2

Review of Portable Cardiography Systems

In this chapter, a detailed review of recent advancements in heart monitoring systems is provided. As discussed in the previous chapter, lack of early-stage detection and hence delay in medication causes heart diseases to reach to an extent where it is difficult to cure [Jiaquan et al., 2010]. For early-stage detection of CVDs, a system should be convenient to use for long-term and should also be user friendly to use it at home or at a workplace. Such features would be favourable to have frequent monitoring of health status of the heart and a significant reduction in unnecessary hospital visits is expected. In view of this, existing portable cardiography systems are reviewed for their suitability in real-life scenarios. The review focuses only on four cardiography systems ECG, PCG, SCG, and PPG, due to their favourable features such as portability and diagnostic efficiency.

2.1 INTRODUCTION

Portable heart monitoring systems have been used in two manners, as shown in Figure 2.1, one is on-site and another is off-site. In on-site monitoring, the acquired heart signal is processed on the patient site, without transmitting it to the remote site. While in off-site, the acquired heart signal is transmitted to a remote site using a wireless module. On-site heart monitoring systems have advantages in the case where low latency feedback is required or wireless access is not accessible. Furthermore, it eliminates data transmission and hence eliminates the radio power consumption. However, the on-site monitoring has limitation that it has only a set of general diagnosis steps and thus unable to perform a detailed diagnosis. On the other hand, in off-site monitoring, diagnosis is performed at remote location with high computation capable processors and supports input from a cardiologist. This makes it suitable for accurate and detailed diagnosis. It is attractive because of higher processing capability and less power restrictions on such remote computation. Off-site monitoring also reduces the false alarm rate and thus reduces visits to clinics or hospitals. In view of these advantages of off-site monitoring, this chapter is intended to provide a detailed review of recent research in the off-site monitoring system.

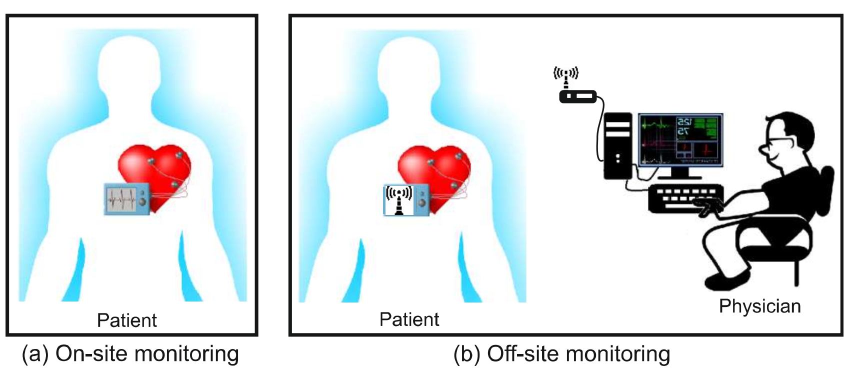

Figure 2.1 : Heart monitoring system

A typical off-site heart monitoring system consists of five modules, as shown in Figure 2.2. The system with first four modules; body sensor, signal conditioning, Analog-to-Digital Converter (ADC) and compression, and wireless module are situated at the patient site. While the fifth module that is noise suppression and classification module is situated at a remote site which can be any computational device with high computational ability. In each module, a brief introduction about the function of the module, recent developments, and their limitation and challenges are discussed.

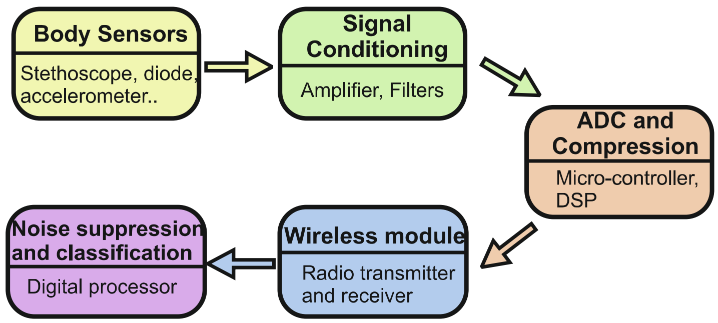

Figure 2.2 : Block diagram of Off-site heart monitoring system

2.2 BODY SENSORS

Different body sensors have been used to acquire the signals related to movement of the heart.

2.2.1 Electrodes (Electrocardiography)

ECG measures the electrical activity of the heart using electrodes placed on both sides of the heart. For signal acquisition, attachment of electrodes to different points on the body restricts patient's mobility [Koivisto et al., 2015]. A lot of research efforts have been targeted in the development of ECG patch monitors. The main problem is that a reliable analysis requires good electrode-to-patient contact and a minimum electrode distance (5-10 cm) which poses a size limitation and electrodes also irritate the skin in long-term use [Koivisto et al., 2015]. Some of the ECG sensors, widely used in practice, can be classified into following three categories.

(a) Wet Sensors

In these types of sensors, Ag-AgCl electrodes are attached to the skin using gel which provides a conducting medium for charge transfer between the electrodes and the body [Nemati et al., 2012]. These sensors provide good signal quality, but it is inconvenient in terms of long-term wear-ability due to use of gel which creates irritation and itching problem [Nemati et al., 2012]. The acquired signal quality may deteriorate due to sweat [Searle and Kirkup, 2000] and due to gel dehydration [Jung et al., 2012].

(b) Dry Sensors

These sensors use a metal plate direct placed on the skin without use of gel. Thus, the problem of irritation and itching caused by gel, have been eliminated [Gómez-Clapers and Casanella, 2012]. Although, it still has direct contact with the skin. Dry sensors are robust to environmental noises and sweat noise but more vulnerable to motion noise compare to wet sensors. The quality of the signal acquired using these sensors depends on the composition of the materials and size of the electrode [Jung et al., 2012]. Increasing size of the electrode gives better capacitance and consequentially good signal quality, but it decreases the patient's convenience.

(c) Capacitive Coupled Sensors

Capacitive Coupled (CC) sensors avoid direct contact with the skin that minimizes patients' inconvenience as in case of the wet and the dry sensors. A thin layer of insulator is placed between the body and metal-plate sensing electrode [Nemati et al., 2012]. The electrode, together with the skin and insulator, form a capacitance that conveys the ECG signal from the body to the sensor. CC sensors have been developed on a chair [Aleksandrowicz and Leonhardt, 2007; Baek et al., 2012], on bed [Lim et al., 2007] and textiles [Cho et al., 2011]. Development of sensors on chair, bed and textiles supports continuous heart monitoring even when working in the office and sleeping. CC sensors are highly sensitive to motion noise as in case of dry sensors. This is because, a movement of electrode changes the coupling capacitance and consequentially the acquired signal [Nemati et al., 2012].

For clinical use, where simplicity of operation, less processing time, and good signal quality is preferred, wet sensors are suitable. Additionally, the availability, relative cheapness, and disposability of wet electrodes overcome hygiene concerns. While, the dry and capacitive electrodes are convenient in use and consistent in performance. These features make these sensors suitable for long-term. However, the performance of these types of electrodes depends on the electrode geometry. Furthermore, these electrodes require proper shielding and settling time to perform comparable to, or better than wet electrode. Researchers in the past have made numerous attempts to overcome these problems [Searle and Kirkup, 2000].

2.2.2 Stethoscope (Phonocardiography)

The stethoscope was invented by René Laennec in 1816. It is basically a transducer which converts vibration signal into acoustic signal and transmits the sounds to the physician's ear [de Lima Hedayioglu, 2009]. The plotting of the heart sound signal is called as phonocardiogram signal. The stethoscope is a user-friendly, effective, and economical instrument and therefore, one of the most basic instruments used in diagnosing health problems and treating patients [Callahan et al., 2007].

There are two general types of stethoscopes, acoustic and electronic. Acoustic stethoscopes transmit sound from a chest-piece to the listener's ear via an air-filled hollow tube. The main limitation of the acoustic stethoscope is that the intensity of some body sounds is below the threshold of audibility [Jatupaiboon et al., 2010]. An electronic stethoscope overcomes this issue by electronically amplifying the heart sounds. However, its signal is highly susceptible to various noises generated due to motion of subject, speech of subject, and ambient sources, because it uses a microphone to convert the acoustic signal into an electrical signal [Gradolewski and Redlarski, 2014]. Therefore, in literature, there have been several attempts to improve electronic stethoscopes for better sound amplification and frequency response [Hedayioglu et al., 2007; Tavel et al., 1994]. Jatupaiboon et al. [Jatupaiboon et al., 2010] incorporate adaptive noise cancellation mechanism to suppress the level of noise from acquired sound. Chao et al. [Chao et al., 2012] implemented the Adaptive Line Enhancer (ALE) filter structure on a Field-Programmable Gate Array (FPGA) based platform to perform filtering in real-time.

As reported in [de Lima Hedayioglu, 2009], for the wide acceptability of stethoscope, it should integrate real-time signal processing to increase the effectiveness of the auscultation. Recent advances in electronics and digital circuits allow us to real-time acquisition, analysis, display, and classification of heart sounds and murmurs. These types of stethoscope are called digital stethoscope. Bredesen and Schmerler [Bredesen and Schmerler, 1993] developed an 'intelligent stethoscope' for automatically diagnosing abnormalities by comparing digitized sounds to reference templates using a signature analysis technique.

The leading suppliers of electronic stethoscopes are Cardionics, Thinklabs, Meditron

(Welch-Allyn) and 3M (Littmann) [Callahan et al., 2007]. Thinklabs uses a novel electronic diaphragm detection system to directly convert sounds into electronic signals. Welch-Allyn Meditron uses a piezo-electric sensor on a metal shaft inside the chest piece, while 3M and Cardionics use conventional microphones.

2.2.3 Accelerometer (Seismocardiography)

Accelerometer used in SCG, measure the vibrations on the surface of the thorax produced by the heart contraction and blood ejected from the ventricles into the vascular tree [Inan et al., 2015; Khosrow-khavar et al., 2015]. Zanetti and Salerno were the first two, who introduced SCG for clinical applications [Zanetti and Salerno, 1991]. The accelerometer sensor generates an electrical signal with its amplitude proportional to the applied acceleration. Since acceleration is the second time derivative of the displacement, acceleration provides good details of heart movement during each cardiac cycle [Wick et al., 2012].

Zanetti's approach used a bulky piezoelectric accelerometer weighing almost one kilogram [Zanetti and Salerno, 1991]. The bulky size of accelerometer hinders its wide acceptability. Recent development of low weight and small size accelerometer make it less obtrusive transducer, consequentially, many researchers are now studying SCG. Different types of accelerometers have been developed, including piezoelectric, electromechanical servo, liquid tilt, and piezo-resistive [control learn zone, 2008]. In recent years, MEMS accelerometers have made tremendous advances in terms of its cost and level of on-chip integration [Sun et al., 2010; Metropolia, 2014]. The MEMS accelerometer based on the principle of capacitance differentiation has high sensitivity and accuracy [Sun et al., 2010].

Castiglioni et al. attached a tri-axial MEMS accelerometer (ST-LIS3L02AL, from ST Microelectronics) on the left clavicle to record SCG signal and later integrate into textiles to make a wearable device for SCG detection [Castiglioni et al., 2007; Rienzo et al., 2012]. Pandia et al. [Pandia et al., 2010] and Bombardini et al. [Bombardini et al., 2011] also used ST-LIS3L02AL to monitor the heart sounds. Bryant et al. used ST-LIS3L02DL (with digital interface) to develop a chest-worn heart monitoring system [Bryant et al., 2010]. Imtiaz et al. used MMA7260QT [Imtiaz et al., 2013]. Among different conventional piezoelectric accelerometers, 393C (PCB Piezotronics) has been extensively used for physiological sounds monitoring [Salerno and Zanetti, 1990]. In addition to piezoelectric sensors, piezoresistive accelerometers have also been used [Bew et al., 1971]. However, piezoresistive accelerometers are generally not as sensitive as piezoelectric accelerometers. Various accelerometers, used for physiological acoustic sensing, are summarized by HU et al. [Hu et al., 2014].

2.2.4 Diode (Photoplethysmography)

PPG uses LEDs and photo-diode which makes it a low cost, non-invasive, easy to use and portable system. Since it operates optically, it is not intrinsically susceptible to capacitive coupling interference as in ECG [Sweeney et al., 2012]. However, photo-diodes are sensitive to natural and artificial light sources. PPG based heart monitoring systems are unobtrusive as size and weight of the device of PPG are low. PPG is generally used in direct contact with the patient's skin as in case of other systems (ECG, PCG, and SCG). To avoid direct contact with skin, Huelsbusch et al. [Huelsbusch and Blazek, 2002] proposed a remote PPG (rPPG) that can acquire PPG signal without contact with skin. The main concern with rPPG is its sensitivity to the subject motion.

2.3 SIGNAL CONDITIONING

Heart signals, acquired by different body sensors, often get contaminated by noise components such as flicker noise, common-mode interference, power-line interference, baseline wandering etc [Liu et al., 2012b]. Also, the amplitude of the acquired signal is typically low. A signal conditioning module typically consists of an algorithm for noise minimization and amplifier to amplify low amplitude signals. This module operates on signals in the analog domain. Power consumption of this module used to be low so as to support long-term operability of heart monitoring systems. For the same purpose, Rieger et al. [Rieger, 2011] proposed a variable gain circuit consists of a continuous-time input stage using lateral bipolar transistors. Spinelli et al. [Spinelli et al., 1999] proposed a driven right leg circuit to reduce common-mode interference. Gomez-Clapers and Casanella [Gómez-Clapers and Casanella, 2012] used dual ground configuration to reduce the noise caused by power line interference and base line wandering. Since most of the heart monitoring systems are digital in nature and needs communication for remote monitoring, following section discusses analog to digital conversation and compression algorithms.

2.4 ANALOG TO DIGITAL CONVERSION AND COMPRESSION

Heart signals (analog) are converted into digital signals for its processing on digital computers. This is done by sampling the heart signal and quantizing the sampled values. This process is done on Digital Signal Processor (DSP) called ADC. Selection of the DSP depends on the desired sampling rate, number of bits to be used for quantisation, operating frequency, and power consumption. As described in Table 2.1, Mixed-Signal Processor (MSP) based processors have lower power consumption compared to the Programmable Interface Controllers (PIC) based processors, while the PIC based processors have a higher operating frequency compared to the MSP based processors. Both types of processors provide multiple working and idle modes according to the required computational power, to optimize the power consumption. DSP with low power consumption supports long-term monitoring of the heart. To optimize the power consumption, Bachmann et al. [Bachmann et al., 2012] proposed a DSP with the capability to perform in different power modes according to required accuracy and available computational power. Power consumption was optimized at different abstraction layers from application optimization and mapping, for the system.

Table 2.1 : Digital signal processors

Processor	No. of bits	Frequency	Power consumption	Used in	Characteristics
PIC24FJ64GA	10	32 MHz	• Run mode: 650 μA • Idle mode: 150 μA • Sleep mode: .1 μA	[Nemati et al., 2012]	• Low operating voltage range. • On-the-fly clock switching.
PIC18f2423	12	40 MHz	• Run mode: 330 μA • Idle mode: 5.8 μA • Sleep mode: 0.1 μA	[Tang et al., 2011]	• Multiple idle and run modes. • Nano watt technology. • On-the-fly clock switching.
PIC16F877	8	20 MHz	• Run mode: 600 μA • Idle mode: 20 μA • Sleep mode: 1 μA	[Shih et al., 2010]	• High performance RISC CPU.
MSP430f2274	10	16 MHz	• Run mode: 270 μA • Idle mode: 0.7 μA • Sleep mode: 0.1 μA	[Gómez-Clapers and Casanella, 2012; Dilmaghani et al., 2011]	• Ultra-fast wake-up. • Ultra-low power. • RISC mixed-signal microprocessors
MSP430F1611	12	8 MHz	• Run mode: 330 μA • Idle mode: 1.1 μA • Sleep mode: 0.2 μA	[Chen et al., 2012]	• Ultra-fast wake-up from stand-by. • Five power saving modes
MSP430F2410	12	16 MHz	• Run mode: 270 μA • Idle mode: 0.3 μA • Sleep mode: 0.1 μA	[Morak et al., 2012]	• Ultra-fast wake-up. • Ultra-low power

Conventional sampling techniques sample signals at or above Nyquist rate, which ensues perfect reconstruction of the signal. Nyquist rate is twice the maximum frequency component present in the signal to be sampled. Typically, heart signal components are below

1 kHz frequency and hence, as per Nyquist rate, 2k samples per second are sufficient to avoid aliasing error. However, even 2k samples per second sampling rate generates a huge number of samples, if the heart is monitored for a long time. Consequentially, the power requirement of DSP increases as the number of samples to be processed are huge. In spite of it, Compressed Sensing (CS) enables sub-Nyquist sampling of signals.

CS is a data acquisition approach that requires only a few incoherent measurements to compress signals that are sparse in some domain [Candes and Wakin, 2008]. Let $[\alpha_{in}]$ be an original input vector of dimension $N \times 1$ and $[\Psi]$ is the $N \times N$ sampling basis or sparsifying matrix containing orthonormal basis (such as a wavelet basis) $[\psi_1, \psi_1, ..., \psi_n]$. Then $[X]$, sparse in $[\Psi]$ domain with length N can be found as

$$[X] = [\Psi][\alpha_{in}] \tag{2.1}$$

Then output compressed vector is defined as:

$$[Y] = [\phi][X] \tag{2.2}$$

where $[\phi]$ is the $M \times N$ measurement or sensing matrix. So, we get an output vector $[Y]$ with length M, where $M < N$. CS captures M measurements from N samples using random linear projections. Now, as the lower number of measurements were taken than the original signal, non-linear optimization techniques are used to reconstruct the original signal [Candes and Wakin, 2008]. Reconstruction of the signal can be achieved as:

$$Min||\widehat{X}||_1 \text{ subject to } [Y] = [\phi][\widehat{X}] \tag{2.3}$$

Perfect reconstruction of the signal depends on the incoherence between $[\Psi]$ and $[\phi]$ matrices. Thus, random matrices can be used as a measurement matrix because random matrices are, with high probability, highly incoherent with any fixed basis $[\Psi]$. CS is considered non-adaptive because measurement matrix $[\phi]$ remains constant.

Several measurement matrix design considerations and reconstruction algorithms have been presented in [Dixon et al., 2012] and found that using Bernoulli measurement matrix, compression ratio of 16 is achievable. Mamaghanian et al. [Mamaghanian et al., 2011] compared CS and the DWT-based compression algorithms and found that CS was inferior to DWT-based algorithm in terms of compression ratio. Despite of it, CS-based compression outperforms in terms of energy efficiency due to its lower complexity and reduced CPU execution time.

After digitization of analog signals, digital signals are compressed to reduce amount of data. The basic purpose of data compression is to represent the original signal with a smaller number of bits than that is needed for the original signal. The compression is typically achieved by removing redundancy from the signal to be compressed. Since power requirement of wireless module directly depends on the amount of data to be transmitted, one of the major advantages with compression is a reduction in power requirement by wireless module. However, there is a loss of information, in general, when signal is reconstructed from the compressed data. A proper balance is maintained with compression ratio and the requirement that the information of diagnostic importance is preserved.

Heart monitoring systems have additional requirement for compression algorithms to be computationally efficient to support long-term monitoring. Various compression algorithms for heart signals have been reported in literature. Wavelet Transform (WT) [Kao et al., 2005; Martinez-Alajarin and Ruiz-Merino, 2004], Walsh transform [Kadrolkar et al., 2012], Hermite function [Sandryhaila et al., 2012], and Discrete Cosine Transform (DCT) [Bendifallah et al., 2011] based compression algorithms first decompose the signal into coefficients by projecting the signal onto basis functions of transforms. Then compression is achieved by retaining only a small number of coefficients which typically preserves essential information of the heart signal. As stated before, computational complexity is crucial for the compression algorithm as these have to be implemented on the patient side. Computational complexity of DWT is O(N), DCT is O(NlogN), Walsh transform is O(NlogN), and Hermite function is $O(N\log_2 N)$. Thus, DWT has lowest computational complexity. However, compression performance of the Hermite function based method is better than DCT and DWT based basic compression algorithms [Sandryhaila et al., 2012]. In these approaches, trade-off between the percentage of retained energy and compression ratio is crucial. Increment in the percentage of retained energy reduces compression ratio and enhances reconstructed signal quality and vice versa. Retained coefficients are compressed using conventional compression algorithms such as zero-removal [Kao et al., 2005], Huffman coding [Kao et al., 2005; Martinez-Alajarin and Ruiz-Merino, 2004], dead zone quantization [Bendifallah et al., 2011], run length coding [Martinez-Alajarin and Ruiz-Merino, 2004; Rajoub, 2002]. While, Sharma et al. [Sharma et al., 2012] applied Multi-Scale Principal Component Analysis (MSPCA) on WT coefficients and then MSPCA coefficients are uniformly quantized and encoded by Huffman coding. All the above algorithms compressed the entire frame with the same compression ratio. On the other hand, researchers have been proposed approaches to use different compression ratio for different block of signals [Kadrolkar et al., 2012; Rajoub, 2002; Wang et al., 2010; Kim et al., 2008]. Different statistical parameters have been calculated to identify the significance of the segment such as Wang et al. [Wang et al., 2010] calculated kurtosis, Kim et al. [Kim et al., 2008] calculated Mean Deviation (MD), Ma et al. [Ma et al., 2012] calculated wavelet coefficient energy. In [Kadrolkar et al., 2012], significance of the segment is calculated based on the energy of the Walsh coefficients. While, Rajoub [Rajoub, 2002] applied DWT and then divide the coefficients into three groups based on the magnitude of coefficients and then applied different thresholding for each group.

Researchers have also proposed compression algorithms that preserve features of heart signal (rather than preserving the waveform) [Alvarado et al., 2012; Kim et al., 2012]. Alvarado et al. [Alvarado et al., 2012] proposed a compression algorithm based on integrator and fire sampler. Similarly, Kim et al. [Kim et al., 2012] proposed an algorithm based on curvature points, which calculated the important information from the signal.

Compression algorithms which require low computation are suitable for long-term heart monitoring. DWT based compression algorithms have lower computational complexity than other algorithms and thus have been used extensively. On the other hand, feature preserving compression algorithms have a high compression ratio. They are suitable for heart signals because diagnosis can be performed based on these features. However, the selection process of the diagnostic features from the heart signal is a complex process. Furthermore, the performance of these types of algorithm deteriorated in the presence of noises.

2.5 WIRELESS MODULE

In off-site monitoring, digitized and compressed heart signals are transmitted to remote site. Analysis and classification of the heart signals are performed at the remote site. Transmitter consists of wireless module which helps to transmit heart signals to remote site. Low power consumption, convenient connection process, and low latency are some important features of wireless modules that promote wider acceptance of heart monitoring systems. In literature, various wireless communication techniques and protocols have been proposed for transmission purpose Table 2.2. Bluetooth 4.0 [Morak et al., 2012] wireless system supports 24 Mbps data rate, working range up-to 100 m, and consumes low power. Bluetooth devices with these features are suitable to be integrated with heart monitoring systems. The Bluetooth wireless systems require initial connection setup that has to be done manually. Patient's intervention is not desirable in a heart monitoring system as it reduces convenience. To overcome this problem an approach was proposed by Morak et al. [Morak et al., 2012] using Radio-Frequency Identification (RFID) and Near Field Communication (NFC). In this approach, the connection establishes by bringing two NFC enabled devices closer and using RFID information of both devices. The drawback of this approach is that it requires permanent activation of Bluetooth which results in extra power consumption. Moreover, NFC can support data rate up-to 424 Kbps only. Since data rate is lower than Bluetooth 4.0, it takes long time to transmit data. A good review of the state-of-art technologies for wireless network was presented by [Bachmann et al., 2012].

Keeping in view the desired features of wireless module, various protocols have been proposed [Nemati et al., 2012; Chen et al., 2012]. Chen et al. [Chen et al., 2012] proposed a reliable protocol based on any-cast routing algorithm. This algorithm automatically selects nearest hop (sink), in case of failure in original path, instead of rebuilding the path from the source node. Thus, it provides a reliable communication as well as reducing traffic overhead and transmission latency. However, selection of the hop process increases the complexity of routing algorithm and the complexity increases power consumption. To optimize power consumption, Nemati et al. [Nemati et al., 2012] proposed an ANT protocol. The ANT protocol was used as a low-data-rate wireless module to reduce the power consumption and size of the sensor. ANT is an adaptive isochronous ad-hoc wireless protocol based on master-slave model. It consumes from 1 mA to 6.3 mA current and supports many topologies such as peer-to-peer, star, tree, and mesh. SimpliciTI is also a low power radio frequency network protocol used in heart monitoring systems [Gómez-Clapers and Casanella, 2012; Dilmaghani et al., 2011]. SimpliciTI was designed by Texas Instruments for easy implementation and deployment on RF platforms. It is Low data rate and low duty cycle protocol and supports star and peer-to-peer network topology.

Tao et al. [Ma et al., 2012] proposed an unequal-error protection approach for heart signals to reduce transmission distortion and to reduce power consumption of wireless transmission. In this approach, more protection is provided to the segment of heart signal which contains diagnostic important features compared to the other segments. Results showed that nearly 40% of transmission energy can be saved compared to the equal error protection.

In a different approach, Atakanet al. [Atakan et al., 2012] introduced the concept of a Body Area Network (BAN) with molecular communication where the messenger molecule is used as a communication carrier from a sender to receiver. However, the communications at the molecular scale are subject to numerous problems, some similar to the ones faced on a larger scale in existing wireless networks.

2.6 NOISE SUPPRESSION AND CLASSIFICATION

Noise suppression and classification module performs automatic machine diagnosis that enhances diagnostic accuracy. It is very helpful in the present scenario where number of cardiologists are low as compared to the number of cardiac patients [WHO, 2011]. In noise suppression step, noises are suppressed from heart signals. In the next step, the heart signal is classified into normal and different CVDs.

2.6.1 Noise Suppression

Noise suppression from heart signals is essential as its presence may lead to imprecise or inaccurate classification of the signals. Various denoising algorithms for the heart signal in time domain and frequency domain have been proposed [Leng et al., 2015]. In the time domain, denoising algorithms have been proposed based on conventional filters (Butterworth filter, Weiner filter, and Chebyshev IIR filter) [Bai and Lu, 2005], Adaptive Noise Canceller

Table 2.2 : Wireless modules

Wireless module	Power consumption (mA)		Size (mm)	Transmission range (m)	Manufacturer	Used in
	Rx	Tx				
CC2420 (zigbee)	18.8	17.4	7x7	70m	Texas instruments	[Lee et al., 2009]
Bluescense (blutooth)	33	33	37x21		Corscience	[Gargiulo et al., 2010]
nRF24E1 (Eco-wireless)	22	10	13x11	10	UC Irvine	[Park et al., 2006]
ANT-AP2	17	15	20x20	30	Dynastream Innovations	[Nemati et al., 2012]
cc2500 (zigbee)	13.3	21.2	4x4	30	Texas instruments	[Gómez-Clapers and Casanella, 2012; Dilmaghani et al., 2011]
UZ2400 (zigbee)	18	22	6x6		Uniband Electronics Corp.	[Chen et al., 2012]
Zebra (zigbee)			16x33	10-500	senTec Elektronik	[Aleksandrowicz and Leonhardt, 2007]
BlueNiceCom-4 (Bluetooth class-2)	65	65	27x16	20	AMBER wireless	[Morak et al., 2012]
Xbee (Emosense)	50	45	24x27	30-90	Digi International Inc.	[Massot et al., 2012]

(ANC), and autocorrelation method [Manikandan and Soman, 2010]. The conventional filters are limited to suppress the noise which is out of the frequency band of the signal components. On the other hand, ANC based algorithms such as Least Mean Square (LMS) [Song et al., 2012; Tan et al., 2015], suppress the noise in an adaptive manner and, hence, suppress in-band noise as well. These algorithms can detect dynamic variation in the signal [Rahman et al., 2012]. LMS calculates filter coefficients that relate to producing the least mean squares of error signal (difference between the desired signal and the filtered signal). Estimation of filter coefficients requires high computation. To reduce the computation of LMS algorithms, various variations in LMS algorithms have been proposed in literature and reported in [Rahman et al., 2012]. To further reduce the computational complexity author proposed [Rahman et al., 2012] sign and error non-linear sign based LMS. The major drawback of the ANC algorithms is that they need a reference (noise source) signal, which is not available in most cases of the real-life scenarios. Manikandan and Soman [Manikandan and Soman, 2010] proposed a computationally efficient denoising algorithm based on lag-1 autocorrelation method [Manikandan and Soman, 2010]. However, the performance of these algorithms significantly degrades as the level of noise increases.

In the frequency domain based denoising algorithms, the time domain signal is first transformed into the frequency domain using a specific transform function such as Fourier transform and WT, and then the transformed signal is processed. Analysis of the signal in frequency domain provides the information about the spectral characteristics of the components presented in the signal and, hence, more efficiency in noise removal can be obtained as compared to the time domain. Sanei et. al. proposed an approach to separate the murmurs from the FHS using singular spectrum analysis [Sanei et al., 2011]. Patidar and Pachori proposed an algorithm to remove murmurs from the PCG signal using constrained tunable-Q wavelet transform [Patidar and Pachori, 2013]. However, both the algorithms require high computational time.

Various denoising algorithms have been developed based on WT [Debbal and Bereksi-Reguig, 2008b]. In these filters, signals are transformed into wavelet coefficients, as discussed previously. Then noise suppression is achieved by discarding the coefficients which are correlated to noises, by applying a threshold. Although, wavelet based filters are able to suppress the in-band noise, but the threshold value plays a crucial role in this approach Gradolewski and Redlarski [2014]. If the threshold is selected high, signal information will be lost, while small value will not have a significant effect on the signal. To obtain optimal denoising parameter for DWT based denoising, Messer et al. [Messer et al., 2001] performed experiments and found that level 5 for the signal decomposition and soft thresholding with rigrsure threshold selection rule gives the best result.

Almasi et al. [Almasi et al., 2013] introduced model-based Bayesian denoising framework which combined the extended Kalman filter and dynamic model of the heart signal. Results demonstrate that proposed method has the superiority over wavelet based denosing. However, the requirement of a model of the heart signal limits the use of this framework.

Researchers have proposed many filtering approaches which analyse diversity between characteristics of heart signal components and characteristics of noises [Lee et al., 2012; Liu et al., 2012b; Manikandan and Soman, 2010]. Lee et al. [Lee et al., 2012] used First order-Intrinsic Mode Function (F-IMF) to minimize motion noise from the heart signals. F-IMF of the clean signal has periodic patterns, whereas noise contaminated signal has highly varying irregular dynamics with lower magnitudes. Thus, noisy segment can be classified from the clean heart signal. Liu et al. [Liu et al., 2012b] removed the noises from heart signal components based on the characteristic of wavelet coefficient that the signal coefficients with large magnitude at a finer scale will also be large in magnitude at coarser scales. On the other hand, the magnitude of coefficients caused by noises will decay rapidly along the scales. Manikandan et al. [Manikandan and Soman, 2010] calculated lag-1 auto-correlation coefficients, which give positive values for heart signal components and negative values for spurious noise.

Quasi-cyclostationary nature of heart signals also has been considered to filter noise from the signals [Tang et al., 2010a,b]. Quasi-cyclostationary means that the morphology of the heart signals does not change abruptly from a cardiac cycle to consecutive cardiac cycle. Thus, Noise suppression can be achieved by correlating the consecutive cycles of the signal because noise components, in general, are uncorrelated. However, quasi-cyclostationary nature of the heart signal may not be fulfilled due to variation in waveform, presence of murmurs, and variation in the timing of the heart sound components. Furthermore, the performance of this approach depends on the segmentation of cycle.

Respiratory system also affects heart signals significantly. To overcome this problem, Chen et al. [Chen et al., 2011] proposed a zero-crossing method. It calculates the time interval between two consecutive upward and downward points (IBI) in the signal. Then the inverse of IBI gives the frequency of breathing signal, which can be removed by notch filtering.

When the heart signal is being recorded continuously, noise often appears in parts of the recorded signal. In some part, noise affects severely to the heart signal while in others it affects mild. In case of severe contamination, that part of the signal can be eliminated from diagnostic consideration while in case of mild contamination, noise suppression algorithm can be used. This approach will improve diagnosis efficiency as well as optimize complexity of denoising algorithms. This approach will be also helpful in-home care systems for alarming to the user for the bad signal quality. Thus, it is of interest to obtain a signal quality index to find out a subsequence with better signal quality with respect to the rest of the cycle. Li et al. [Li et al., 2013] proposed an optimum heart sound selection scheme based on cycle frequency spectral density. In this approach, the quality of the heart sound signal depends on the periodicity of the heart signal. In [Beritelli and Spadaccini, 2009], the quality index was calculated using the Cepstral distance between homogeneous cardiac sounds. In this algorithm, first, the heart signal was segmented into separate cardiac cycle using wavelet based approach. After segmentation, Mel Frequency Cepstral Coefficient (MFCC) was calculated for each cycle. Finally, the reciprocal of distance between MFCC coefficients of consecutive cycle gives the quality score. The performance of this algorithm depends on the segmentation of the heart signal into cardiac cycle. Naseri [Naseri et al., 2013] described an approach to identify the level of noise in the heart signal cycle. In this approach, first, the signal is segmented into separate heart cycle. Then, cycles are clustered into a finite number of groups based on geometrical parameter and spectral content. Next, median of these clusters is correlated to the test cycle features. Finally, by applying a threshold, the cycle is prescribed as clean or noisy. Although, requirement of a test cycle features limits the use of this approach.

2.6.2 Analysis and Classification

Analysis and classification of the heart signals are challenging tasks due to non-stationary nature of them. Moreover, time-to-time varying morphology of heart signals from Intra- and inter-patient needs sophisticated classification algorithms. Classification of heart signals is performed by analysing diagnostic features present in the signal. Since different signals provide different diagnostic features, therefore analysis and classification of these signals are provided separately for each sensor, as follow.

(a) Electrocardiography

ECG signal consists of different waves P, Q, R, S, T, and U. Each wave is associated with particular functionality of the heart, as discussed in Chapter 1. Analysis of the shape of these waves leads to diagnosis of CVDs including MI, hypertensive heart diseases, arrhythmia, and CHD. The impact of CVDs can be seen on the waves in ECG signal. MI causes ST elevation or depression depending on the severity of the infarction. Location of the infarction can be identified by analysing ECG signals of different leads. In case of hypertension, QRS voltage increases due to both thickening of wall (pressure overload) and dilatation of chamber (volume overload) of the left ventricle. The RR (R wave to next R wave) interval is critical in the diagnosis of many arrhythmias such as premature ventricular contractions, left and right bundled branch blocks, and paced beats [Bashir et al., 2012]. ECG has been used in combination with the PCG to assess the E-M window [Kim et al., 1984]. E-M window is the difference between electrical systole (QT) and mechanical systole(QS2).

Classification of the ECG signal is performed by analysing shape of the waves present in the signal. Parameters of the shape of the waves act as features for classification algorithms. Computational requirement of classification algorithms depends directly on the number of the features used and the accuracy of classification depends on the quality of the features. Thus, feature selection plays a prominent role in the classification of the ECG signals. In literature, many approaches have been proposed to select optimal features. Bashir et al. [Bashir et al., 2012] calculated QRS, P, and T wave's morphological parameters as features to detect different arrhythmia. Then, a parameter score was calculated for an adaptive selection of feature subset for particular arrhythmia. Accordingly, there will be a different feature set for each arrhythmia, which enhances the accuracy, and at the same time reduces the computational burden. While, Llamedo et al. [Llamedo and Martinez, 2011] calculated interval features and morphological features for classification of arrhythmia. Interval features were calculated from R peaks, and morphological features were calculated from three sources, R-R interval, 2-D vectorcardiogram loop, and DWT of the ECG signal. Then outliers from the feature set were removed based on Kurtosis coefficients. Mar et al. [Mar et al., 2011] applied sequential forward floating search algorithm with a new criterion function index. The drawback of the proposed method is that in many cases the subset with highest criterion value has a very large number of features. Kamath [Kamath, 2011] selected mean of Teager Energy Operator (TEO) in the time domain and frequency domain as features set. Key characteristic of the TEO is that it models energy of the source that generated signal rather than the energy of the signal itself. Hence, any deviations in the regular rhythmic activity of the heart get reflected in the TEO. Most of the above algorithms face the same challenge, requirement of a large number of the feature set. The Large number of feature set is required for diagnosis of the different types of diseases, but it results in large computational complexity. Another challenge is due to variation in morphological descriptors of the heart signal with time.

Since mathematical operators work in the time domain, these are computationally efficient and hence consume low power. Mathematical morphological operators have been used [Zhang and Lian, 2009] to extract structural information of the ECG signal. However, computational requirement increases as increment in order of the operators. To optimize computation requirement, Zhang et al. [Zhang and Bae, 2012] proposed 1 dilation and 1 erosion based morphology operator sets. However, the effectiveness of these algorithms depends on the selection of three structural components of the operator, shape, length, and amplitude.

T wave delineation is crucial as prolongation of T wave to end of the T wave is associated with ventricular pre-arrhythmicity and sudden cardiac death. Noriega et al. [Noriega et al., 2012] analysed respiration effect on T wave. Atrial Fibrillation (AF) is associated with an increased risk of cardiovascular and coronary artery disease, hypertension, etc. AF is typically diagnosed by analysing irregular RR intervals. Huang et al. [Huang et al., 2011] proposed an algorithm to classify AF by analysing RR interval.

(b) Phonocardiography

As discussed previously, PCG signal consists of two FHS (S1 and S2) and two other sounds (S3 and S4). Characteristics (intensity, frequency, and duration) of these sound components change due to the presence of CVDs. Additional murmur sounds may also be present in the PCG signal due to the presence of CVDs. Although PCG can indicate abnormalities caused by important CVDs, it is used extensively for diagnosis of valvular diseases as sound components are produced by the valvular activity [Boutana et al., 2011]. Heart sound classification algorithms first partition the PCG signal into S1, S2, systole, and diastole intervals, by identifying the FHS. After the segmentation, classification of the PCG signal is performed by analysing the characteristics of these components. Thus, the primary task in automatic analysis of the heart sound signal is the segmentation of it. However, segmentation is a challenging task due to the presence of noise and murmur sounds. Moreover, the length of the cardiac cycle varies with time due to physiological and pathological cases.

As a consequence, various segmentation algorithms for the PCG signal have been proposed in the literature. Autocorrelation based methods have been used to predict the length of the cardiac cycle and then the signal is segmented [Kao and Wei, 2011; Yuenyong et al., 2011]. However, these algorithms suffer in the presence of noise and also the cycle duration varies from each beat-to-beat due to Heart Rate Variability (HRV) and due to arrhythmia. Tang et al. [Tang et al., 2012] proposed a dynamic clustering based method to segment the PCG signal. The main problem with this technique is that it requires prediction of the cardiac cycle, which is difficult in most cases of pathologies. Therefore, the performance of the method degrades in such cases.

Another approach is based on envelope method, which has been used extensively for the segmentation of PCG signal. Envelope of the PCG signal has been obtained using Shannon entropy [Yadollahi and Moussavi, 2006], Normalized Average Shannon Energy (NASE) [Gavrovska et al., 2014; Ramos et al., 2013], Hilbert Transform (HT) [Atbi et al., 2013], Homomorphic filtering [Yuenyong et al., 2011; Gupta et al., 2007], Short-term log energy [Zia et al., 2011], and Blanket fractal dimension [Paskaš et al., 2014]. Jiang and Choi [Jiang and Choi, 2006] proposed a new method to obtain the envelope of the PCG signal called as Cardiac Sound Characteristic Waveform (CSCW), which is based on the single-degree-of-freedom model of a spring-mass system. In another work [Choi and Jiang, 2008], they compared the performance of CSCW, Shannon energy, and Hilbert transform and found that the CSCW relatively better emphasise the FHS. Few researchers obtained the envelope using combinations of multiple time domain features [Ramos et al., 2013; Kumar et al., 2006] and morphological features [Safara et al., 2012]. Sun et al. [Sun et al., 2014] integrated two envelope techniques, Viola integral method and short-time Hilbert transform. However, extraction of the envelope significantly affected due to the presence of noise and presence of murmur sounds [Ramos et al., 2013]. The main challenge for the envelope extraction based algorithm is the selection of the threshold value. A higher value of threshold missed the S1 and S2, while the lower value of threshold detects spurious components and inaccurate S1 and S2. To resolve this problem, Atbi et al. [Atbi et al., 2013] proposed a two-step thresholding scheme. In the first step, the threshold is selected to detect S1 and S2 and in the next step, to detect murmurs. Envelop extraction based algorithms are computationally low complex. However, the performance of these algorithms depends on the morphology of the PCG signal. Furthermore, it becomes difficult to detect FHS, where murmurs are merged with them.

Frequency domain transformation techniques such as Fourier transform, discrete cosine transform, auto-regressive based spectral analysis techniques provide frequency characteristics of PCG signal components. However, time-frequency domain analysis is more suitable for the PCG signal analysis due to the diagnostic significance of timing and frequency of the components. Time-frequency analysis of the PCG signal has been done using Short Time Fourier Transform (STFT) [Boutana et al., 2011; Balasubramaniam and Nedumaran, 2010], WT [Balasubramaniam and Nedumaran, 2010; Syed et al., 2007]. Boutana et al. [Boutana et al., 2011] classified murmurs by analysing the Renyi marginal entropy of STFT coefficients. Renyi marginal entropy remains high for murmurs and low for FHS. While, Balasubramaniam and Nedumaran [Balasubramaniam and Nedumaran, 2010] implemented the PCG analysis algorithm using STFT and wavelet on digital signal processing board. In [Syed et al., 2007], first, PCG signal is segmented into intervals associated with cardiac cycle. Then intervals were grouped together based on similarities between their STFT coefficients.

PCG signals have been classified using Artificial Intelligence (AI) algorithms such as Hidden Markov Model (HMM) [Kwak and Kwon, 2012] and neural network [Reed et al., 2004; Barschdorf et al., 1995]. Extracted features from the PCG signals using time-frequency analysis tools such as wavelet, are used as feature points for these AI techniques [Reed et al., 2004; Barschdorf et al., 1995]. Use of the machine learning algorithms reduces tedious envelop analysis and its disadvantage in case of murmurs can be avoided but at the cost of having to prepare the training dataset. To prepare the training dataset for PCG signal, Ahlstrom et al. [Ahlstrom et al., 2006] proposed a feature subset selection algorithm from features of different domains, including Shannon energy, wavelet, fractal dimension, and recurrent quantification analysis.

PCG signal modelling is also performed to generate test data to analyse efficacy of the developed algorithms [Sava et al., 1996; Zhang et al., 1998]. Modelling of the PCG signal has been done using exponential damped sinusoidal model [Sava et al., 1996] and matching pursuit method [Zhang et al., 1998]. These methods provide complete parameterization of the signal but require a large number of components. Whereas linear chirp signal modelling is not suitable for PCG signal because components of PCG signal do not have a linear relationship with time. To achieve better accuracy, Xu et al. [Xu et al., 2000] proposed non-linear chirp signal modelling of the heart sound components.

(c) Seismocardiography

SCG measures mechanical vibrations produced by heart during each cardiac cycle. As discussed in Chapter 1, the SCG signal is composed of many waves. Each wave is associated with a particular event of the cardiac cycle. Using these cardiac cycle events, several diagnostically important cardiac cycle periods have been obtained, such as LVET [Tavakolian et al., 2014; Rienzo et al., 2013b], PEP [Tavakolian et al., 2014], systole and diastole [Tavakolian et al., 2013], and quiescent phase [Wick et al., 2012, 2015].

In [Sun et al., 2010], Sun et al. studied the relationship between the cardiac event position in SCG with ultrasound signal and shown SCG as an accurate indicator of cardiac events. Thus, SCG signal can be used to detect cardiac cycle boundary, heart rate [Nguyen et al., 2012], HRV [Ramos-Castro et al., 2012]. SCG signals have been also used to obtain Systolic Blood Pressure (SBP) [Imtiaz et al., 2013]. It was shown that SBP has the correlation with starting point of the SCG signal in x-axis to the midpoint of the z-axis. However, SCG has been used for the heart monitoring purpose, but its sensitivity to motion noise imposes limitation on its wide use.

Characterization of the relation between the SCG signal and the ECG signal provides significant information related to heart functionality. Wick et al. [Wick et al., 2012] analysed relation between the R wave of the ECG and the AC wave of SCG signal. The R-AC period varies across two individual and also for the same person at different heart rate. This study strongly suggested the cardiac events also vary in the same manner. Tavakolian et al. [Tavakolian et al., 2012] analysed period between the R wave of the ECG and the AO wave of SCG to analyse the myocardial contractility. This period is called as PEP. Increment in the PEP indicates reduction in contractility of myocardial.

SCG also have been used to diagnose several CVDs such as CAD [Wilson et al., 1993; Korzeniowska-Kubacka et al., 2005, 2007], myocardial ischemia [Salerno et al., 1991], haemorrhage [Tavakolian et al., 2014]. It has shown more reliability and accuracy to diagnose CVD [Salerno et al., 1991], CAD [Wilson et al., 1993], and to extract cardiac periods [Tavakolian et al., 2013; Wick et al., 2012, 2015], compared to the other systems.

(d) Photoplethysmography

PPG signal contains sufficient parameters to measure heart rate, arterial oxygen saturation, and information related to respiratory system [Venema et al., 2013; Li and Warren, 2012; Venema et al., 2012]. As discussed in the previous chapter, PPG measures variation in intensity of light, reflected or transmitted, induced by variation in the amount of blood in blood vessels. Respiration information can be extracted using three vital parameters; PPG amplitude, variation in SpO2, and respiratory sinus arrhythmia [Venema et al., 2013]. Now a day, pulse oximeters (variant of PPG) are being used extensively for heart monitoring [Venema et al., 2013; Li and Warren, 2012; Venema et al., 2012; Gil et al., 2013]. It measures multiple PPG signals at different wavelengths viz., red (660nm) and infrared (940nm). Pulse oximeters have been used for sleep apnea detection [Venema et al., 2013], pulse wave velocity calculation [Li and Warren, 2012], hypoxia detection [Venema et al., 2012], HRV analysis [Gil et al., 2013]. The pulse oximeters have been developed as an in-ear sensor for cardiovascular monitoring [Venema et al., 2013, 2012]. This setup of sensor could offer three important advantages: 1) comfortable to wear and hence, suitable for long-term monitoring, 2) the tight-fitting could reduce interference from motion artefacts, and 3) robustness to conditions such as temperature or skin perfusion.

However, PPG signals get contaminated primarily due to ambient light, motion artefacts and other physiological process. To extract information from the contaminated PPG signals, Madhav et al. [Madhav et al., 2013] proposed an MSPCA based algorithm. In this algorithm, noise suppression from the PPG signals was achieved using wavelet decomposition and reconstruction. Selection of coefficients to reconstruct relatively clean signal was done based on two measures, energy contribution level and Kurtosis. After reconstruction of the clean signal, Principal Component Analysis (PCA) was performed to extract information about the respiratory system. Li and Warren [Li and Warren, 2012] developed a sensor circuit in which photodetecters are radially distributed around the LED to increase the sensing area. This set-up improved the signal quality without filtering algorithm. Whereas, Stuban et al. [Stuban and Niwayama, 2012] analysed optimal corner frequency of low pass filter for PPG signal. Setting the corner frequency to the fundamental frequency of the PPG signal resulted in decreased noise, and consequently, decreased standard deviation. Haan et al. [Haan and Jeanne, 2013] analysed robustness of the chrominance based algorithms to separate motion induced distortion from rPPG signals in case of modest and vigorous motion.

2.7 USE OF MOBILE

The latest generation of mobile phones (smartphones) is increasingly used for health monitoring, due to their powerful on-board computing capability, large memory, large screens and open operating systems that encourage application development. Technical features of mobile phone including text messaging, camera, internet access, inbuilt sensors, make it an appropriate platform for improving health care services [Klasnja and Pratt, 2012]. Wireless technologies, including GPRS, GSM, 3GSatelite, Wireless and LAN networks have been used for wireless transmission of the heart signal [Kyriacou et al., 2009]. Mobile phones are also suitable platform to develop a heart monitoring system because of (1) the widespread adoption of phones, (2) people's tendency to carry their phones with them everywhere, and (3) context awareness features [Klasnja and Pratt, 2012]. Furthermore, visible representation of the health status of the patient on mobile, encourage to be attentive to health promoting behaviour.

Mobile phones are being used for long-term heart monitoring at home for both on-site monitoring and off-site monitoring. Smartphone based software applications can help clinicians in identifying acute symptoms, decreasing unnecessary tests to understand principles of disease diagnosis, and communication facility among clinicians [Klasnja and Pratt, 2012; Mosa et al., 2012]. In addition, mobile applications have been used for remote coaching, public health research, primary care, emergency care, health information for self, drug reference, medical training, to encourage for primary care check-up, and many more. Mobile phone based health monitoring systems have been discussed in [Mosa et al., 2012]. Some of them are as follows: (1) 'Cardiomobile' is comprised of a heart and activity monitor, single lead ECG, GPS receiver, and programmed smartphone. The smartphone sends ECG rate, walking speed, heart rate, elapsed distance, and patient location to a secure server for real-time monitoring by a qualified exercise scientist. (2) Pulmonary Rehabilitation is an application for Chronic Obstructive Pulmonary Disease (COPD) rehabilitation and self-management, developed for smartphones. (3) 'mVisum' is a specialized application for cardiology communications that monitor ECG data, alarm the user in abnormal case, and transmit data to clinician. (4) 'iCPR' is a Cardio-Pulmonary Resuscitation (CPR) training application. This application measures the chest compression rate and gives audiovisual feedback, improving the performance of chest compression by helping the user to achieve the correct chest compression rate. Another smartphone based health monitoring system 'BioSign' is reviewed in [Tarassenko et al., 2006]. 'BioSign' system alerts the patient in case of abnormality. It represents the health status of the patient as a patient status index, which is calculated based on five vital parameters, heart rate, breathing rate, blood pressure, arterial oxygen saturation, and skin temperature.

To enhance the user acceptability, Skully et al. [Scully et al., 2012] proposed a reflection photoplethysmography based on imaging by mobile phones. In this approach, the palmer side of the left index finger was placed over the camera lens of mobile with its flash turned on. Then variation of intensity in captured video indicates the heartbeat. This approach does not require any extra hardware. However, sensitivity of device get affected due to motion and pressure variation of the finger. Another approach proposed by Poh et al. [Poh et al., 2012] integrate reflective photo-diode into earphone which are unobtrusive, and low in size and weight. Then, the acquired signal was sent to mobile phone for monitoring purpose. Major challenges for smartphone based health care systems include cost, network bandwidth, battery power efficiency, small screen size, computer viruses etc. [Mosa et al., 2012].

2.8 CONCLUSIONS

The chapter provided a detailed review of recent advancements in portable heart monitoring systems, ECG, PCG, SCG, and PPG. These systems are reviewed for their features of adequate diagnostic capability, robust against noise, convenient to subject and unobtrusiveness, and following are the conclusions.

ECG signal contains information about the electrical activity of the heart. Thus, provides better insight on the issues related to electrical conduction abnormality of the heart. On the other hand, the PCG signal acquires acoustic sounds produced by the heart valves (mechanical action) and thus useful in the diagnosis of the valvular diseases. Due to the different source of producing these signals (ECG and PCG), the diagnosis of a problem (e.g. Structural abnormalities) from the PCG signal does not imply the same problem diagnosed from the ECG signal, and vice versa. The combination of ECG and PCG has been used to assess the E-M window. As SCG signal is produced by the acceleration of the heart and the acceleration is the second derivative of the displacement, such signal carries more diagnostic information about the heart as compared to the PCG signal. The PPG signal provides only limited information about the heart. It measures the blood variation in the blood vessels. Although, the combination of PPG with ECG or PCG has been used for the assessment of Pulse Transit Time (PTT), which is an important diagnostic parameter in case of obstructive sleep apnea detection and blood pressure measurement.

For clinical use, all above methods are suitable as Signal-to-Noise Ratio (SNR) remains high. At home, in the presence of the environmental and motion noise, the robustness of the sensor to the noises is a major issue. In the case of ECG, wet sensors are robust to noise while dry and capacitive sensors are vulnerable to noise. PCG is more vulnerable to patient's motion noise and environmental noise compared to the ECG. On the other hand, SCG is robust against environmental noise and against motion noise up to an extent.

ECG has limitations in long-term monitoring of heart due to the requirement of skin contact of electrodes and use of gel, which sometimes causes itching problem. Moreover, for signal acquisition, attachment of electrodes to different points on the body restricts patient's mobility. PCG has advantages over ECG in terms of comfort of the patient and easy to operate. SCG is superior to both PCG and ECG in terms of comfort because of the low weight (<3g) accelerometers. PPG is also comfortable in terms of wearability and therefore used widely for continuous heart monitoring. To increase the unobtrusiveness, in the case of ECG and PPG, researchers have proposed sensors that do not require skin contact.

As discussed above, the heart sound signal based systems, PCG and SCG are comfortable to the user and provides ample diagnostic features to monitor the health status of the heart. Moreover, the heart sound signal provides an early diagnostic marker for valvular diseases which are increasing every year. In view of this, analysis of heart sound signal is of paramount importance. However, these systems are vulnerable to environmental noises. Therefore, the following chapters address the issue of noise contamination of the heart sound signal.

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