Review of Energy Efficient factors for ECG Devices

R.MEENAKSHI, C.HEMANTH, R.MENAKA
School of Electronics Engineering
VIT University
Chennai
INDIA
r.meenakshi2015@vit.ac.in, hemanth.c@vit.ac.in, menaka.r@vit.ac.in

Abstract: - Many embedded devices have been proposed and implemented for long term Electrocardiogram (ECG) monitoring which can be either a recording system only used to acquire, store and transmit signals while consuming huge energy or an analyzing system which detects and extract required information and transmits this information but does not retain signals/time history for further diagnosis. Long term monitoring devices need a hybrid of both these systems. The architecture and design of long term ECG monitoring devices is a trade-off of a number of intertwined factors not limited to user convenience (lightweight, non-interference with day to day activities, free movement), Energy efficiency, reliability and cost while ensuring safety. However, all long-term ECG monitoring devices fundamentally need to have an embedded effective and efficient filtering and detection scheme which ensures high reliability of detection and energy efficiency. This paper surveys and summarizes primary research work in the area of filtering and detection of ECG signals in the context of reliable and energy efficient long term ECG monitoring.

Key-Words: - ECG monitoring, ECG analysis, Energy efficiency, Transmission, Filtering, Detection, Denoising, Ventricular fibrillation

1 Introduction

Electrocardiogram (ECG/EKG) analysis [1] is used for diagnosis of heart diseases which detects the abnormalities (arrhythmias), which manifests as an irregularity in the heart rate or in the origin/conduction of the cardiac electrical activity.

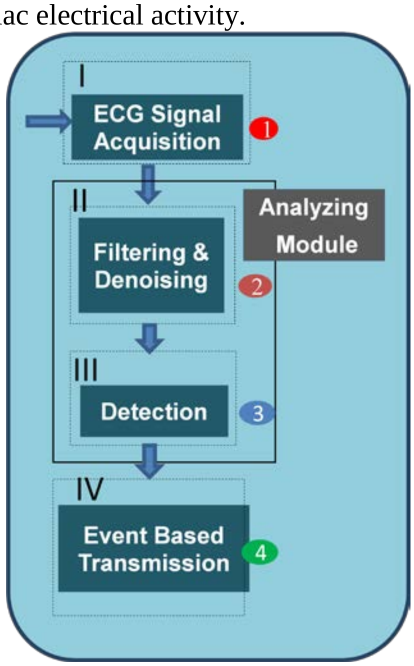

Fig.1: Various steps involved in Long Term ECG monitoring System

An unorganized abnormal heartbeat rhythm known as Ventricular fibrillation (VF) [2,5,6], which results in the heart not pumping blood as it should. If the irregular/abnormal heartbeat occurs in the atria, then it is known as atrial fibrillation (AF).

In this condition though beats are irregular, the heart pumping is continued. Increasingly, long term ECG monitoring is being used as a means of health monitoring to help people suffering from cardiac diseases in the intensive care units for arrhythmias especially ventricular fibrillation.

Embedded devices used for ECG monitoring can be broadly divided into two types. The first type is purely an acquisition system which acquires stores and transmits continuous data to health centers for monitoring. The second type acquires and processes data by filtering out noise and detecting events and sends out only event based data and can be labeled as analyzing systems. Energy consumption for both systems varies. Energy requirements for the first type are associated with continuous signal acquisition and transmission, whereas for the second type it is associated with signal acquisition and computational effort for processing data.

Pure acquisition and data transmission devices [10,12] consume relatively larger energy than analyzing systems that acquire, analyze and only transmit event based data. The analyzing system is the preferred means for identifying arrhythmias in the context of long term ECG monitoring with energy saving.

Energy required Continuous signal acquisition.
Energy loss incurred for processing involved with Filtering and denoising.
Energy loss incurred for processing involved with Filtering and denoising.
Energy required for Transmission.

Fig.2: Energy loss for analyzing systems

Fig.2 also shows that there is an energy requirement for each stage of the identified process of the analyzing system. Steps II and III [21,22,23] form the analyzing module that processes the data to generate event based information to transmit instead of transmitting all data as in the case of an acquisition system, thus reducing energy consumption. Analyzing systems similar to that in Fig.1 employ information extraction and Data compression methods [25-28] to reduce storage, size, detect VF and transmit event based data. The architecture and design [29] of long term ECG monitoring devices [30,32,34,36] is a trade-off of a number of intertwined factors considering user convenience (lightweight and free movement), Energy efficiency, reliability and cost. In this paper the various filtering and detection schemes that have been implemented are reviewed and qualitative investigations of their impact on energy efficiency and recommendations for energy efficient implementation is provided.

2 Literature Survey

Information used in this survey is primarily from various peer reviewed journals, Master and Doctoral thesis in the area of Long term ECG Monitoring. Surveyed papers are bracketed into eight categories as shown in Fig.3.

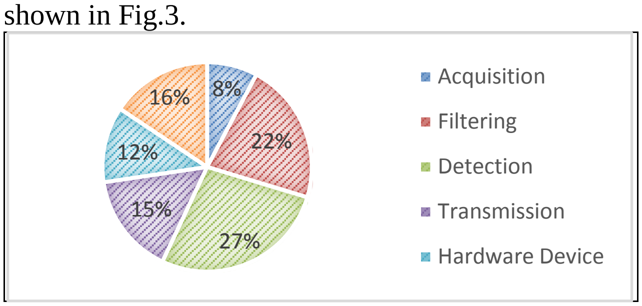

Fig.3: Papers surveyed per classification

The chart shows the percentage of reference papers considered for each identified classification. This survey focuses on the techniques accomplished by employing signal processing techniques and hence will be limited to steps II and III.

3 Filtering and Denoising

Wireless Ambulatory ECG recording is now routinely used to detect arrhythmias and cardiac abnormalities. As the ECG signal contains numerous artifacts, these artifacts have to be removed before monitoring, from the receiver point-of-view, so that a correct decision can be taken. Thus, it is necessary to remove the different artifacts present in the ECG signal and there is a need for filtering the ECG. Primary reasons for noise can be attributed to corruption by baseline wander, power-line interference, muscle noise, motion artifacts [37] and channel and transmission noise in the context of long term ECG monitoring. In table 1 the abbreviations used for different noises are given.

Table 1: Abbreviations of different parameters

BW	Baseline Wander
PLI	Power Line Interference
MA	Muscle Artefacts
MA	Motion Artefacts
AWGN	Additive White Gaussian Noise
SNRI	Signal to Noise Ratio Improvement
MSE	Mean Square Error
PRD	Percent Root mean square Difference

Signal denoising methods are evaluated based on the ability of the signal to be close to the original signal. Signal to Noise Ratio Improvement (SNRI), Mean Square Error (MSE) and Percent Root mean square Difference (PRD) are the commonly used measures.

Signal-to-Noise Ratio Improvement (SNRI)

$$\mathrm{SNRI} = 10 \log \frac{\sum_{i=1}^{N} (\mathrm{v}[\mathrm{i}]-\mathrm{u}[\mathrm{i}])^2}{\sum_{i=1}^{N} (\hat{\mathrm{u}}[\mathrm{i}]-\mathrm{u}[\mathrm{i}])^2} \qquad (1)$$

Mean Square Error (MSE)

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} (\hat{u}[i] - u[i])^2 \qquad (2)$$

Percent Root mean square Difference (PRD)

$$\mathrm{PRD} = 100 \sqrt{\frac{\mathrm{MSE}}{\frac{1}{\mathrm{N}} \sum_{i=1}^{N} u^2[i]}} \qquad (3)$$

Additional performance parameters like computational complexity, convergence rate and steady state error of the employed method are also important in the context of long term ECG monitoring with embedded devices.

3.1 Approaches based on Digital filters

The simplest filtering methods use a second order Butterworth high-pass filter [38] or a band pass filter [39]. These methods primarily remove baseline wander [40] and half-wave rectification is further used to reduce the ambiguities for R-Peak detection.

3.2 Approaches based on Adaptive Filters

Adaptive filtering techniques permit to detect the time varying potentials and to track the dynamic variations of the signals. Several adaptive filter structures as in Fig.4 [43-45] are proposed for noise cancellation and arrhythmia detection. Different filter structures are presented to eliminate the diverse forms of noise: baseline wander, 60 Hz power line interference, muscle noise, and motion artifact. An adaptive recurrent filter structure is proposed for acquiring the impulse response of the normal QRS complex. The next set of schemes [46-49] employs the **Least Mean Squares (LMS)** algorithm with some modifications or enhancements to address improvements to one or more of the above-mentioned performance parameters.

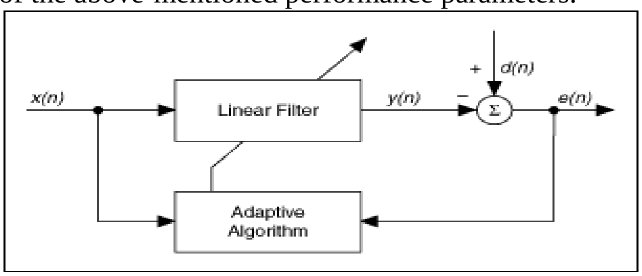

Fig.4: Adaptive filter structure.

A steady-state convergence analysis for the LMS algorithm with deterministic reference inputs showed that the steady-state weight vector is biased and thus the adaptive estimate does not approach the Wiener solution. To handle this drawback, another strategy was considered for estimating the coefficients of the linear expansion, namely, the B**lock LMS (BLMS) algorithm**, in which the coefficient vector is updated only once for every occurrence based on a block gradient estimation. A major advantage of the block or the transform domain LMS algorithm is that the input signals are approximately uncorrelated. The BLMS algorithm [47, 48] is determined to be steady-state unbiased and with a lower variance than the LMS algorithm. Also, several modifications are presented in literature to improve the performance of the LMS algorithm. Several less computational complex adaptive algorithms are presented based on data normalization.

The **NLMS algorithm [43]** is another class of adaptive algorithm used to train the coefficients of adaptive filter. This algorithm accounts the variation in signal level at filter output and selecting the normalized step size parameter that results in a stable as well as a fast converging algorithm.

The weight update relation for NLMS algorithm is as follows:

$$\mathrm{w(n+1)} = \mathrm{w(n)} + \frac{\mu}{p+X^t(n)X(n)} X(n)e(n) \quad (4)$$

The variable step can be written as

$$\mu(n) = \frac{\mu}{p+X^t(n)X(n)} \quad (5)$$

Here, the fixed convergence factor is to control maladjustment. The parameter is set to avoid the denominator being too small and the step size parameter too big.

Improved versions [46] of LMS and Normalized Least Mean Square (NLMS) algorithms using a Fast Lane Approach, based on parallel evaluation of several competing predictors are proposed and are applied to respiratory motion data from motion-compensated radio surgery. Instead of using the instantaneous data vector for normalization, the squared norm of the error vector can be used. The length of the error vector is the instantaneous number of iterations. Because the step size is normalized with reference to error, this algorithm is called the **Error Nonlinear LMS (ENLMS) algorithm.** A common major drawback of adaptive noise cancellers using LMS-based algorithms is the large value of excess mean-square error which results in signal distortion in the noise-canceled signal. In the ENLMS algorithm, the time-varying step-size is inversely proportional to the squared norm of error vector rather than the input data vector as in NLMS algorithm.

On the other hand, some additional computations are required to compute. In order to cope up with both the complexity and convergence issues without any restrictive tradeoff, error normalized sign-based algorithms such as the **error nonlinear signed regressor LMS (ENSRLMS) algorithm, the error nonlinear sign LMS (ENSLMS) algorithm, and the error nonlinear sign-sign LMS (ENSSLMS) algorithm** for the removal of noise from ECG signal are proposed.

The additional computations can be further reduced by using a **block-based ENLMS (BB-ENLMS) algorithm** in which the input data is partitioned into blocks and the maximum magnitude within each block is used to compute μ(n). The convergence characteristics of various algorithms such as **block-based ENSRLMS (BB-ENSRLMS), block-based ENSLMS (BB-ENSLMS), and block-based ENSSLMS (BB-ENSSLMS),** exhibit better performance in terms of both convergence rate and excess mean square error than the normal realizations.

3.3 Wavelet Based approach

The next set of schemes [50-56] is based on the usage of wavelet transforms and modified hybrid methods using wavelet transforms.

A **Non-Local Wavelet Transform (NLWT)** domain method [50] to denoise measured ECG signal with Additive White Gaussian Noise (AWGN) using correlations among both local and non-local samples of the signal has been proposed. A windowing method in EMD domain [51] is used to filter out the noise from the initial. The **Non-Local Means (NLM) approach** to 1-D signal processing [57, 58] for denoising of biomedical signals has also been proposed. Here, using ECG as an example, a straightforward NLM-based denoising scheme provides signal-to-noise ratio improvements very similar to state of the art wavelet-based methods [59-65]. An Artificial Neural Network (ANN) adaptive whitening filter [66] is used for removal of time-varying non-linear characteristic noise and has been determined to be more effective than a bandpass filtering method.

Before summarizing the performance of the filtering and denoising methods mentioned in Table 2, the following should be kept in mind that while most of the surveyed papers use the MIT-BIH database files as input, they necessarily cannot be compared on an apple to apple basis due to different measurement metrics. Further, relative comparison metrics like computational complexity, convergence rate and energy efficiency use the LMS algorithm as a baseline relative reference. Reference [50] incorporating the NLWT method does not however comment on the complexity and computational effort involved which can be used to qualitatively assess relative energy requirements.

In table 2, summary of the different Schemes/ Algorithms used for the purposes of ECG filtering and denoising for the removal of baseline wander, power-line interference, muscle efficiency of these methods relatively is given. The number of computations required for the proposed block-based ENSRLMS is independent of filter length L [43] and energy efficiency E is computed with other algorithms on a relative basis.

Table 2: Performance comparison of different Filtering Schemes

S. No.	Description	Reference	Computational complexity	Energy Efficiency	NOISE					Criteria			Comments
					PLI	BW	MA	EM	AWGN	SNRI [dB]	MSE	PRD	
1	Least mean squares [LMS]	45	L+1	E	7.6	2.74	4.61	3.33	No		0.1362		Dataset of five ECG records: data 100, data105, data 108, data 203, and data 228 from MIT-BIH
2	Normalized least mean squares [NLMS]	46	2L+1	2E							0.1308		
3	Error nonlinear signed regressor LMS [ENSRLMS]	43	1	3E	9.92	9.01	9.05	9.2	No		0.1292		
4	Error nonlinear sign LMS[ENSLMS]	43	L	3E	7.99	6.6	7.78	7.03	No		0.1303		
5	Error nonlinear sign-sign LMS [ENSSLMS]	43	L	3E	7.18	5.72	6.93	6.02	No		0.1315		
6	Block Error nonlinear signed regressor LMS[BB-ENSRLMS]	43	1	3E	11.5	9.4	10.2	10.3	No		0.1287		
7	Block Error nonlinear sign LMS[BB-ENSLMS]	43	L	3E	9.17	7.2	8.47	7.63	No		0.1297		
8	Block Error nonlinear sign-sign LMS [BB-ENSSLMS]	43	L	3E	8.28	6.3	7.5	6.79	No		0.1312		
9	Hybrid EMD Wavelet[EMD]	51		E					No	08-06	0.05 - 0.002	50-13	6-20 db Noise input
10	Non-Local Means[NLM]	57		E					No	18-12	0.002-0.0015	17-15	
11	Non-Local Wavelet transform[NLWT]	50		E					Yes	30-20	0.0015-0.001	15-16	

Based on table 2 metrics comparison for the different methods, the Non-Local Wavelet Transform (NLWT) followed by the Block-Based Error Nonlinear Signed Regressor LMS (BB-ENSRLMS) are better suited. These algorithms report MSE and SNRI values which are better than other methods for the removal of ECG signal noise due to baseline wander, power line interference, muscle artifacts and motion artifacts.

As mentioned earlier, the LMS is used as a base reference to qualitatively compare metrics of other methods. While lower values for computational complexity and lower convergence rate are desired, higher energy efficiency is desired for the relative comparison. The BB-ENSRLMS would be more energy efficient than the NLWT method due to less computational complexity. The NLWT method has better accuracy in the presence of noise which is important for reliable detection. It can be inferred from table 2 that wavelet based methods can perform better in the presence of noise due to muscle artifacts, motion artifacts and transmission. For denoising and nonparametric function estimation, the method followed is to transform the data into the wavelet domain, threshold the wavelet coefficients, and invert the transform.

The NLWT method results in relatively better metrics but does not however comment on the complexity and computational effort involved which can be used to qualitatively assess relative energy requirements. Wavelet methods require that a mother wavelet which is a close approximation to the original function to be recovered be chosen and the level of detail and approximation coefficients required also be determined as both these choices have an impact on the accuracy, computational effort and complexity. Based on analysis a Coiflet at level 3 is optimal for most records for filtering out noise.

4 Detection

The automatic detection of ECG waves is important to cardiac disease diagnosis. A good performance of an automatic ECG analyzing system depends heavily upon the accurate and reliable detection of the QRS complex, as well as the T and P waves. A number of detection and analysis techniques have been evolved to classify ventricular fibrillation (VF) from normal sinus rhythm (SR).Detection of the life-threatening VF is one of the primary objectives of the detection phase. Various methods have been employed or proposed by authors for detection with the primary goal being to differentiate between a VF and a non-VF.

Table 3: Parameter Description

	Parameter	Description
Se	Sensitivity	Probability to detect VF
Sp	Specificity	Probability to detect Non-VF
A	Accuracy	Probability that classifies VF is truly VF
P+	Positive Predictivity	Probability of obtaining a correct decision

The parameters can be calculated with the following relations

$$Se = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})} \qquad (6)$$

$$Sp = \frac{\mathrm{TN}}{(\mathrm{TN} + \mathrm{FP})} \qquad (7)$$

$$\mathrm{P+} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FP})} \qquad (8)$$

$$\mathrm{A} = \frac{\mathrm{TP} + \mathrm{TN}}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})} \qquad (9)$$

Where,

TP – True Positive, TN – True negative,

FP – False Positive, FN – False Negative

The algorithm's Computational complexity and rate of convergence which effect system design influencing energy consumption [67, 68] in the context of Long term ECG monitoring are important parameters. However, existing literature does not have much focus on these parameters and no data is available to comment or make comparisons.

4.1 Wavelet based detection Approach

The first set of methods listed is based on different implementations of the wavelet transform. References [69-72] use the method of **continuous wavelet transforms** [70] also employing a morphology consistency evaluation for the detection of disorganized VF (Ventricular Fibrillation) from organized Sinus Rhythm (SR) without interrupting the ongoing chest compression (cardiac massage). A QRS detection algorithm based on the **dyadic wavelet transform** (DYWT) multiscale-product scheme in an Application Specific Integrated Circuit (ASIC) which can be used for real-time biomedical signal processing applications has been implemented [73].Wavelet detail coefficients have been used for the detection of different QRS morphologies and is based on the power spectrum of QRS complexes in different energy levels since it differs from normal beats to abnormal ones [74]. This property is used to discriminate between true beats (normal and abnormal) and false beats.

A **Discrete Wavelet Transform** (DWT) based feature extraction technique in the QT segment [75] is employed for the purpose of detection by first, denoising the signal by decomposing it using DWT technique and discarding the coefficients corresponding to the noise components. A multi resolution approach along with an adaptive thresholding is used for the detection of R-peaks. Then Q, S peak, QRS onset and offset points are identified. Finally, the T wave is detected. By detecting the baseline of the ECG data, height of R, Q, S and T waves are calculated.

A **down sampling Wavelet Transform** for R-Peak detection [76] is employed in an application specific integrated circuit (ASIC) design for both recording and R-peak detection for energy efficiency, low cost and high signal quality using data compression and dual-Ping-Pong-memory architecture.

Techniques of coefficients truncation, resource sharing, parameters optimization and periodic extension are adopted to reduce hardware cost, improve signal quality and achieve a high compress ratio (CR). Similarly, a down-sampling QRS complex detection algorithm [77] is used in order to meet the requirement of low-power dissipation for electrocardiogram related applications. Another real time QRS complex detector based on the **Redundant Discrete Wavelet Transform** (RDWT) [78] using both scales and wavelet coefficients, and the wavelet coefficient energy are used for detection.

A QRS detection processor structured by a scale-3 quadratic spline wavelet transform followed by a maxima modulus recognition stage [79] is used to extract the RR-interval between the QRS complex for evaluating the heart rate variability with the goal of reducing system power in the context of long term ECG monitoring. Apart from the Wavelet transform, numerous methods have been proposed and applied. A simple moving average-based computing method for real-time QRS detection along with wavelet-based denoising procedure to effectively reduce the noise level has been proposed [80].

4.2 Detection based on Classifiers

An arrhythmia VF/VT (Ventricular Fibrillation and Ventricular tachycardia) detection algorithm that combines a number of ECG parameters by using support vector machines (SVM) classifiers [81] is used to identify 13 parameters accounting for temporal (morphological), spectral, and complexity features of the ECG signal. A VF/VT classification algorithm using a machine learning algorithm [82] is used to extract 14 metrics from a specific window length of the ECG and a genetic algorithm is then used to select the optimal variable combinations for feature selection and tested with a SVM Classifier. A linear discriminant analysis (LDA) classifier using spectral energy of the constituent waves as the discriminative feature [83] reducing computational complexity is proposed as an ultra-lower power circuit that could be integrated with the ECG sensor node.

4.3 Detection based on Digital Filters

A model-based ECG filtering approach [38] is used to model normal, ventricular heartbeats, and morphologies not previously encountered to facilitate accurate online filtering and analysis of physiological signals. A **Switching Kalman Filter approach** is then used to enable the automatic selection of the most likely mode (beat type), while simultaneously filtering the signal using appropriate prior knowledge.

A non-linear temporal feature, named the dynamic plosion index [39] suitable for detection of transients in a signal is used to iteratively obtain initial estimates of the QRS and then further refined to obtain a higher temporal accuracy. This method detects the R-Peaks without the need of any thresholding and differentiating operation.

Performance of five VF detection techniques selected for their high accuracy and low computational cost is compared [85]. A point-process-based method [87] is used for real time R–R interval error detection and correction.

An algorithm based on the Hilbert transform [92] is used to determine the sensitivity, specificity and the area under its receiver operating characteristic curve (ROC) for a continuous analysis by selecting the data in steps of one second without any pre-selection.

Model-based statistics and frequency based approaches [94] are used to extract three main physiological characteristics of Atrial Fibrillation (AF), namely P wave absence, heart rate irregularity and atrial activity.

Detectors including a linear or nonlinear polynomial filter, which enhances and rectifies the QRS complex, and a simple, adaptive maxima detector [95] is used to determine optimum QRS. A real-time algorithm [97] for detection of the QRS complexes of ECG signals recognizes QRS complexes based upon digital analyses of slope, amplitude, and width.

The Table 4 provides a comparison of the performance of different metrics for various detection schemes surveyed and described above. The following should be kept in mind that while most of the surveyed papers use the MIT-BIH database files as input, they necessarily cannot be compared on an apple to apple basis due to one or more of the issues, like Selective input file, differing metrics and Parameter Selection and Tuning.

Based on the performance reported for different detection schemes, it can be stated that detection methods based on the less complex Ventricular Fibrillation Filter, Modified Exponential Algorithm, and Time Delay Algorithm show lower sensitivity and specificity than methods based on the continuous/discrete wavelet transform, dynamic Plosion index, Auto Correlation and Hilbert Transform and the five-step method. The more complex methods provide better relative detection. The dynamic Plosion index method which can be used to detect the R-Peak is simpler to implement with reduced complexity and computational effort than other better performing methods.

Table 4: Performance comparison of different Detection Schemes

S. No	Method	Se %	Sp %	Acc %	P+ %	Ref	Database
1	Auto Correlation and Hilbert Transform	99.93		99.88	99.95	[1]	MITDB
2	Switching Kalman Filters	97.3			99.96	[38]	MITDB
3	Dynamic Plosion Index	99.52			99.7	[39]	MITDB
4	Continuous Wavelet Transform (CWT)	99.87	98.42	98.64	91.75	[69]	CINC,MITDB
5	Morphology Consistency with CWT (without artifacts)	92	93	93		[70]	ECG signals recorded from AEDs
	VF Filter	88	72	77			
	Spectrum Analysis	71	76	75			
	Lempel–Ziv Complexity Measurement	81	76	78			
	Morphology Consistency with CWT (with Artifacts)	91	85	87		[70]	
	VF Filter	72	40	52			
	Spectrum Analysis	68	53	59			
	Lempel–Ziv Complexity Measurement	72	81	78			
6	Wavelet Multiscale Analysis	99.63			99.89	[73]	MITDB
7	Wavelet Coefficients	99.64			99.82	[74]	MITDB
8	Multi resolution Wavelet Analysis	99.6			99.5	[75]	MITDB
9	Compression Algorithm with ASIC Design for ECG recording and R-Peak Detection	99.72			99.49	[76]	MITDB
10	Down Sampling Wavelet Transform	99			99	[77]	MITDB
11	Redundant Discrete Wavelet Transform	99.32				[78]	MITDB
12	Quadratic Spline Wavelet Transform	99.31			99.7	[79]	MITDB
13	Wavelet Denoising and Moving Average Filter	99.55			99.49	[80]	MITDB
14	Feature Selection and Support Vector Machines	91.9	97.1	96.8	61.6	[81]	MITDB, CUDB
15	Machine Learning Algorithm	96.2	96.2	96.3		[82]	CUDB, VFDB, AHADB
16	Linear Discriminant Analysis (LDA)	86.54	94.23	90.38		[83]	Physionet/ Cinc
17	Ventricular Fibrillation Filter (VFF)	71.41	79.88			[85] [102]	CUDB
	Modified Exponential Algorithm (MEA)	56.49	83.75				
	Time Delay Algorithm (TD)	72.51	88.08				
	Complexity Measure (Lempel–Ziv) (CPLX)	55.14	87.85				
	Threshold Crossing Interval (TCI)	67.89	75.45				
18	Real-Time Automated Point Process Method	94.19	99.98	99.91	98.73	[87]	MITDB
19	Hilbert Transform	83.1	96.2	95.1	67.6	[92]	MITDB,CUDB, AHADB
20	Model Based Detection Algorithm	93.8	96.09			[94]	MITDB
21	Polynomial Filter & Genetic Algorithm	99.6			99.51	[95]	MITDB
22	Real-Time QRS Detection Algorithm			99.3		[97]	MITDB
23	Combination of First-Derivative, Hilbert and Wavelet Transforms, adaptive threshold	99.15			99.18	[101]	MITDB
24	Five Step Method	93.89	99.44	95.18	95.14	[112]	MITDB

Based on the comparison in Table 4, the below detection algorithms can be determined to be the best performing in the context of VF detection due to high values of sensitivity (Se), specificity (Sp), Accuracy (Acc) and positive predictability (P+).

1. Continuous Wavelet Transform

2. Real time automated point process method
3. Hilbert Transform

In particular, the method using Hilbert Transform is more reliable for VF detection than other surveyed papers in that the values are determined based on a continuous analysis without any pre-selection. However, all methods are computationally expensive compared to the dynamic Plosion index method which is better suited due the reduced complexity resulting in lower computational requirement and thus lower energy requirement. An implementation of this method was carried out to determine effectiveness of this method for R-peak detection.

Based on this it can be inferred that the dynamic Plosion index method when processing a relatively clean signal (using Wavelet transform filtering) performs reliably with less computational effort which can result in lower energy requirements, helping to make the embedded device more energy efficient.

5 Future Research Issues

(i) Embedded Microcontroller for Energy efficiency

Developing an ECG acquisition device which can be controlled by an embedded microcontroller to improve energy efficiency.

(ii) Sensing Techniques based on energy consumption

Compressive sensing [114-118] is increasingly being applied to ECG acquisition and reconstruction with the aim of saving the sensing and computational resources, thus lowering energy consumption [103] for ECG embedded devices.

(iii) Energy efficient Communication techniques

The model also reduces energy of each stage by sensing, compressing and transmitting reduced data as compared to the model in Fig.1. The transmitted data is processed by more powerful computing systems in the health care centers/hospitals. The process itself involves signal reconstruction using algorithms based on knowledge of properties of sparsity and incoherence of the ECG signal, filtering out frequencies of non-interest, denoising and detection. This allows more reliable and computationally complex reconstruction, filtering and detection schemes to be incorporated to provide remedial feedback.

(iv) Integrated Approach

A full integration of hardware (body areas sensors, environmental sensors, and communication protocols), software (data management, preprocessing, detection algorithms, and applications) and services (call center and recommendation system) for real time healthcare monitoring and detection is still in early stage of development and needs further research.

6 Conclusion

Wearable ECG devices are increasingly being employed to monitor patients with heart related diseases. Design requirements of these devices comprise of many functions under mobility constraints, one of which is that they receive and transmit wireless ECG data which dictates energy requirements of the device. This paper surveyed different methods used or proposed for the purposes of noise removal of ECG signals and different methods for detection of Ventricular fibrillation. However, all methods discussed do not quantify the effect of their implementation with regards to energy consumption incurred due to their relative complexities for real time monitoring. From the perspective of long term ECG monitoring, Wavelet based transforms perform better based on reported performance in removing the many different noises, although requiring more computational power and hence more energy. Based on investigation of noise corrupted ECG signals using different mother wavelets at different decomposition levels, a level 3 Coiflet with Heuristic-Sure soft thresholding for the removal of noisy ECG signals for filtering and denoising is recommended. The Dynamic Plosion Index is better suited for VF Detection when employed with a relatively clean signal and results in lower energy requirement for the embedded device due to reduced computational requirements. Further it is proposed that an architectural change similar to pure signal acquisition systems, but enabled by compressive sensing would result in an energy efficient long term ECG monitor device.

References

[1] Jaya Prakash Sahoo, Dr. Samit Ari, “Analysis of ECG signal for Detection of Cardiac Arrhythmias,” Master of Technology Thesis in Telematics and Signal Processing, National Institute of Technology, Rourkela, 2011.

[2] Margaret K. Delano, “A Long-Term Wearable Electrocardiogram (ECG) Measurement System,” Masters of Engineering in Electrical Engineering and Computer Science at the Massachusetts Institute of Technology, Jun 2012.

[3] Bert-Uwe Köhler, Carsten Hennig, Reinhold Orglmeister, “The Principles of Software QRS Detection,” IEEE Engineering in Medicine and Biology, vol. 21, no. 1, pp.42-57, Feb 2002.

[4] Anton Amann, Robert Tratnig, Karl Unterkofler, “Reliability of Old and New Ventricular Fibrillation Detection Algorithms for Automated External

Defibrillators," BioMed. Eng. Online, vol. 4, no. 60, pp. 1–15, Oct. 2005.
[5] Logan Porter, "Wireless-in-home ECG monitoring system with remote access,", Thesis Prepared for the Degree of Master of Science, University of North Texas, Aug 2012.
[6] Tobias Cibis, Benjamin H. Groh, Heike Gatermann, Heike Leutheuser and Bjoern M. Eskofier, "Wearable Real-Time ECG Monitoring with Emergency Alert System," IEEE, 978-1-4244-9270-1/15, pp. 6074-6077, 2015.
[7] Amna Abdullah, Asma Ismael, Aisha Rashid, Ali Abou-ElNour, and Mohammed Tarique, "Real Time Wireless Health Monitoring Application Using Mobile Devices," International Journal of Computer Networks & Communications, vol.7, no.3, pp.13-30, May 2015.
[8] Shuenn-Yuh Lee, Jia-Hua Hong, Cheng-Han Hsieh, Ming-Chun Liang, Shih-Yu Chang Chien, and Kuang-Hao Lin, "Low-Power Wireless ECG Acquisition and Classification System for Body Sensor Networks." IEEE Journal of Biomedical and Health Informatics, 2013.
[9] Alvaro Alesanco and Jose Garcıa, "Clinical Assessment of Wireless ECG Transmission in Real-Time Cardiac Telemonitoring," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 5, Sep 2010.
[10] Alfredo I. Hernández, Fernando Mora, Guillermo Villegas, Gianfranco Passariello, and Guy Carrault," Real-Time ECG Transmission Via Internet for Nonclinical Applications", IEEE Transactions on Information Technology In Biomedicine, vol. 5, no. 3, pp.253-257, Sep 2001.
[11] Sibasankar Padhy, L.N.Sharma, S.Dandapat, "Multilead ECG data compression using SVD in multiresolution domain," Biomedical Signal Processing and Control, vol. 23, pp. 10–18, 2016.
[12] Catalina Monica Fira and Liviu Gora, "An ECG Signals Compression Method and Its Validation Using NNs," IEEE Transactions on Biomedical Engineering, vol. 55, no. 4, pp. 1319-1326, Apr 2008.
[13] YanivZigel, Arnon Cohen and Amos Katz, "ECG Signal Compression Using Analysis by Synthesis Coding," IEEE Transactions on Biomedical Engineering, vol. 47, no.10, pp. 1308-1316, Oct 2000.
[14] Hossein Mamaghanian, Nadia Khaled, David Atienza and Pierre Vandergheynst, "Compressed Sensing for Real-Time Energy-Efficient ECG Compression on Wireless Body Sensor Nodes," IEEE Transactions on Biomedical Engineering, vol. 58, no. 9, pp. 2456-2466, Sep 2011.
[15] JusakJusak, Ira Puspasari, "Wireless Tele-Auscultation for PhonocardiographSignal Recording Through Zigbee Networks," IEEE Asia Pacific Conference on Wireless and Mobile, pp. 95-100, 2012.
[16] Kyungtae Kang, Kyung-JoonPark, Jae-Jin Song, Chang-Hwan Yoon, and Lui Sha, "A Medical-Grade Wireless Architecture for Remote Electrocardiography," IEEE Transactions on Information Technology in Biomedicine, vol. 15, no. 2, pp. 6-16, Mar 2011.
[17] J. Kim and C.-H. Chu, "Analysis of energy consumption for wearable ECG devices," IEEE Sensors Proceedings, pp. 962–965, Nov 2014.
[18] Xin Liu, Yuanjin Zheng, Myint Wai Phyu, Bin Zhao, MinkyuJe and Xiaojun Yuan, "Multiple Functional ECG Signal is Processing for Wearable Applications of Long-Term Cardiac Monitoring," IEEE Transactions on Biomedical Engineering, vol. 58, no.2, pp. 380-389, Feb 2011.
[19] Liang-Hung Wang, Tsung-Yen Chen, Shuenn-Yuh Lee, Tai-Hsuan Yang, Shi-Yan Huang, Jen-Hao Wu and Kuang-Hao Lin, "A Wireless Electrocardiogram Detection for Personal Health Monitoring," 2013 IEEE, International Conferenrce on Orange Technologies, pp. 43-46, 2013.
[20] Raquel Bailón, Leif Sörnmo and Pablo Laguna, 'A Robust Method for ECG-Based Estimation of the Respiratory Frequency During Stress Testing," IEEE Transactions on Biomedical Engineering, vol. 53, no. 7, pp. 1273-1285, Jul 2006.
[21] Julien Oster, Joachim Behar, Omid Sayadi, ShamimNemati, Alistair E W Johnson, Gari D Clifford, "Semi-supervised ECG Ventricular Beat Classification with Novelty Detection Based on Switching Kalman Filters," IEEE Transactions on Biomedical Engineering, 2015.
[22] A. G. Ramakrishnan, A. P. Prathosh and T. V. Ananthapadmanabha, "Threshold-Independent QRS Detection Using the Dynamic Plosion Index," IEEE Signal Processing letters, vol. 21, no. 5, pp. 554-558, May 2014.
[23] Manpreet Kaur, Birmohan Singh, Seema, "Comparisons of Different Approaches for Removal of Baseline Wander from ECG Signal," Proceedings published by International Journal of Computer Applications (IJCA), pp. 30-36, 2011.
[24] Muhammad Zia Ur Rahman, Rafi AhamedShaik,and D. V. Rama Koti Reddy, "Efficient and Simplified Adaptive Noise Cancelers for ECG Sensor Based Remote Health Monitoring," IEEE Sensors Journal vol. 12, no. 3, pp. 566-573, Mar 2012.
[25] Nitish V. Thakor, Yi-Sheng Zhu, "Applications of Adaptive Filtering to ECG Analysis: Noise Cancellation and Arrhythmia Detection," IEEE Transactions on Biomedical Engineering, vol. 18, no. 8, pp. 785-794, Aug 1991.
[26] Floris Ernst, Alexander Schlaefer, Sonja Dieterich, AchimSchweikard, "A Fast Lane Approach to LMS prediction of respiratory motion signals," Biomedical Signal Processing and Control, vol. 3, pp. 291–299, 2008.
[27] S. Olmos, L. Surnow, P. Laguna, "Block LMS Adaptive Filter with deterministic reference inputs for Event-Related Signals", 2001 Proceedings of the 23rd Annual EMBS International Conference, October 25-28.

[28] S. Olmos, L. Sornmol, P. Laguna, "Block Adaptive Filters with Deterministic Reference Inputs for Event-Related Signals: BLMS and BRLS," IEEE Transactions on Signal processing, vol. 50, no. 5, pp. 1102-1112, May 2002.
[29] Mohammed AlMahamdy, H. Bryan Riley, "Performance Study of Different Denoising Methods for ECG Signals", ScienceDirect, Procedia Computer Science, Vol. 37, pp. 325 – 332, 2014.
[30] Santosh Kumar Yadav, Rohit Sinha, Prabin Kumar Bora, "Electrocardiogram signal denoising using non-local wavelet transform domain filtering," IET Signal Processing, vol. 9, Iss. 1, pp. 88–96, 2015.
[31] Md.AshfanoorKabir, Celia Shahnaz, "An ECG Signal Denoising Method Based on Enhancement Algorithms in EMD and Wavelet Domains," IEEE, Tencon 2011.
[32] Brian H. Tracey and Eric L. Miller, "Nonlocal Means Denoising of ECG Signals," IEEE Transactions on Biomedical Engineering, vol. 59, no. 9, pp. 2383-2386, Sept.2012.
[33] Md. AshfanoorKabir, Celia Shahnaz, "Denoising of ECG signals based on noise reduction algorithms in EMD and wavelet domains," Biomedical Signal Processing and Control, vol.7, pp. 481– 489, Jan. 2012.
[34] Manuel Blanco-Velascoa, BinweiWengb, Kenneth E. Barner, "ECG signal denoising and baselinewander correction based on the empirical mode decomposition," Computers in Biology and Medicine, vol. 38, pp. 1 – 13, 2008.
[35] Salim Lahmiri "Comparative study of ECG signal denoising by wavelet thresholding in empirical and variational mode decomposition domains," The Institution of Engineering and Technology, Healthcare Technology Letters, 2014, Vol. 1, Iss. 3, pp. 104–109, Jun 2014.
[36] Md. AshfanoorKabir& Celia Shahnaz, "Comparison of ECG Signal Denoising Algorithms in EMD and Wavelet Domains," IJRRAS, vol. 11, Issue 3, Jun, 2012.
[37] Antoni Buades, Bartomeu Coll, Jean-Michel Morel, "A non-local algorithm for image denoising," Proc. / CVPR, IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE Computer Society Conference on Computer Vision and Pattern Recognition vol. 2, pp. 60- 65, Jul 2005.
[38] Nagendra H, S.Mukherjee, "Application of Wavelet Techniques in ECG Signal Processing: An Overview," International Journal of Engineering Science and Technology (IJEST), ISSN: 0975-5462 Vol. 3 No.10, pp. 7432-7443 Oct. 2011.
[39] Paul S Addison, "Wavelet transforms and the ECG: a review," Institute of Physics Publishing, Vol.26, pp. R155–R199, 2005.
[40] Shweta Jain, M.P. Parsai, "Comparative Analysis of Various Wavelet Families used for R-Wave Detection of ECG Waveforms," International Journal of Innovative Research in Science, Engineering and Technology, Vol. 2, Issue 10, pp. 5177-5181 Oct. 2013.
[41] Kapil Tajane, Rahul Pitale, Dr. Jayant Umale, "Review Paper: Comparative Analysis of Mother Wavelet Functions with The ECG Signals," Int. Journal of Engineering Research and Applications, ISSN: 2248-9622, Vol. 4, Issue 1(Version 4), pp.38-41, Jan 2014.
[42] Marius Roşu, Sever Paşca, "A WBAN-ECG Approach for Real-time Long-term Monitoring," IEEE, 978-1-4673-5980-1/13, May 2013.
[43] MikhledAlfaouri and Khaled Daqrouq, "ECG Signal Denoising By Wavelet Transform Thresholding," American Journal of Applied Sciences ISSN 1546-9239, pp. 276-281, 2008.
[44] P. Karthikeyan, M. Murugappan, and S.Yaacob, "ECG Signal Denoising Using Wavelet Thresholding Techniques in Human Stress Assessment." International Journal on Electrical Engineering and Informatics, vol 4, no. 2, Jul 2012.
[45] Q. Xue, Y. H. Hu, and W. J. Tompkins, "Neural-networks-based adaptive matched filtering for QRS detection," IEEE Transactions on Biomedical Engineering, vol. 39, no. 4, pp. 317–329, Apr. 1992.
[46] Mathias Wilhelms, Olaf Dossel and Gunnar Seemann, "In Silico Investigation of Electrically Silent Acute Cardiac Ischemia in the Human Ventricles," IEEE Transactions on Biomedical Engineering, vol. 58, no.10, pp. 2961-2964, Oct 2011.
[47] A. Ruha, S. Sallinen, and S. Nissila, "A real-time microprocessor QRS detector system with a 1-ms timing accuracy for the measurement of ambulatory HRV," IEEE Transactions on Biomedical Engineering, vol. 44, no. 2, pp. 159–167, Feb. 1997.
[48] Maxime Yochum, Charlo,tteRenaudb, Sabir Jacquira, "Automatic detection of P, QRS and T patterns in 12 leads ECG signalbased on CWT," Biomedical Signal Processing and Control, vol.25, 46–52, 2016.
[49] Yongqin Li, Joe Bisera, Max Harry Weil and Wanchun Tang, "An Algorithm Used for Ventricular Fibrillation Detection Without Interrupting Chest Compression," IEEE Transactions on Biomedical Engineering, vol. 59, no. 1, pp.78-86, Jan 2012.
[50] C. Li, C. Zheng, and C. Tai, 'Detection of ECG characteristic points using wavelet transforms," IEEE Transactions on Biomedical Engineering, vol. 42, no. 1, pp. 21–28, Jan. 1995.
[51] Liang Kai, Zhang Xu, Wang Yuan, Huang Suibiao, Guan Ning, Pang Wangyong, Li Bin, Chen Hongda, "A System of Portable ECG Monitoring Based on Bluetooth Mobile Phone," IEEE, 978-1- 61284-704-7/11. 2011.
[52] Myint Wai Phyu, Yuanjin Zheng, Bin Zhao, Liu Xin and Yi Sheng Wang, "A Real-Time ECG QRS Detection ASIC Based on Wavelet Multiscale Analysis," IEEE Asian Solid-State Circuits Conference, pp. 293-296, Nov 2009.
[53] ZahiaZidelmal, Ahmed Amirou, Mourad Adnane, Adel Belouchrani, "QRS detection based on wavelet coefficients," Computer Methods and Programs in Biomedicine, vol.107, pp. 490–496, 2012.

[54] S. Banerjee, R. Gupta, M. Mitra, "Delineation of ECG characteristic features using multi resolution wavelet analysis method," Measurement 45, pp. 474–487, 2012.

[55] Yao Zou, Jun Han, Sizhong Xuan, Shan Huang, Xinqian Weng, DabinFang,andXiaoyang Zeng, "An Energy Efficient Design for ECG Recording and R-peak Detection Based on Wavelet Transform," IEEE Transactions on circuits and systems-II:Express briefs. vol. 11, no. 4, Oct 2014.

[56] E. Arrais Junior, R. A. M. Valentim and G. B. Brandão, "Real Time QRS Detection Based on Redundant Discrete Wavelet Transform," IEEE Latin America Transactions, vol. 14, no. 4, pp. 1662-1668, Apr 2016.

[57] Chio-In Ieong, Pui-In Mak, Chi-Pang Lam, Cheng Dong, Mang-I Vai, Peng-Un Mak, Sio-Hang Pun, Feng Wan, and Rui P. Martins, "A 0.83µW QRS Detection Processor Using Quadratic Spline Wavelet Transform for Wireless ECG Acquisition in 0.35µm CMOS," IEEE Transactions on Biomedical Circuits And Systems, vol. 6, no. 6, pp. 586-595, Dec 2012.

[58] S. Chen, H. Chen, and H. Chan, "A real-time QRS detection method based on moving-averaging incorporating with wavelet denoising," Computer Methods Programs Biomed., vol. 82, pp. 187–195, Mar.2006.

[59] Felipe Alonso-Atienza, Eduardo Morgado, Lorena Fern´andez-Mart´ınez, ArcadiGarc´ıa-Alberola,Jose´ Luis Rojo-A´ lvarez, "Detection of Life-Threatening Arrhythmias Using Feature Selection and Support Vector Machines," IEEE Transactions on Biomedical Engineering, vol. 61, no. 3, pp. 832-840, Mar 2014.

[60] Qiao Li, CadathurRajagopalan and Gari D. Clifford, "Ventricular Fibrillation and Tachycardia Classification Using a Machine Learning Approach," IEEE Transactions on Biomedical Engineering, vol. 61, no. 6, pp.1607-1613, June 2014.

[61] Taihai Chen, Evangelos B. Mazomenos, KoushikMaharatna, SrinandanDasmahapatra and Mahesan Niranjan, "Design of a Low-Power On-Body ECG Classifier for Remote Cardiovascular Monitoring Systems," IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 3, no. 1, pp. 75-85, Mar 2013.

[62] A.H. Ismail, M. Fries, R. Rossaint and S. Leonhardt , "Validating the Reliability of Five Ventricular Fibrillation Detecting Algorithms," IFMBE Proceedings 22, pp. 26–29, 2008

[63] Luca Citi, Emery N. Brown, Riccardo Barbieri, "A Real-Time Automated Point-Process Method for the Detection and Correction of Erroneous and Ectopic Heartbeats," IEEE Transactions on Biomedical Engineering, vol. 59, no. 10, pp. 2828-2837, Oct 2012.

[64] A Amann, R Tratnig, K Unterkofler, "A New Ventricular Fibrillation Detection Algorithm for Automated External Defibrillators," IEEE Proc. Computers in Cardiology, pp. 559-562, Sep. 2005.

[65] R. Couceiro, P. Carvalho, J. Henriques, M. Antunes, M. Harris, J. Habetha, "Detection of Atrial Fibrillation Using Model-based ECG Analysis," 2008 IEEE, pp. 1-5, 2008.

[66] R. Poli, S. Cagnoni, and G. Valli, "Genetic design of optimum linear and nonlinear QRS detectors," IEEE Transactions on Biomedical Engineering, vol. 42, no.11, pp. 1137–1141, Nov. 1995.

[67] J. Pan and W. J. Tompkins, "A real time QRS detection algorithm," IEEE Transactions on Biomedical Engineering, vol. 32, no. 3, pp. 230–236, Mar. 1985.

[68] João P.V. Madeiro, Paulo C. Cortez, João A.L. Marques, Carlos R.V. Seisdedos, Carlos R.M.R. Sobrinho, "An innovative approach of QRS segmentation based on first-derivative, Hilbert and Wavelet Transforms," Medical Engineering & Physics 34, pp. 1236– 1246, 2012.

[69] J. Kim and C.-H. Chu, "ETD: An extended time delay algorithm for ventricular fibrillation detection," Proc. 36th Annual International Conference IEEE Eng. Med. Biol. Soc. (EMBC), pp. 6479-6482, Aug. 2014.

[70] Sanjeev Kumar Jain and BasabiBhaumik," An Energy Efficient ECG Signal Processor Detecting Cardiovascular Diseases on Smartphone", IEEE Transactions on Biomedical Circuits and Systems, Jul. 2016.

[71] A.Ebrahimzadeh, B.Shakiba, A. Khazaee, "Detection of electrocardiogram signals using an efficient method," Applied Soft Computing 22, pp. 108–117, May2014.

[72] Tao Ma, Pradhumna Lal Shrestha, Michael Hempel, Dongming Peng, Hamid Sharif, and Hsiao-Hwa Chen, "Assurance of Energy Efficiency and Data Security for ECG Transmission in BASNs," IEEE Transactions on Biomedical Engineering, vol. 59, no. 4, pp.1041-1048 Apr 2012.

[73] Luisa F. Polania and Kenneth E. Barner, "A Weighted ℓ1 Minimization Algorithm for Compressed Sensing ECG," IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP), pp. 4413-4417, 2014.

[74] Weiwei Li, Ting Jiang, and Ning Wang, "Compressed Sensing Based onthe Characteristic Correlation of ECG in Hybrid Wireless Sensor 0Network," International Journal of Distributed Sensor Networks, Article ID 325103, 8 pages, 2015.

[75] Jun Zhang, ZhenghuiGu, Zhu Liang Yu and Yuanqing Li, "Energy-Efficient ECG Compression on Wireless Biosensors via Minimal Coherence Sensing and Weighted ℓ1Minimization Reconstruction," IEEE Journal of Biomedical and Health Informatics, 2013.

[76] Jeevan K. Pant and Sridhar Krishnan, "Reconstruction of ECG Signals for Compressive Sensing by Promoting sparsity on the Gradient," IEEE, 2013.