Chapter 2
Literature Review

Ambulatory electrocardiography and the use of A-ECG signal is increasing in clinical practice to detect abnormal electrical behavior of the heart during ordinary daily activities of a patient. It is a convenient option for recording the long term heart activities of a patient without hospitalization. While it provides the freedom from hospitalization, it also carries certain inherent difficulties with it. As the subject carries routine physical activities like moving arms up/down, walking, sitting down, standing up, climbing stairs etc, effects and consequences of these activities will directly be reflected on the recorded ECG. One of the major consequences is the Motion artifacts getting merged with the original ECG signal. This work aims to study the detection, classification and quantification of the BMAs/PAs; and the effects of various body/physical activities on the A-ECG. In this chapter, a survey of wearable or Ambulatory ECG monitoring systems has been presented. Moreover, the methods to detect the BMAs and to remove the motion artifacts associated with the A-ECG signals have also been studied and described.

2.1 A Survey of Modern Wearable ECG Recording and Monitoring Systems

This section describes about the existing wearable ECG recording and monitoring systems found in the literature. The A-ECG signals are nowadays recorded by very small-size, lightweight, wearable devices (WD), which can continuously record A-ECG for many hours and even for many days. One such WD has been developed by V. Vaid and Lal et al. [40], [41] at the department of Electrical Engineering of IIT Bombay. A prototype of this WD which can record A-ECG from any one of the primary leads at a time is depicted in fig. 2.1.

Okada et al. [55] have developed a wearable ECG recorder for daily stress measurement. Fig. 2.2 shows a portable electrocardiograph with the case open (left) and closed (right). The body is collapsible and made of plastic. The size is W44 x D17 x H58 mm and the weight is 45 g including a battery and a memory card (1 GB). There are two switches (ON/OFF, START/STOP) and two light emitting diodes (LEDs). Green LED is an operation indicator, and red LED is a detection indicator. Red LED flashes when each R-wave is detected. The memory card and battery can be easily replaced. A printed-circuit board has four layer structures which
sandwiched a power source and ground layers. It has three acceleration sensors (3 axis built-in chip sensor).

Figure 2.1: A single-lead wearable ECG recorder developed by Lal et al. [41] at IIT Bombay. Copyright ©IEEE 2006.

ECG and the acceleration data are recorded at 1 kHz sampling rate up to more than 24 hours. After measurement, the memory card is dismounted, and the data are transferred to a personal computer (PC) for signal processing (off-line analysis). The system consists of a built-in four channel analog to digital converter, amplifiers (Burr-Brown INA326 and Texas Instruments OPA2335, 50 dB), a filter (0.1 – 100 Hz), 3-axis acceleration sensors (ST Microelectronics Co.), a microcomputer and a memory card. An acceleration sensor is used to monitor the subject’s posture and/or body movement simultaneously with ECG. The sensor has a full scale of ±2 G (gravitation in m/s²). This range is enough to measure an acceleration range of a body in daily life such as walks, works, household tasks, etc. The microcomputer is AduC840 series (Analog Devices Inc.). An MMC (multi-media card) mobile type memory card is used. ECG and three acceleration data are buffered as binary data in RAM (random memory access) area of a microcomputer. Buffered data are written in the memory card by a single block write-command every 512 bytes which is a block size of MMC mobile card. A 1 GB MMC mobile card can record four channel data (ECG and three accelerations) up to 27 hours with 1 kHz sampling speed.

Park, Bai et al. [56] have developed an ultra-wearable, low power ECG monitoring system. Wearability is the most crucial issue in designing a wireless ECG monitoring system. Probably, none of the existing miniature sensing systems can be considered truly wearable in the strict
sense, not just because they are still bulky but also because conventional ECG sensors can cause skin irritation. Therefore, authors have used QUASAR’s innovative ECG sensor and an ultra-compact wireless sensor node (Eco) specially designed for wearable applications, shown in Fig. 2.3.

Figure 2.2: Portable ECG recorder [55] Copyright © IEEE 2010.

Their system is equipped with 1 Mbps proprietary radio instead of IEEE 802.15.4, a very low power transceiver that consumes less than 10 mA in transmission mode (1 Mbps, 0 dBm) and 22 mA in receiving mode; and USB, Ethernet and Wi-Fi connectivity. Thus, very important design issues like high throughput, ultra-low power and universal connectivity have been addressed. Due to innovative ECG and wireless sensors the quality of the recorded ECG signal is inherently superior, as shown in fig. 2.4. However, the authors have not mentioned the use of accelerometer, if any, which is necessary for acquiring motion data.

A cellular phone based online ECG processing system for ambulatory and continuous detection has been developed by Chen et al. [57]. It aids cardiovascular disease (CVD) patients to monitor their heart status and detect abnormalities in their normal daily life. This system is a solution to supplement the limitations in conventional clinic examination such as the difficulty in capturing rare events, off-hospital monitoring of patients’ heart status and the immediate dissemination of physician's instruction to the patients. The Mobicare Cardio Monitoring System, shown in fig. 2.5, consists of a cellular phone embedded with real time ECG processing...
algorithms (MobiECG), a wireless ECG sensor, a web based server, a patients' database and a user interface.

Figure 2.3: (a) QUASAR ECG Sensors, (b) Sensors attached on a T-shirts and worn on a human body [56] Copyright ©IEEE 2006

Figure 2.4: Data Comparison: Green trace is from QUASAR sensor, Blue trace is from conventional electrode [56] Copyright © IEEE 2006

The wireless ECG sensor used in this system serves to capture one channel ECG, one 3D accelerometer signal and to transmit those signal data via Bluetooth to cell phones. The key role of MobiECG here is to works as a local processor to process data in real time. It receives ECG and accelerometer data from wireless ECG sensor via Bluetooth, filters the data, detects QRS complex, identifies Q onset and T offset, and calculates intensity of patient's body movement using obtained accelerometer data.

A context-aware (patient's activity) ECG processing is carried out by MobiECG and it will send the abnormal ECG data over a cellular network (GPRS/3G) to hospitals or care centers to alarm physician only when it detects abnormal ECG signal. In order to avoid the continuous transmission of normal ECG data to physicians and to prevent the flooding of the
telecommunication channel, no ECG data is sent out by MobiECG when abnormality is not detected.

Figure 2.5: Mobicare Cardio Monitoring Framework [57] Copyright ©IEEE 2007

A new wireless technology for tele-homecare purposes proposed by Fensli et al. [58] (fig. 2.6) gives better possibilities for monitoring of vital parameters with wearable biomedical sensors, and gives the patient the freedom to be mobile and still be under continuously monitoring and thereby to render better quality of patient care. They describe a new concept for wireless and wearable electrocardiogram (ECG) sensor transmitting signals to a diagnostic station at the hospital, and this concept is intended for detecting rarely occurrences of cardiac arrhythmias and to follow up critical patients from their home while they are carrying out daily activities.

Figure 2.6: Principal components of the wireless ECG-system [58] Copyright ©IEEE 2005.

In [59] authors describe a method for the online classification of sleep/wake states based on cardiorespiratory signals produced by wearable sensors. The method was conceived in view of its applicability to a wearable sleepiness monitoring device, the Heally recording system. The method uses a fast Fourier transform as the main feature extraction tool and a feed forward
artificial neural network as a classifier. The ECG and respiratory effort were recorded with a Heally system, shown in fig. 2.7, (Koralewski Industrie Elektronik, Celle, Germany). The Heally system is a portable recording system that uses an inductive belt sensor for measuring ribcage respiratory effort and gel electrodes for measuring ECG. Authors have chosen the sampling frequencies according to the requirements for digitalized PSG. The respiratory signal is sampled at 50 Hz and the 1-lead ECG at 100 Hz. In addition, the Heally system offers the possibility to measure the EMG (recorded from the right shoulder muscle trapezius at 200 Hz) and EOG (recorded at 200 Hz) as reference. EOG was only measured during the night in order to not disturb the subjects too much during daily activities.

Figure 2.7: Heally recording system mounted on a shirt: 1) ECG gel electrodes, 2) inductive belt sensor, 3) electronics modules, and 4) NiMH battery [59] Copyright ©IEEE 2009.

Placing wearable sensors in multiple body locations can be quite cumbersome when the user has to collect data on a daily basis or for longer periods of continuous monitoring. Thus, many approaches based on multiple integrated sensor modalities have been proposed [60]-[64], since it is much more comfortable for the user to wear a single device. Moreover, incorporating multimodal information can yield additional physiological and environmental cues, such as heart rate, light, skin resistance, temperature, audio, global positioning system (GPS) location etc.

Therefore, Ming Li et al. [65] have proposed a multimodal physical activity recognition system by fusing temporal and cepstral information, in which they have used multimodal wearable sensors within the KNOWME network as shown in fig. 2.8. The KNOWME [66] network utilizes heterogeneous sensors simultaneously, which send their measurements to a Nokia N95 cell phone via Bluetooth. Flexible sensor measurement choices can include ECG signals, accelerometer signals, heart rate, and blood oxygen levels as well as other vital signs. Furthermore, external sensor data are combined with data from the mobile phone’s built-in...
sensors (GPS and accelerometer signal). Thus, the mobile phone can display and transmit the combined health record to a back-end server (e.g. Google Health Server) in real time.

![Diagram of KNOWME wearable body area network system](image)

Figure 2.8: KNOWME wearable body area network system [65], [66] Copyright ©IEEE 2010.

In [87], an integrated electrocardiogram (ECG) signal-processing scheme is proposed. Using a systematic wavelet transform algorithm, the signal-processing scheme can realize multiple functions in real time, including baseline-drift removal, noise suppression, QRS detection, heart beat rate prediction and classification, and clean ECG reconstruction. Utilizing the novel low-cost hardware architecture, the scheme is implemented in ASICs with 0.18 μm CMOS technology. The ECG signal processor chip achieves low area and power consumptions, and is highly suitable for wearable applications of long-term cardiac monitoring.

HeartToGo- a windows mobile smartphone-based wearable cardiovascular diseases (CVD) detection system; capable of performing real-time ECG acquisition and display, feature extraction, and beat classification has been developed in [88]. The system is capable of classifying the premature ventricular contraction (PVC) as well as generating the cardiac summary report consisting of the average, high, and low heart rate, and the total number of beats, as well as the number of normal and PVC beats, as shown in fig. 2.9. Similar wearable recorders using varieties of sensors and supporting technologies have been reported in [89]-[92].

![Image of HeartToGo system](image)

Figure 2.9: HeartToGo system and cardiac summary report [88] Copyright ©IEEE 2010.
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*Sampling rate for respiratory signal; **PPG =Pulse Plethysmograph; HR = Heart rate; RR = Respiration rate

In [93] authors have fused the heart rate and accelerometer data for activity assessment and classification. The authors have used ProeTEX (PROtective Electronic TEXtiles for emergency operators) that aims at demonstrating the suitability of wearable technologies to improve the safety, efficiency, and coordination of emergency operators, such as fire fighters or Civil
Protection rescuers. The algorithm combines both features extracted from the signal of a tri-axial accelerometer and one ECG lead. Microprocessors integrated in the garments detect the signal magnitude area of inertial acceleration, step frequency, trunk inclination, heart rate (HR), and HR trend in real time. The classifier uses these signals as inputs and classifies them to nine classes: certain physical activities (walking, running, moving on site), intensities (intense, mild, or at rest) and postures (lying down, standing up). Specific classes have been identified as dangerous to the rescuer during operation, such as, “subject motionless lying down” or “subject resting with abnormal HR.

In [94] authors have categorized the physical activities (PAs) into low-level (e.g. lying, sitting, sit fidgeting, standing, stand fidgeting, playing wii, slow walking, brisk walking, and running) description and high-level (e.g. Eating a meal, Reading, Talking on Phone, Travel by walking and activities during exercises) descriptions. high-level descriptions may include various low-level physical activities simultaneously sitting can be observed in both homework and eating a meal categories, hence an automated monitoring system cannot determine whether the subject is doing his/her homework or having a meal when it detects the subject is sitting. In order to mitigate these ambiguities, authors have introduced the concept of latent topics in physical activities. It is hypothesized that each high level physical activity consists of a set of latent topics and each latent topic has a set of low-level physical activities.

2.2 A Review of Methods for Analysis of A-ECG Signal

In this section a comprehensive survey on various signal processing techniques commonly used for A-ECG signals have been presented. These techniques include detecting the noise/motion artifacts in A-ECG signals, cancellation of noise episodes from A-ECG/W-ECG signals, extracting motion artifacts from A-ECG signals, classifying the physical/body movements of the subject, compressing the signals etc. using numerous tools like principal component analysis (PCA), wavelet transform, adaptive filtering and many more.

For analyzing the ambulatory ECG signal in terms of motion artifacts or quantification, and for that matter for any kind of automated ECG signal analysis, it is necessary to accurately detect the QRS complex. In this section, a comprehensive survey of QRS complex detection methods has been carried out. The QRS complex is the most prominent and peculiar segment of an ECG signal. The detection of the QRS complex is the most important task in automated ECG signal analysis. For the analysis of the A-ECG signals as mentioned above and for any kind of automated ECG signal analysis for that matter the pre-processing stage requires an accurate
detection of QRS complex. For example, in [1]-[4] ST-T analysis is done after detection of QRS waves.

In [5]-[9], body position movements and motion artifacts in ambulatory ECG are analyzed after detection of QRS locations. In [10] adaptive recurrent filter is proposed, which requires a QRS detector for implementation. A similar kind of adaptive filter is applied in [11] for separating motion artifacts from ECG, which requires QRS detector in preprocessing steps. In [12]-[14] non-linear PCA (NLPCA) based ECG pattern recognition and classification is implemented in which initially it requires accurate recognition of QRS wave. In [15]-[20] ECG beat and arrhythmia classification based on artificial neural network (ANN) and support vector machine (SVM) are implemented in which QRS detection is required. Once the QRS complex has been identified, a more detailed examination of ECG signal, including the heart rate, the ST segment, etc., can be performed.

Pan and Tompkins [21] 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. In [22]-[24] authors have used first and second derivative-based approach for QRS detection from an ECG signal.

Wavelet transform (WT) has been extensively used by the research community for analysis and feature extraction of ECG signals. Many types of wavelets like Daubichies, Biorthogonal spline, Symlets and even newly developed wavelets with different scales, decomposition and threshold levels have been reported in [25]-[31] for QRS detection. 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 QRS wave of ECG signals [25].

In [32]-[33] Hilbert transform has been applied for detecting the onset and offset of QRS complex. The Hilbert transform is very useful for signal demodulation without knowing the carrier frequency. If we consider a QRS complex as a modulated waveform, the beginning and end of the QRS complex envelope calculated using the Hilbert transform coincide with the QRS onset and offset respectively.
Mathematical morphology, which is based on set operations, provides an approach to the development of nonlinear signal processing operators that incorporate shape information of a signal. In mathematical morphological operations, the result of a set transformed by another set depends on the shapes of the two sets involved. The shape of a signal is determined by the values that the signal takes on. The shape information of the signal is extracted by using a structuring element to operate on the signal [34]. In [34]-[36], [82] authors explore various morphological operators for QRS complex detection. Chauhan and Mehta in [37] have developed an adaptive/dynamic threshold based QRS detection algorithm, which is further enhanced and modified in [38]-[39].

The purpose of the AECG by WD is long-term monitoring of the heart while the patient is allowed to perform his/her routine activities. Many a times the infrequent symptoms of heart disorders that are not detected during short-time clinical check-up can become visible in the long-term AECG during the situations encountered in the real-life. Therefore, AECG is becoming more popular instead of hospitalization of the suspect-patient for the purpose of the long-term cardiac monitoring. In [44]-[46] authors have used wearable approaches for long-term wellness monitoring of patients. The wearable sensor based systems in [55]-[58], [60], [61] have been used for measuring daily stress levels in patients; continuous ECG and arrhythmia monitoring/detecting.

In [47], [48], [50] and [51], authors have presented detection of ECG based body position changes, analysis of transient ST segment changes, body position changes detection and ischemia monitoring during ambulatory patient monitoring.

In [59] authors have combined ECG and respiratory efforts signals for sleep and wake classification. J. Parkka et al. in [62], [63] have used wearable sensors for detecting daily and sport activities using neural networks. In [64]-[66] authors used wearable system (KNOWME) for multimodal physical activities recognition and obesity sensing for pediatric and adult patients. A. Sharma et al. in [69] have performed frequency based activities classification using accelerometer data. Alcaraz et al. [73] have classified paroxysmal and persistent atrial fibrillation using ambulatory ECG signal. Hyejung Kim et al. [76] have performed ECG signal compression and classification based on Quad level vector algorithm from ECG Holter system. Curone et al. [77] have fused heart rate and accelerometer data for activity assessment of rescuers during emergency interventions.
In addition to the above mentioned methods, ECG beat classification; atrial fibrillation detection; ST-T segment analysis; ischemia detection, detection of obstructive sleep apnea (OSA) syndrome; elderly patient monitoring; automatic respiration rate detection and over and above, of course long-term cardiac/physiological monitoring are the common use of the wearable/wearable sensor-based systems.

In [16], [17], [52], [53], [84] and [99]-[106] authors have used artificial neural networks (ANN) for various purposes like QRS complex detection; ECG motion artifact characterization; classification of mental and physical load; ECG arrhythmias recognition; ECG signal detection and classification; VPB detection; ECG beat classification.

Neuro-fuzzy classifiers (NFC), which adopt the adaptive neuro-fuzzy inference system (ANFIS) architecture, combine fuzzy rule base and membership functions with neural networks for data/pattern classification. The overall architecture complexity of NFC is more as two different technologies incorporated in a single classifier. The Researchers have extensively used NFC/ANFIS for numerous applications like ECG signal classification, ischemia prediction and detection [108]-[113].

In [18]-[20], [74], [114]-[121] authors have used support vector machines (SVM) for ECG beat detection and classification; ECG arrhythmia classification; Obstructive sleep apnea syndrome detection, cardiac abnormality detection, real-time sleep quality assessment and even human daily activity recognition from ECG recordings. The authors have combined wavelets and kernel PCA with SVM and even used multi-stage, multi-resolution and multi-class SVM for above ECG signal classification and analysis.