Chapter 2

Literature Review

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2.5 Summary and discussion
2.1 Preface

Ambulatory ECG is significantly affected due to motion artifacts. There are many methods of motion artifact removal techniques so that the waveform of the AECG signal can be analyzed to assess cardiac abnormalities and to diagnose for various cardiac disorders [36]. For AECG signal analysis QRS complex detection, delineation of wave boundaries, linear filtering, multi-resolution analysis, signal space decomposition, neural network and fuzzy logic based methods are frequently used in the literature. A brief review of the literature relevant to ECG analysis is presented in this chapter.

2.2 Survey of wearable systems and W-ECG recorders

The design and development of wearable biosensor systems for health monitoring have garnered lots of attention in the scientific community and the industry during the last years. Mainly motivated by increasing healthcare costs and propelled by recent technological advances in miniature biosensing devices, smart textiles, microelectronics, and wireless communications. The continuous advance of wearable sensor-based systems will potentially transform the future of healthcare by enabling proactive personal health management and ubiquitous monitoring of a patient’s health condition. These systems can comprise various types of small physiological sensors, transmission modules, processing capabilities and thus facilitate low-cost wearable obtrusive solutions for continuous all-day and anyplace health, mental and activity status monitoring [65].

In the medical field, a Holter is a portable device for continuously monitoring various electrical activities of the cardiovascular system for at least 24 hours. They are also suitable when analyzing patients after myocardial infarction. Another interesting innovation is the presence of a tri-axial movement sensor, which records the patient physical activity. This helps to the cardiologist better analyze the recorded events belonging to the patient activity and diary. In fig. 2.1, a patient carries a Holter monitor.
With the miniaturization of electrical circuits and components, very small size, light weight, W-ECG(Wearable-ECG) is now available for ambulatory cardiac monitoring. One such W-ECG has been developed by Baghini et al. [3] at the Department of Electrical Engineering at IIT Bombay, and the corresponding wearable recorder is called a locket. A prototype of the locket which can record ECG from any one of the primary leads continuously for 48 hours into an inbuilt ash memory cell is depicted in Fig. 2.2. W-ECG is a variant of the standard ECG in the sense that the electrode placements are on frontal trunk approximating the positions of the limb sites in the standard ECG. Some W-ECG may have fewer leads in order to reduce the number of electrodes and complexity.

A commonly used lead II configuration for W-ECG is shown in Fig. 2.3. The purpose of W-ECG is long-term monitoring of the heart while the patient is allowed to perform his/her routine activities. Infrequent or irregular symptoms of heart disorders that may not be detected during brief clinical checkups may be detected through long-term monitoring. However, a major difficulty with any skin electrode based physiological monitoring is that the motion of electrodes induces artifacts in the recorded signal. This type of artifact arising due to a nonphysiological reason and at a superficial level of the skin is called motion artifact [3].
Fig. 2.2 Single-lead wearable ECG recorder called locket, developed by Baghini et al. [3] at IIT Bombay, placed by the side of a 15cm ruler. © 2007 IEEE.

![Wearable ECG Recorder](image1)

Fig. 2.3 Wearable ECG has worn in lead II configuration. The electrodes are placed on trunk proximate to the positions for standard lead II ECG indicated by RA, RL and LL. RA, RL and LL stand for right arm, right leg and left leg positions of the electrodes, respectively.

Wearable ECG recording system aiming to provide continuous monitoring of ECG signals, which is amplified by the instrumentation amplifier (INA 321 from Texas Instruments). The acquired ECG signals are converted into the suitable format by the ultra-low power microcontroller (MSP 430FG439) for storage in the SD-card as shown in fig. 2.4 [59].
Authors in [70] introduces a system approach to motion artifact reduction in ambulatory recordings. A custom ultra-low-power ECG analog front-end read-out for simultaneous measurement of ECG and electrode-tissue impedance, from the same electrode, is reported. Integrating this front-end, we describe a wireless patch for the monitoring of 3-lead ECG, electrode electrical artifact and 3D-acceleration. Beyond ECG monitoring, this wireless patch provides the additional necessary data to filter out motion artifact. Two algorithm methods are tested. The first method applies ICA for de-noising multi-lead ECG recordings. The second method is an adaptive filter that uses skin/electrode impedance as the measurement of noise. Algorithms, circuits and system provide a platform for reliable ECG monitoring on-the-move.

Authors in [58] proposed Holter recorder of low complexity designed using a mixed signal processor (MSP) as shown in fig. 2.5. They used the mixed signal processor MSP430, which is an ultra-low-power 16-bit RISC MSP from Texas Instruments; it provides the ultimate solution for battery-powered and portable measurement applications. To decrease the complexity of analog circuits and the interference of 50 Hz noise from power lines, they used the MSP to implement a finite impulse response (FIR) filter, which is equiripple design; so that analog circuits only have a band pass filter (BPF) and an amplifier for the preprocessing of ECG signals. An efficient MAC in an MSP430 is used to perform the convolution which is faster than the conventional MCU. They utilized the ring buffer for the input samples and the symmetrical characteristic of FIR filter for reducing the number of coefficients to perform the convolution. As an experimental result, the processed ECG signal is clear. Then the ECG
signal is saved in the SD-Card memory, transmitted wirelessly through Bluetooth or transmitted directly via RS232. To avoid a keyboard and an LCD consisting in the Holter recorder, they used the Smartphone with Bluetooth as a terminal to minimize the volume of the Holter recorder.

![Signal-flow graph representation of this Holter System.](image)

2.3 ECG signal analysis methods

In AECG signal analysis, researchers are developing, different artifacts removal techniques [3,20,31]. The waveform of the artifact-free AECG signal can be analyzed to assess cardiac abnormalities and lesion of the heart, infer into pathological and biological mechanisms of the heart, and diagnose for various cardiac disorders. There are many methods used for AECG signal analysis as previously discussed. For AECG signal analysis, first is the QRS complex detection, which is an important basic task.

2.3.1 (a) Detection of QRS complex and delineation of ECG wave

QRS detection is very important in all types of ECG signal processing. The QRS detection forms the basis of most ECG analysis algorithms, particularly those used for arrhythmia monitoring [11]. Once QRS complex has been identified, a more detailed examination of ECG signals, including the heart rate, the ST segment, etc., can be performed. So detection of the QRS complex is the most important task in automated ECG signal analysis. For example, Authors in [24, 25] suggested ST-T analysis was done after detection of QRS waves. Authors
in [17, 20] suggested a body position movements and motion artifacts in ambulatory ECG are analyzed after detection of QRS locations, and an adaptive recurrent filter is proposed, which requires a QRS detector for implementation.

Authors in [27] have first devised an effective yet simplistic algorithm for real-time QRS detection. Since then a lot of efforts have been devoted by the researchers in this direction, and they have come out with varieties of algorithms for detecting the QRS complex. Authors in [28, 29] have used first and second derivative-based approach for QRS detection from an ECG signal.

Authors in [68] DWT based feature extraction technique in the QT segment of digitized electrocardiograph recordings is proposed. At first, the signal is denoised by decomposing it using DWT technique and discarding the coefficients corresponding to the noise components. A multiresolution 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 wave are calculated. For R-peak detection, proposed algorithm yields sensitivity and positive productivity of 99.8% and 99.6%, respectively, with MIT BIH Arrhythmia database, 99.84% and 99.98% respectively with PTB diagnostic ECG database.

Wavelet transform (WT) has been extensively used by the research community for analysis and feature extraction of ECG signals [33, 45]. Many types of wavelets like Daubichies, Biorthogonal spline, Symlets and even newly developed wavelets with different scales, decomposition and threshold levels have been reported for QRS detection. The wavelet transform is a very promising technique for time-frequency analysis. By decomposing the signal into elementary building blocks that are well localized both in time and frequency, the WT can characterize the local regularity of signals. This feature can be used to distinguish ECG waves from noise, artifacts and baseline drift. The local maxima of the WT modulus at different scales can be used to locate the sharp variation points like a QRS wave of ECG signals. Hilbert transform has been applied for detecting the onset and offset of QRS complex [5].

The above-mentioned algorithms provide an adequate amount of accuracy in QRS detections but at the expense of heavy computational complexities and long time durations. Therefore, the first and second derivative-based QRS detection algorithms have been studied and
implemented, which overcome the above-mentioned drawbacks of other algorithms. They have been found computationally simple, less time consuming though very effective and accurate. The MIT/BIH ECG database has been used for experiments. As many as 25 test sets of the ECG waves of different morphologies, including the challenge 2010 test set A, B and C have been simulated on the matlab environment. It has been observed that the accuracy rate of the QRS detection algorithm based on the first and second derivative is increased by adopting the variable thresholds instead of fixed threshold mentioned in [28].

2.3.1 (b) Algorithm based on first derivative

A. Algorithm Based on First Derivative and Amplitude Threshold

The concept of this algorithm has been adopted from [28]. The first derivative, $Y(n)$, is calculated at each point of the ECG signal $X(n)$:

$$Y(n) = X(n+1) - X(n-1) \quad \ldots (1)$$

The first derivative array, then searches for points, which exceed a constant threshold:

$$Y(i) > 0.15 \text{ (Th1)} \quad \ldots (2)$$

Then the next three consecutive derivative values $Y(i+1)$, $Y(i+2)$ and $Y(i+3)$ must also exceed this constant threshold. If the above conditions are met, then point $i$ can be classified as a QRS candidate. In this work, we have modified the value of the threshold and termed it as (Th2). The value of Th2 has not been kept fixed instead it has been varied between 0.18 to 0.35, depending on the rate of detection of QRS complex in ECG signal as previously suggested in Pan-Tompkins algorithm. In most of the cases, the value of Th2 was found to be around 0.3. This is done for reliable detection of the QRS waves, which cannot be obtained with the constant threshold (Th1=0.15) defined in [28]. Fig. 2.6 shows the simulation results of the above-mentioned algorithm for MIT/BIH challenge 2010 test set B. The average detection rate of this algorithm is 98.36% with Th2 as against 95.26% obtained with Th1, see Table 2.1. Thus modifying the value of the constant threshold (Th1) to the variable threshold (Th2) has improved the detection rate of QRS waves.

B. Algorithm Based on First Derivative Only

The first derivative $Y(n)$ is calculated for each point of the ECG signal $X(n)$, using the formula specified in [28] as:

$$Y(n) = [X(n+2) - 2X(n-2) + X(n+1) - X(n-1)] \quad \ldots (3)$$
The slope threshold (Th3) is calculated as $0.7 \times \text{max}(Y)$ [28]. The first derivative array was searched for points, which exceed the slope threshold. The first point that exceeds the slope threshold, i.e. $Y(i) > Th3$ is taken as the QRS onset point. For this algorithm also instead of fixed threshold (Th3), a variable threshold (Th4) is used following the previously mentioned criterion of the rate of QRS detection. Fig. 2.7 shows the detected QRS waves for MIT/BIH challenge 2010 test set B using the above-mentioned algorithm using Th4. For most of the ECG data sets, the value of Th4 was set to $0.6 \times \text{max}(Y)$. The performance of this algorithm with Th4 is found superior than that obtained with of Th3.

2.3.1 (c) Algorithm based on the second derivative

The absolute values of the first and second derivatives, $Y0(n)$ and $Y1(n)$, of the ECG signal, $X(n)$ are calculated as in [28], as follows:

\[
Y0(n) = X(n + 1) - X(n - 1) \quad \text{.....(4)}
\]

\[
Y1(n) = X(n + 2) - 2X(n) + X(n - 2) \quad \text{.....(5)}
\]

These two arrays are scaled and then summed:

\[
Y2(n) = 1.3 \times Y0(n) + 1.1 \times Y1(n) \quad \text{.....(6)}
\]

This array is scanned until a threshold is met or exceeded:

\[
Y2(i) \geq 1.0 \text{ (Th5)} \quad \text{.....(7)}
\]

Once this occurs, the next eight points are compared with the threshold. If six or more of these eight points meet or exceed the threshold, the criterion for identification of a QRS candidate is met. The fixed threshold value (Th5 = 1.0) in (7), as suggested in [28], is too much coarse for some ECG signals, particularly the ones in which T waves are having equal or greater amplitude levels. This is the reason for the poor performance of this algorithm, which has been upgraded by selecting the variable threshold (Th6). The value of Th6 has been varied from 0.25 to 0.55 for improving the accuracy of the QRS detection. Fig. 2.8 depicts the experimental results from this algorithm applied on the same ECG test set.
2.3.1 (d) Results

Table 2.1 to summarize the experimental results for the three algorithms implemented in the matlab environment. The ECG database includes the MIT/BIH arrhythmia test sets (data set no. 100 to 207) and challenge 2010 test sets A, B, and C (A09, B47, B52 and C09). A total of 16 data sets and 19200 beats of ECG signals were tested for evaluating these algorithms. Total 57600 beats have been tested through these algorithms; out of which QRS waves have been correctly detected for 56370 beats, i.e. 97.86% with variable thresholds (Th2, Th4 and Th6), whereas with fixed thresholds (Th1, Th3 and Th5) this rate is 94.85%. Comparing the three algorithms, the first derivative only based algorithm has an edge over the other two algorithms, as it attained the highest detection rate. The first and second derivative based algorithm performs poorly due to the high threshold value (Th5 = 1.0).
Fig. 2.6 Detection of QRS complex First derivative and Amplitude Threshold based algorithm (a) ECG signal (b) First Derivative of the signal, (c) Detected QRS waves.

Fig. 2.7 Detection of QRS complex based on First Derivative (a) ECG signals (b) First Derivative of the signal, (c) Detected QRS waves.
Fig. 2.8 Detection of QRS complex based on Second Derivative (a) ECG signal, (b) Absolute First derivative of the signal, (c) Absolute Second derivative of the signal, (d) Detected QRS waves.
Table 2.1 Number of false beats of first derivative and amplitude based QRS detection with Th1 and Th2 (b) first derivative based QRS detection with Th3 and Th4 (c) second derivative based QRS detection algorithm with Th5 and Th6

<table>
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<tr>
<th>Sr. no.</th>
<th>Tape no. #</th>
<th>No. of beats</th>
<th>(a) No. of false detection beats</th>
<th>(b) No. of false detection beats</th>
<th>(c) No. of false detection beats</th>
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<tr>
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<td></td>
<td></td>
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<td>Th3</td>
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<td>1200</td>
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<td>0</td>
<td>0</td>
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</tr>
<tr>
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<td>1200</td>
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<td>0</td>
<td>85</td>
</tr>
<tr>
<td>13</td>
<td>A09</td>
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<td>120</td>
<td>48</td>
<td>114</td>
</tr>
<tr>
<td>14</td>
<td>B47</td>
<td>1200</td>
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<td>0</td>
<td>257</td>
</tr>
<tr>
<td>15</td>
<td>B52</td>
<td>1200</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>16</td>
<td>C09</td>
<td>1200</td>
<td>25</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>19200</td>
<td>952</td>
<td>315</td>
<td>803</td>
</tr>
</tbody>
</table>
In the previous section, we have reviewed some of the QRS detection techniques in the literature. For automated analysis of the ECG, detections of P and T waves are also important as the P wave represents atrial activity, and the T wave is related to repolarization of the ventricles. In a cardiac cycle, the sequence of occurrence of these waves is P-QRS-T. Therefore, we can search for P and T waves in appropriate time windows after the QRS complex is located. However, it is recommended that any fibrillation condition should be detected before proceeding with the waveform analysis. The T wave is the wave with the next highest level of energy in the cardiac cycle. The location of T wave from the R peak depends on the current beat period, measured at the time interval between two consecutive R peaks, which is simply called RR interval. The search window for T wave is defined from the R peak position during the interval from 140 to 500ms if mean (RR interval) > 700 ms and for smaller RR intervals, the search window is defined in the range 100ms to 0.7*RR interval (in ms). The ECG detection points Q, R, S and T are located using a low-pass filter from the differentiated ECG. A quadratic spline wavelet is used at four dyadic scales starting from the scale of 2 at a sampling rate of 250Hz. The first two scales are used for detecting QRS and the next two scales are used for detecting P and T waves in appropriately chosen time windows with respect to the location of R peak in the QRS complex. Assuming that the P-wave occurs in a specified time window of 240 to 400 ms preceding the R wave of the QRS complex in each cardiac cycle; three different P wave detection algorithms are discussed. These techniques are based on the derivatives of the ECG signal in a specified window. The first method is called the amplitude and first derivative based algorithm. This technique subjects the first derivative of the ECG signal in a specified time window to a predefined threshold value. The criterion applied for P wave detection is: the positive derivative at three consecutive points in the window should exceed the threshold followed by two consecutive points having the negative derivative crossing the threshold within 48ms, and all the sample values in the signal in between these two crossing points must exceed a predefined amplitude threshold. The second technique searches for a point in the time window at which the negative derivative exceeds the threshold value and in the third method, a combination of second derivative and a smoothed first derivative signal is subjected to a threshold value for detection of the P wave. There is a model-based approach for the analysis of different segments of the cardiac cycle, i.e., P, QRS and T waves. P, QRS, ST and T are expressed as linear combinations of Hermite functions. This modeling required 2, 7, 2 and 4 Hermite coefficients represent P, QRS, ST and T, respectively. A discrete cosine transform based modeling is proposed for delineation of P, QRS and T waves. The biphasic function given by
pole-zero model of order (2, 2) is used for this representation. It shows that P and T each has a single biphasic function, whereas QRS can be represented as two or three biphasic functions. These segmentations of ECG waves are useful for further analysis and compression of ECG signals. The level and slope of the ST segment are sensitive to levels of physical activity. The ST level is measured with respect to the baseline or isoelectric level of the ECG which can be detected by searching for the test line segment between P and Q waves. A method for determining the measurement point for the ST level in terms of current heart rate is given. The ST level is measured at J + 80ms where J is the first inaction point after the S wave. In order to provide immunity against motion artifacts, the ST levels are measured after taking an average from several consecutive beats with similar morphology and perfect alignment. A different approach of ECG segmentation uses a mixed number of functions where the middle and end points of the functions are matched with the wave shapes in ECG signal. This kind of segmentation is used for recognition of ST segments. A similar approach using a piecewise linear approximation, here a line segment is initiated from the start of the cardiac cycle and is extended up to the point for which the error in the approximation of the ECG segment is less than a mixed empirical value. A new segment starts from the end point of the previous segment. The advantage of this method is that the cardiac cycle can be described in terms of fewer parameters like slopes and lengths of the line segments [3].

2.3.2 Linear shift variant filter based methods

Two main approaches used are linear filtering and polynomial fitting. Basically, make a high-pass filter to cut off the lower frequency components (the baseline wanders). Baseline wander can cause problems to analysis, especially when examining the low-frequency ST-T segment. Authors in [62] suggested that a baseline wandering can mask some important features of the ECG signal, hence it is desirable to remove this noise for proper analysis and display of the ECG signal. In most of the ECG recordings the respiration, electrode impedance changes due to perspiration and increased body movements are the main causes of the baseline wandering. Respiratory signal wanders between 0.15 Hz and 0.5 Hz frequencies. The design of a linear, time-invariant, high-pass filter for removal of baseline wander involves several considerations, of which the most crucial is the choice of filter cutoff frequency and phase response characteristic. The cutoff frequency should be chosen so that the clinical
information from the ECG signals remains undistorted while as much as possible of the baseline wander is removed.

Authors in [60] suggested an effect of filtering techniques on the time-domain analysis of the ECG. Multi-lead ECG recordings obtained from chronic atrial fibrillation (AF) patients after successful external cardioversion have been acquired. Many high-pass filtering techniques and three cutoff frequency values were used: Bessel and Butterworth four-pole and two-pole bidirectional and unidirectional filters, at 0.01, 0.05 and 0.5 Hz low cutoff frequency. As a reference, a beat-by-beat linear, piecewise interpolation was used to remove baseline wander, on each P-wave and results showed that ECG filtering affects the estimation of P-wave duration in a manner that depends upon the type of filter used: particularly, the bidirectional filters caused negligible variation of P-wave duration, while unidirectional ones provoked an increase higher than 8%.

Electromagnetic fields from power lines can cause 50 Hz sinusoidal interference, possibly accompanied by some of its harmonics. Such noise can cause problems interpreting low amplitude waveforms and spurious waveforms can be introduced. A very simple approach to filtering power line interference is to create a filter defined by a complex conjugated pair of zeros that lie on the unit circle at the interfering frequency $\omega_0$. The filter can be improved by adding a pair of complex-conjugated poles positioned at the same angle as the zeros, but at a radius. The radius, then determines the notch bandwidth.

Authors in [61] introduce the digital filtering method to cope with the noise artifacts in the ECG signal. The Chebyshev I and Chebyshev type II filters are applied to the ECG signal. They also give the comparison of both types of the filter. All the designs are implemented using the MATLAB FDA tool. ECG data is acquired from the Instrumentation amplifier designed in the Laboratory. For the interfacing of an ECG amplifier to the computer advantech 711B add on card has been used. The results of the filter are compared to other filters also. From the result, it is seen that both the filters reduce the low and high frequency. The power line noise is also reduced. It is seen that a tip of the QRS complex is distorted. The outputs of the Chebyshev II filter show that after using a filter, there is a distortion of the ST part of the waveform. They found that both digital filters work satisfactory with some limitations.
2.3.3 Adaptive filter based methods

Adaptive filter based methods are also in use for ECG signal processing. Authors in [52] suggested, several adaptive filter algorithms were proposed for noise cancellation of ECG signals and determining the accuracy of ECG signal features. Adaptive filters function based on minimizing the error between input signal, which is a noisy ECG signal and its reference input, which is one of many correlated artifacts present in the ECG signal. Different adaptive filter algorithms used in they are Least Mean Squares (LMS), Normalized Least Mean Squares (NLMS), Kernel Least Mean Squares (KLMS) and Normalized Kernel Least Mean Squares (NKLMS). Their main focus is to compare the performance of the new kernel adaptive filter to already existing least mean squares filter. For results, the clean ECG signal was compared to the filtered ECG signal using one of the above algorithms and the accuracy of detecting peak locations of P, Q, R, S and T waves were evaluated. The basic LMS algorithm works best on the linear data, where mapping between the input signal and the desired signal is linear. For nonlinear data, that mapping between the desired signal and the input signal is nonlinear; the LMS algorithm will show poor performance. To improve performance, the LMS algorithm must be reformulated to be capable of learning nonlinear mapping. To create a nonlinear mapping, KLMS algorithm uses Gaussian Reproducing Kernel Hilbert Space (RKHS) to transform the input into higher-dimensional feature space. Since an input signal is in a higher dimension, it will provide richer representation of it and therefore, its stochastic gradient descent will be more effective for nonlinear mapping of the LMS algorithm for nonlinear problems. NLMS algorithm that was derived from the LMS algorithm to improve performance of the LMS algorithm, the NKLMS algorithm is driven from the KLMS algorithm to improve KLMS algorithm performance. This paper will also attempt to explain different noise sources in ECG signals, how they are caused and how they can be canceled. They also demonstrate the usage of different adaptive filtering techniques to cancel noise sources from an ECG signal and accurately detect its characteristics.

Authors in [9] suggested a simple and efficient normalized LMS algorithm was proposed for removal of noise from ECG signal. That is suitable for application requiring large signal to noise ratio with less computational complexity using simple addition and shift operation and achieves considerably speedup over other LMS based realization. In [10] block LMS algorithm is used to remove artifact preserving low frequency component of ECG.
Authors in [22] suggested the problem of noise cancellation from ECG signal using error normalization-based adaptive filters, their block-based versions were proposed and tested on real signals with different artifacts obtained from the MIT-BIH database. For this, the input and the desired response signals are properly chosen in such a way that the filter output is the best least squared estimating of the original ECG signal. Among the six algorithms, the BB-ENSRLMS (Block based error nonlinear sign-sign LMS) performs better than the other. From the simulated results, clearly these algorithms remove the artifacts efficiently present in the ECG signal. Authors in [21] suggested an Adaptive Kalman Filter for ECG Signal Enhancement used; filter operates by sequentially estimating the measurement and process noise covariance and uses this covariance to estimate the Kalman gain and update the estimated ECG complexes.

2.3.4 Wavelet based methods

Recently, the wavelet transform has been proven to be a useful tool for non-stationary signal analysis [49]. The wavelet based methods are extensively used in pre-processing, denoising and analysis of ECG signals. Authors in [7] suggested DWT method used to extract ECG parameters in a three-step process: first, the low-frequency components are removed using DWT transformation, second the noise into the signal is suppressed using the DWT based denoising techniques and finally ECG parameters are extracted. In [8] the morphology of ECG is used for classification of the ECG beats. To extract the shape related features from the ECG signal, three-level Daubechies-1 DWT is used after noise suppression in the ECG signal through a digital filter. In [50] The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is a useful tool to implement Wavelet transform for digital signals. The 1-D DWT is computed by successive low-pass and high-pass filtering of the discrete 1-D signal. The input signal $x[n]$ is low-pass filtered using the block denoted by $g[n]$ as well as high-pass filtered using $h[n]$ using the cutoff frequency, $fc = fs/2$. Thus, the original input signal $x[n]$ will be down-sampled by two. This is also called as decomposition of the signal. At each level, the high-pass filter produces the detail information, while the low-pass filter associated with the scaling function produces coarse approximations, the low-pass filter output, is further down-sampled by two through the low-pass and high-pass filter blocks. Therefore, one can go on decomposing the input signal up to $n^{th}$ level. The cardiac portion of the signal is reconstructed, by eliminating higher frequency wavelet coefficients.
Authors in [11] suggested undecimated wavelet transform was used for denoising ECG. Authors in [12] suggested a spatial correlation filtering, and stationary wavelet transform was proposed to eliminate the noise in ECG signal. The spatial correlation filtering is applied to shrink the wavelet coefficient, and the stationary wavelet transform used to decompose the noisy signal. Authors in [13] suggested a stationary wavelet transform used for optimal denoise ECG signal in which signal to noise ratio is adjusted from 1 to 10 dB and the result is evaluated by visual inspection, then conclude using symlet4; decomposition at level 5 and hard shrinkage function with the empirical bayesian threshold can get superior denoise performance. Authors in [16] suggested an integrated ECG signal processing scheme, using a systematic wavelet transform (WT) algorithm; this signal processing scheme can realize multiple functions in real-time, including baseline drift removal, noise suppression, QRS detection, heart beat rate (HBR) prediction & classification, and clean ECG reconstruction. Authors in [23] suggested a wavelet-based denoising technique is investigated for suppressing EMG noise and motion artifact in ambulatory ECG. EMG noise is reduced by thresholding the wavelet coefficients using an improved thresholding function combining the features of hard and soft thresholding. Motion artifact is reduced by limiting the wavelet coefficients. Thresholds for both the denoising steps are estimated using the statistics of the noisy signal. Denoising of simulated noisy ECG signals resulted in an average SNR improvement of 11.4 dB, and its application on ambulatory ECG recordings resulted in L2 norm, and max-min based improvement indices close to one. It significantly improved R-peak detection in both the cases. Authors in [71] introduce a new method which removes these artifacts. This is done by obtaining an estimate of the artifacts using the stationary wavelet transformation. An automatic multi-resolution thresholding scheme which uses a robustified QRS detection is proposed.

2.4 Classification and detection technique

One of the main objectives of the thesis is classification and detection of AECG signal. As previously discussed there are many methods used for the above purpose as explained below.

2.4.1 Principal component analysis (PCA) and Recursive principal component analysis (RPCA) based method

The PCA is a technique used for finding the most suitable bases to represent the given data. This is because there may be some redundancy in the data and, therefore, the dimension can
be reduced. In this case, the bases would be such that even a few of the vectors from the bases can represent the data satisfactorily without much loss in terms of the errors in the reconstruction. Using PCA the vectors forming such bases can be found in an ordered manner. They have also discussed a BMA specific PCA-based filtering method for removal of the induced motion artifact due to the particular BMA without affecting the morphologies of P and T waves in the cardiac cycle. The performance of the PCA-based filtering is verified by locating P and T waves using an automated method with and without using the proposed filtering. The improvement due to the filtering is shown using the histograms of detected P and T wave locations [3]. PCA and ICA are techniques that are commonly used in the multivariate statistical analysis to reduce the number of dimensions from a numerical measurement of several variables. With this dimensional reduction, these techniques look for simplifying a statistical problem with the minimal loss of information. These methods are also used in signal processing for separating a linear combination of signals generated from sources that are statistically independent. Applying PCA or ICA to ECG leads that are statistically independent gives new signals or principal/independent components. These transformations can be reverted after selecting a subset of components in order to filter out part of the original information. Authors in [54] investigated the performance of PCA and ICA in denoising ECG signals recorded in ambulatory conditions.

A time-domain cardiac activity mean and the motion artifact noise into the ECG signal are modeled by Hermite polynomial expansion and principal component analysis; a set of time-domain accelerometer feature was extracted. A support vector machine is employed for supervised classification using time domain features and cepstral features extracted from ECG and accelerometer signals based on frame level analysis are modeled using Gaussian mixture models (GMM). To reduce the dimension of tri-axial accelerometer cepstral features, which are concatenated and fused at the feature level hetroscaedastic linear discrimination analysis is performed. Finally to improve overall recognition performance, fusion of the multi modal and multi domain subsystem at the score level is performed [14].

The AECG is analyzed beat-by-beat using a recursive principal component analysis (RPCA) based method in [19]. Authors in [53] used RPCA based algorithm was applied for detecting and quantifying the motion artifact episodes encountered in an ECG signal. They have presented an offline analysis of the RPCA-based algorithm for detecting the motion artifacts episodes appearing in an ECG signal. They used the ECG signals available from Physionet
(MIT-BIH arrhythmia database). Motion artifacts have been synthetically generated by low-pass filtering the random noise with spectral ranges (B): 0–5 Hz, 0–10 Hz. The primary aim of the analysis is to determine the minimum level of noise (i.e. Highest SNR) that can be detected by the algorithm with 100% accuracy. In the process, they have verified that the RPCA error magnitude is significantly greater for the noisy episodes as compared to the clean ECG signal portions. Further, the error magnitude gradually increases as the spectral range for low-pass filter for noise increases, i.e. for 0–10 Hz spectral range, the error magnitude is higher as compared to the rest of the spectral range. For tap #203 and #208 the RPCA error has a lot of false peaks, particularly at low noise. Hence, to reduce these peaks the noise level is increased, so that there are distinct peaks at noisy durations only. For tap #119, for higher SNRs the RPCA error corresponding to abnormal beats(bigeminy/trigeminy, etc.) is comparable (or even higher) with respect to the RPCA error of noisy beats, whereas for higher noise levels (smaller SNRs) the same is smaller than that of noisy RPCA errors. The trend is the same for all forgetting factors ($\alpha$) values. Thus, the false beats are better identified by the algorithm at smaller noise levels in tap #119. For all taps, the usual trend is that the noisy RPCA error for a higher SNR is greater than the clean RPCA error for the low SNR. This is maintained for all taps and all forgetting factors ($\alpha$). This is because the RPCA algorithm is a learning-based algorithm, and the clean episodes are preceded by the noisy episodes. The RPCA algorithm is useful for temporal segmentation of ECG beats with respect to the type of physical activity (PA). The quantification of the RPCA algorithm has been made by applying it over 25 ECG datasets of different morphologies and genres with three different values of SNRs for each forgetting factor and for each of B spectral ranges. Authors in [17, 18] suggested the separability of motion artifacts due to different types of PA is tested by classifying them automatically based on the nature of the PA. It has in addition observed that a different pace level of the PA has a different impact on the generation of motion artifacts in AECG. The RPCA based error signal is derived from AECG as an index of motion artifacts and also as a measure of the impact at different pace levels on AECG, simply referred as an impact signal [3].
2.4.2 Independent component analysis based method

Authors in [51] introduce automatic noise detection and removal technique based on independent component analysis (ICA) preventing the signal distortion and attenuation. The ICA is a popular blind source separation technique, which has provided reliable solution for noise reduction problems in the ECG. According to the ICA, observed signals are separated to the independent sources by decomposing the mixture signals with direction to maximize non-Gaussianity. One important characteristic of the ICA is that the method is restricted to a Gaussian random variable. The traditional assumption in ECG de-noising is that ECG and motion artifact are statistically independent corresponding to the basic assumption of the ICA. However, movements influence of cardiac dynamics, thus it is not always satisfied. Furthermore, ICA based motion removal algorithm may distort ECG signals by eliminating important components. Thus they proposed 4 decision rules to avoid above limitation. Noisiness and Gaussianity were considered by approximation of negentropy which shows zero for the Gaussian random variable under a condition of the Central Limit Theorem. Because the distribution of a sum of random variables follows a Gaussian distribution, if the approximation of negentropy for ECG during exercise is decreased compared to the signal during rest, the segment of the signal regarded as a noisy signal. Also, if the approximation of negentropy closes to zero, it is considered to the Gaussian variable. Under this condition, the algorithm regards it as out of processing range, and moves on to the next segment of data.

Whitening is useful processing before the ICA. Through the process, observed random vector is uncorrelated and its variance equals unity. In the probability distribution aspect, it means that the distribution moves outside of the mean value. If the distribution of the whitening result shows a similarity in the distribution of the input random vector, it can be said vector is already uncorrelated. In this case, the algorithm also decides to stop processing and starts with the next segment of data. After the ICA, motion artifact component was found using the cross correlation coefficient. The channel which has the lowest correlation with each other was selected and filtered. To consider motion artifact and an ECG were not perfectly separated, they applied HPF to selected component, not set to zero.

The algorithm was compared with several approaches to evaluate the implications of the proposed method such as applying filters and decision rules. One of the important problems in the ambulatory ECG analysis is the absence of reference signal. In this, R-peak centered ensembles were generated and averaged data regard to the reference signal of each trial.
Ambulatory ECG is highly contaminated with motion artifacts, but most of the noise components are eliminated on the averaged signal covers a large range of movements for various subjects and results ‘Low Gaussian-Prop.’ means cross correlation coefficient between observed ECG and reference signals, because the algorithm detected the signals is Gaussian variables and returned original signals. These results can be regarded standard for ‘Low Gaussian-’. Thus the results that are lower than this standard are explained that ECG was distorted by the applied method such as ‘Low Gaussian-Con.’ of the subject 3. Furthermore, there are the results that have high variation among the channels, such as ‘Low Gaussian-Con.’ of the subject. It is considered that the necessary components were eliminated during de-noising. For the results shown, their proposed method showed higher correlation with the reference signal. In some results presented better results than our algorithm, such as a result from S1 using a modified conventional method. Stability, however, which is based on a variation of the results from the results proves the proposed algorithm. A proposed method successfully removed the motion artifacts in ambulatory ECG without distortion. Furthermore, reconstructed ECG processed by this method showed higher correlation with the estimated reference ECG than the signals processed by other methods. Because the proposed algorithm jumps over an unnecessary process, it is expected to reduce processing rate. In addition, the method which is based on short-term segmented (5 seconds) dataset offers possibilities for real-time processing of ECG. Finally, the proposed algorithm has a potential to be applied for long-term ECG monitoring in daily life.

Principal component analysis (PCA) or independent component analysis (ICA) is used to transform multiple input ECG signals into principal or independent components in component space in accordance with reference signals. The transformation is dynamically adjusted in accordance with noise characteristics within the ECG signals. A subset of principal or independent components is selected in accordance with the noise characteristics determined from the ECG signals, from additional non-ECG related signals and from environment-related signals. The subset is processed in accordance with the noise characteristics. In one embodiment, an inverse transform is applied to transform the principal or independent components back to ECG signals with reduced noise from which ECG properties can more accurately be determined. In another embodiment, the selected subset of principal or independent components may have a beat detection or arrhythmia detection algorithm applied directly thereto to determine instantaneous heart rate values or atrial activity [67].
Authors in [69], the performance of PCA and ICA in the context of cleaning noisy ECGs in ambulatory conditions was investigated. With this aim, ECGs with artificial motion artifacts were generated by combining clean 8-channel ECGs with 8-channel noise signals at SNR values ranging from 10 down to -10 dB. For each SNR, 600 different simulated ECGs of 10-second length were selected. 8-channel PCA and ICA were applied and then inverted after selecting a subset of components. In order to evaluate the performance of PCA and ICA algorithms, the output of a beat detection algorithm was applied to both the output signal after PCA/ICA filtering and compared to the detections in the signal before filtering. Applying both PCA and ICA and retaining the optimal component subset, yielded sensitivity (Se) of 100% for all SNR values studied. In terms of Positive predictivity (+P), applying PCA, yielded to an improvement for all SNR values as compared to no cleaning (+P=95.45% vs. 83.09% for SNR=0dB; +P=56.87% vs. 48.81% for SNR=-10dB). However, ICA filtering gave a higher improvement in +P for all SNR values (+P=100.00% for SNR=0dB; +P=61.38% for SNR=-10dB). An automatic method for selecting the components was proposed. By using this method, both PCA and ICA gave an improvement as compared to no filtering over all SNR values. ICA had a better performance (SNR=-5dB, improvement in +P of 8.33% for PCA and 22.92% for ICA).

2.4.3 Neural network and fuzzy logic based method

Neural networks are also used for detection of events and pattern classifications in the ECG signal analysis. An adaptive neuro-fuzzy filtering, which is basically a nonlinear system structure presented the noise cancellation of biomedical signals (like an ECG, PPG, etc.) measured by ubiquitous wearable sensor node (USN node). In this non-linear adaptive filter which uses a fuzzy neural network (FNN) to treat with the unknown noise, and artifacts present in biomedical signals. The presented work based on ANFF (Adaptive Neuro Fuzzy Filter), where the adaptation process includes neural network learning ability and fuzzy if-then rules with the optimal weight setting ability. ANFF is basically a fuzzy filtering implemented in the framework of adaptive neural network environment [15].

The method of wavelet decomposition and artificial neural network presented in this, demonstrated its noise reduction capability of highly nonlinear and nonstationary signals through an application of the ECG. In the specific models given, the delayed values of relevant signals in the system are used as inputs to wavelet decomposition. Its outputs are, then, filtered through the process of coefficient thresholding, which removes the majority of
coefficients that are not relevant to the signal of interest. Next, these remaining coefficients are used as inputs to multilayer neural networks. Methods for the adjustment of parameters in generalized neural networks are treated, and the concept of back propagation was introduced to generate partial derivatives of a performance index with respect to adjustable parameters. From the implementation shown, the recovered signals are shown to have good SNR improvement over the contaminated signals. Once trained, the neural network can recognize the wavelet decomposed coefficients of a particular patient and can reconstruct the signal with most of the noise removed. With sufficient training, the network may be applied to process the ECG signals in real-time [56].

Authors in [55] propose an ECG denoising method based on a feed forward neural network with three hidden layers. Particularly useful for very noisy signals, this approach uses the available ECG channels to reconstruct a noisy channel. They tested the method, on all the records from Physionet MIT-BIH Arrhythmia Database, adding electrode motion artifact noise. This denoising method improved the performance of publicly available ECG analysis programs on noisy ECG signals.

Authors in [63] suggested an ECG classification approach for Ischemic Heart Disease (IHD) diagnosis using a neuro-fuzzy model called Fuzzy-Gaussian Neural Network (FGNN). That focuses on the neuro-fuzzy classifier called FGNN to recognize the ECG signals for IHD diagnosis. The proposed ECG processing cascade has two main stages: (a) Feature extraction from the QRST zone of ECG signals using either the PCA or the Discrete Cosine Transform (DCT); (b) Pattern classification for IHD diagnosis using the FGNN. They have performed the software implementation and have experimented the proposed neuro-fuzzy model for IHD diagnosis. They have used an ECG database of 40 subjects, where 20 subjects are IHD patients, and the other 20 are normal ones. The best performance has been of 100% IHD recognition score. The result is exciting as much as they have used only one lead of ECG records as input data, while the current diagnostic approaches require the set of 12 lead ECG signals.

2.4.4 Support vector machine

Authors in [64] proposed a classifier motivated from statistical learning theory, i.e., Support Vector Machine (SVM), has been explored for detection and delineation of these wave components. Digital filtering techniques are used to remove interference present in ECG
signal. The feature extraction is done using a modified definition of the slope of the ECG signals. The performance of the proposed algorithm is validated using ECG recordings from dataset-3 of the Common Standards for Quantitative Electrocardiography (CSE) multi-lead measurement library. The results of accuracy, i.e., 94.4%, obtained to clearly indicate a high degree of agreement with the manual annotations made by the referees of CSE dataset-3. The numeric figure of 94.4% of accuracy for a CSE DS-3 database shows the efficacy of SVM-based algorithm for more accurate and more reliable detection and delineation of P, QRS, and T-wave components of ECG signals. In previous reported research, a heuristic path with an application and extensive experimentation preceding theory was used. In contrast, the development of SVMs involved sound theory first, then implementation and experiments. So, the SVM algorithm of delineation may be capable of enhancing specific rhythms in ECG signals, which may in turn prove helpful in accurately detecting the P, QRS, and T-wave components. The simulated/graphical results prove that the proposed method leads to a better visual and automated ECG analysis, which is not only desirable in basic physiological studies, but also a prerequisite for a widespread utilization of delineation technique in clinical studies, where simplicity and effectiveness of information are of primary importance.

Authors in [65] proposed an SVM-based arrhythmia classification algorithm. Seventeen original input features were extracted from preprocessed signals by wavelet transform; 2 rhythm-related features and 15 wavelet coefficient features. To improve the learning efficiency of the classifier, they attempted to reduce the original features to 4, the linear combination of original features, by linear discriminant analysis (LDA). Comparing the performance of the SVM classifier with different input features, the performance with features by LDA showed higher than with that by PCA and even with original features. So, they could see that LDA could reduce feature dimensions and act as a useful tool to improve the classifier performance at lower learning costs. To evaluate the SVM arrhythmia classifier, a cross-validation method was adopted. That is, the performance of it was compared with that of the Multilayer Perceptrons (MLP) classifier and Fuzzy Inference System (FIS) classifier using dimension reduced features. The proposed SVM classifier showed satisfactory performances in discriminating six types of arrhythmia beats. The accuracies of discrimination of normal sinus rhythm (NSR), atrial premature contraction (APC), supraventricular tachycardia (SVT), premature ventricular contraction (PVC), ventricular tachycardia (VT) and ventricular fibrillation (VF) were 99.307%, 99.274%, 99.854%, 98.344%, 99.441% and 99.883%, respectively.
2.5 Summary and discussion

In this chapter, a brief survey of about wearable systems and W-ECG recorders are provided. In AECG analysis one of the basic tasks is like detection of the QRS complex. For that we used three different algorithms, namely- first derivative and amplitude threshold based, first derivative only based and first and second derivative based- for QRS complex detection have been implemented in MIT/BIH ECG database. Total 16 ECG data sets have been taken into count that includes the arrhythmia beats and challenge 2010 test sets A, B and C in order to include the variations in the ECG wave morphologies. Total 57600 beats have been tested through these algorithms; out of which QRS waves have been correctly detected for 56370 beats, i.e. 97.86% with variable thresholds (Th2, Th4 and Th6), whereas with fixed thresholds (Th1, Th3 and Th5) suggested in [28] this rate has been found to be 94.85%. Comparing the three algorithms, the first derivative only based algorithm has an edge over the other two algorithms, as it attained the highest detection rate. The first and second derivative based algorithm performs poorly due to the high threshold value (Th5 = 1.0, used in [28]). But, using the variable and flexible values of thresholds definitely improves the QRS detection performance. The other algorithms provide an adequate amount of accuracy in QRS detections but at the expense of heavy computational complexities and long time durations. Therefore, the first and second derivative-based QRS detection algorithms have been studied and implemented, which overcome the drawbacks of other algorithms. They have been found computationally simple, less time consuming though very effective and accurate. It has been observed that the accuracy rate of the QRS detection algorithm based on the first and second derivative is increased by adopting the variable thresholds instead of fixed threshold mentioned in [28].

In [70], report an integrated approach to motion artifact reduction in ECG combining electrode position selection, algorithm development, design of customized integrated circuits and final integration in wearable electrode patch. In [71] a new method to detect and to remove outliers in ECG data generated by movement of the patient has been introduced. It is able to recover corrupted QRS complexes and removes temporary baseline shifts. In [68] authors proposed method uses multiresolution feature extraction using DWT, which can be used for feature extraction from ECG data. In [69] PCA or ICA is used to transform multiple input ECG signals into principal or independent components in component space in accordance with reference signals.
Then we discussed various methods for AECG signal analysis like delineation of Wave Boundaries of ECG, Linear shift variant filter based methods. Adaptive filter based methods and Wavelet-based methods for pre-processing, denoising and analysis of ECG signals. Principal component analysis (PCA), RPCA; Independent component analysis based method, Neural network; Fuzzy logic based analysis and support vector machine algorithm for AECG analysis, classification and detection of motion artifacts are reviewed briefly.

The possibility of artifact detection and filtering was initially explored earlier than ECG signals were analyzed using wavelet transform and a neural network. At the same time, the reported performance is not very satisfactory as the wavelet-based representation does not separate the in-band BMA signal from the ECG. In other works related to BMA analysis of non ambulatory ECG, body position changes are detected in ischemia monitoring using support vector machine (SVM) and Gaussian mixture models (GMM). The motion artifacts have a significant overlap in frequency with ECG signal, so filtering based on spectral separation is of limited use. So we use RPCA suggested by pawar at al. [26] to detect abrupt changes in motion artifacts due to body movement activity(BMA) transition. The RPCA algorithm is also tested for actually induced motion artifact due to performing various usual physical activities like a movement of hands, waist, walking, sitting up and down and we find that with 100% accuracy motion artifact is detected. We also used wavelet based method and ICA for motion artifact detection in AECG.

The effect of the pace of activities is also analyzed by allowing the different pace levels: slow and fast, for four particular volunteers. Videos are recorded for post-verification of the start and end of activities as well as for pace levels (slow and fast). The results derived from the automated analysis of AECG signals, regarding the nature of the motion, match with the recorded video. The motion artifact signal is separated from the ambulatory ECG signal using biorthogonal wavelets. We also used a novel, a blind source separation technique based on ICA is proposed for separating motion artifacts from AECG signals; with different movement as suggested in the previous experiment. The ICA technique applied to synthesized AECG signals as well as real AECG signal. Motion artifact and clean ECG signal are separated successfully, and the results are verified using the factual truth, i.e. either using video in case of actual AECG signals or using the original clean ECG signal in case of synthesis AECG.