. Clifford, “Signal quality and data fusion for false alarm reduction in the intensive care unit,” J. Electrocardiol., vol. 45, no. 6, pp. 596-603, 2012.

[4] D. Tobon Vallejo, T. Falk, and M. Maier, “MS-QI: A modulation spectrum-based ECG quality index for telehealth applications,” IEEE Trans. Biomed. Eng., vol. 63, no. 8, pp. 1613-1622, Aug 2016.

[5] C. Orphanidou et al., “Signal quality indices for the electrocardiogram and photoplethysmogram: derivation and applications to wireless moni-toring,” IEEE J. Biomed. Health Informatics, vol. 19, no. 3, pp. 832-840, 2015.

[6] D. Castro, P. Flix, and J. Presedo, “A method for context-based adaptive QRS clustering in real-time,” IEEE J. Biomed. Health Informatics, vol. 19, no. 5, pp. 1660-1671, Sept 2015.

[7] T. Takalokastari, E. Alasaarela, M. Kinnunen, and T. Jms, “Quality of the wireless electrocardiogram signal during physical exercise in different age groups,” IEEE J. Biomed. Health Informatics, vol. 18, no. 3, pp. 1058-1064, 2014.

[8] U. Satija, B. Ramkumar, M. S. Manikandan, “A robust sparse signal decomposition framework for baseline wander removal from ECG signal” in Proc. IEEE Region 10 Conference (TENCON), Singapore, pp. 2470-2473, 2016.

[9] U. Satija, B. Ramkumar, M. S. Manikandan, “An unified sparse signal decomposition and reconstruction framework for elimination of muscle artifacts from ECG signal,” in Proc. IEEE ICASSP, March 2016.

[10] E. Morgado, et al., “Quality estimation of the electrocardiogram using cross-correlation among leads,” Biomed. Eng. Online, vol. 14, no. 1, p. 59, June 2015.

[11] A. Alesanco, and J. Garca, “Automatic real-time ECG coding methodol-ogy guaranteeing signal interpretation quality,” IEEE Trans. Biomed. Eng., vol. 55, no. 11, pp. 2519-2527, 2008.

[12] J. Behar, J. Oster, Q. Li, and G. D. Clifford, “ECG signal quality during arrhythmia and its application to false alarm reduction,” IEEE Trans. Biomed. Eng., vol. 60, no. 6, pp. 1660-1666, 2013.

[13] P. X. Quesnel, A. D. C. Chan, and H. Yang, “Real-time biosignal quality analysis of ambulatory ECG for detection of myocardial ischemia,” IEEE Int. Symposium, Med. Meas. Appl. Process., pp. 1-5, May 2013.

[14] G. D. Clifford, J. Behar, Q. Li, and I. Rezek, “Signal quality indices and data fusion for determining clinical acceptability of electrocardiograms,” Physiol. Meas., vol. 33, no. 9, pp. 1419-1437, 2012.

[15] L. Johannesen, L. Galeotti, “Automatic ECG quality scoring method-ology: mimicking human annotators,” Physiol. Meas., vol. 33, no. 9, pp. 1479-1490, 2012.

[16] Q. Li, R. G. Mark and G. D. Clifford, “Robust heart rate estimation from multiple asynchronous noisy sources using signal quality indices and a Kalman filter,” Physiol. Meas., vol. 29, no. 1, pp. 15-32, 2008.