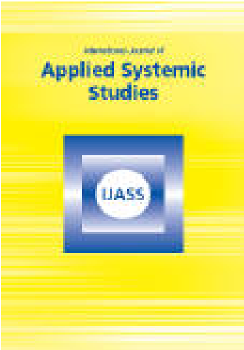

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Biomedical signal processing for health monitoring applications: a review

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Biomedical signal processing for health monitoring applications: a review

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Abstract: Biomedical health monitoring systems are evolving rapidly and using non-invasive and cost effective sensors. These systems can monitor physiological parameters of the body to monitor health conditions and provide feedback. These new generation systems can use advance technologies to build intelligent systems for health monitoring and timely diseases detection and diagnosis. Biomedical signal processing and analysis of the patterns in the signals plays important role in building efficient systems, life sciences and research and is rapidly expanding in this domain. This review paper is significant as no existing review paper is giving complete information on biomedical signal processing phases as a whole. It makes four contributions; first, it gives activity flow for developing biomedical signal processing systems. Second, reviews various recent applications researched and kinds of low cost, non-invasive sensors used for biomedical health monitoring. Third, categorisation and enlisting of signal processing techniques like signal sampling, segmentation, filtering, feature extraction, dimensionality reduction and machine learning techniques in healthcare domain. Fourth, it reviews challenges in using signal processing techniques and gives future perspectives which can be helpful for the researchers to use advance techniques to build intelligent systems for reliable decision making.

Keywords: biomedical signal processing; signal pre-processing; biologicals signals; review.

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1 Motivation of research

Health monitoring systems are rapidly evolving and have potential to automate healthcare system for patient monitoring. Biosignals play important role in today's wearable integrated health monitoring system. Human body is a living source of all kinds of biological signals. Improper functioning of human body can be detected through these biological signal changes (Ahamed et al., 2015) and are the indicators for change in health conditions. These biosignals can be well acquired through wearable sensor miniatures placed on the body. The wearable having mini biosensors can measure physiological parameters like heart rate, respiration rate, oxygen saturation, blood pressure, body temperature, ECG, etc. Real-time signal processing can be performed on wearable or embedded lightweight chip in smartphone (Hao et al., 2013; Jain and Kanhangad, 2018; Mohamed and Youssef, 2017; Li and Fernando, 2016) for monitoring and detection of any adverse effect like stroke or disease diagnosis.

Human body biosignals are weak and noisy. Non-invasive, non-intrusive sensors read biosignals continuously and are core elements of long-term health monitoring systems (Deen, 2015; Pantelopoulos and Bourbakis, 2010). The signals obtained need to be processed to remove noise producing clear signal. Multiple signal noise removal techniques are available and need to be chosen for desired output. Signal analysis is performed which involves extraction of linear and nonlinear features from the signal, reduction in dimensionality of features and finally pattern recognition is performed to learn the patient pattern.

Sensor-based systems can be built to monitor patient's health continuously. In recent years various sensors based biomedical health monitoring systems are built. Majumdar et al. (2017) have done comparison of several low cost non-invasive commercial products in health monitoring and done survey of several health monitoring systems including cardiovascular monitoring systems, body temperature monitoring systems, galvanic skin response (GSR) monitoring systems, blood oxygen saturation (SpO2) systems, multisensory monitoring systems, activity monitoring systems, textile-based sensory systems and communication technologies are also discussed. Authors have tried well to explain these health monitoring systems giving information on sensors used and their placement on body, feature extraction, classification methods used, communication technologies, measured parameters, in the similar applications developed but still fails to give detailed process flow idea and available methods of signal processing for building such applications. Krishnan and Athavale (2018) reviewed signal feature extraction methods in different domains like time, frequency along with their advantages and disadvantages and sample application areas which forms the basis for machine learning and artificial intelligence. Author has concentrated on feature extraction methods but leaving a gap for knowing signal processing requirements before and after extraction of features for pattern learning. Recently assistive robots and biomedical devices have been used widely for improving life of disabled and elderly people. Rechy Ramirez and Hu (2015) reviewed deployment and research challenges for specifically two biosignals, electromyography (EMG) and electroencephalography (EEG) used in these kind of applications which is again signal specific. Mukhopadhyay (2015) reviewed human activity monitoring systems based on wearable sensors, sensor networks, type of activities, methodologies and discussed associated research challenges. Cornacchia et al. (2017) also done survey on wearable sensor approaches for activity detection and classification, covering multiple sensor modalities like accelerometer, gyroscope, pressure sensor, their number and placement and activities detected, similarly review by Ansermino et al. (2010) on sensor-based activity recognition system. This is again a focus on specific application. From all above recent research survey works it is observed that there is a need of knowing kinds of biomedical health monitoring applications developed and the sensors used in them before building and the basic information on development stages and signal processing methods involved in building such applications, categorisation and enlisting of these methods for all the phases like signal pre-processing techniques (sampling, segmentation and filtering), features extraction, dimensionality reduction and machine learning enabling researcher to develop a intelligent system.

The contribution of this work is:

1 To give activity flow of the biomedical signal processing systems.

2 To review various recent applications researched with kinds of low cost, non-invasive sensors used for biomedical health monitoring.

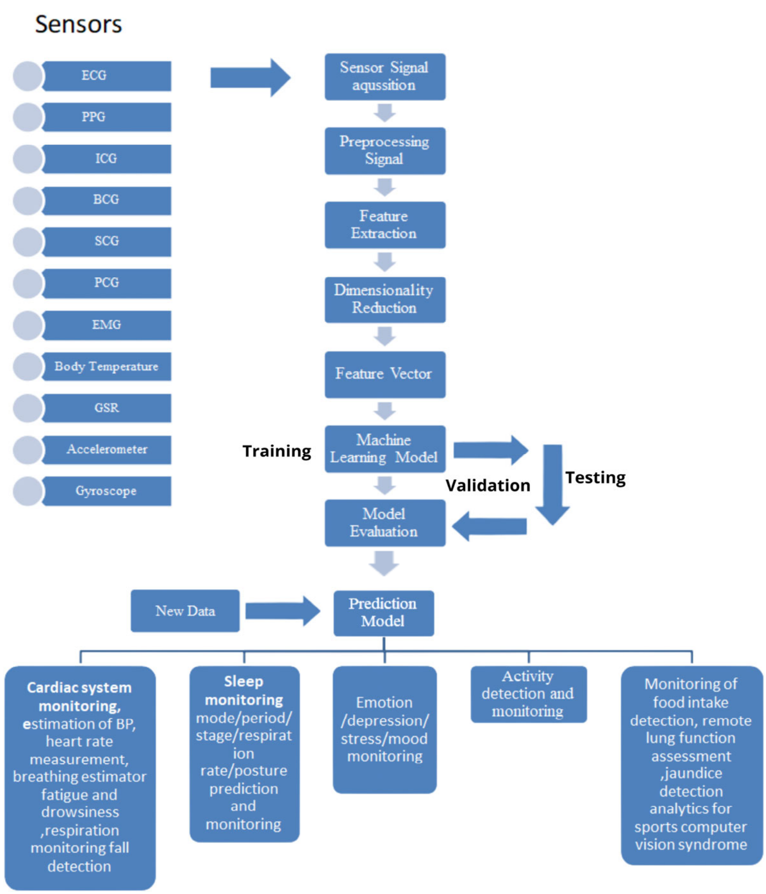
3 Categorisation and enlisting of signal processing techniques like signal pre-processing, feature extraction, dimensionality reduction and machine learning in healthcare domain.

4 To review research challenges in using signal processing techniques and giving future perspectives which can be helpful for the researchers to apply advance techniques to build intelligent systems for reliable decision making.

2 Sensor-based health monitoring system

Many sensors can be used to generate biosignals and patients vital signs can be monitored for various health conditions (Sanfilippo and Pettersen, 2016; Garbarino et al., 2015). Signal processing plays important role in (Krishnan and Athavale, 2018) analysing signals through measurement, quality improvement (Ansermino et al., 2010), reconstruction, feature extraction, feature selection and applying suitable machine learning technique. A typical sensor based health monitoring system representation is shown in Figure 1. It uses non-invasive, non-intrusive sensors like electrocardiogram (ECG), photoplethysmograph (PPG), impedance cardiogram (ICG), ballistocardiogram (BCG), seismocardiogram (SCG), phonocardiogram (PCG), body temperature, GSR, accelerometer, gyroscope for building wearable health monitoring systems and biosignals like heart rate, respiration rate, breathing rate, oxygen saturation, blood pressure, body temperature, ECG, EMG, EEG, can be generated for monitoring. The generated signal is weak and noisy, so a strong acquisition system is needed to capture the analog signal and convert it into digital signal which can be embedded on the wearable device. This acquired signal is pre-processed with proper sampling rate, window size and filtered for noise removal using appropriate filtering technique. The clear biosignal is sent for extracting features. The features are further selected, reduced for further processing which forms a feature vector. These vectors are supplied as training dataset to the classification model. Choice of appropriate learning model is very important for better accuracy. The model is evaluated, validated for acceptance. The tested model is used for predicting diseases. Machine learning techniques are used for patient health pattern recognition and detection, diagnosis of any disease. Multiple wearable health monitoring systems can be developed as shown in Figure 1 for intelligent healthcare automation.

Figure 1 Sensor-based health monitoring system representation (see online version for colours)



3 Sensors-based healthcare applications

In health monitoring systems, sensors (Majumder et al., 2017) can be integrated in cloths, elastic bands, belts, or implanted in human body. The signal acquisition system collects raw biosignals from various sensors and these signals are used to measure physiological signs of the patients for health monitoring. The sensors measure physiological signs and can be used in daily objects like sleeping cushion (Gu et al., 2009), weighing scales (Hyuk et al., 2009), chair (Wu et al., 2006), cameras (Patil et al., 2017; Sano and Picard, 2013), and also in wearable's like eyeglasses (Zheng et al., 2012), mobiles (Poon et al., 2006b), watches (Poon et al., 2006a,), shirts (Zhang et al., 2006), rings (Shaltis et al., 2008), belts. Table 1 show various non-invasive sensors used in various healthcare applications.

Table 1 Sensors in healthcare applications

Area	*Sensors and signals*	*References*
Estimation of BP, hypertension	ECG, PPG	Kumar and Anand (2006), Reddy and Rao (1994) and Miao et al. (2017)
	ECG, PPG, arterial blood pressure (ABP) signal	Kachuee et al. (2017)
	HK2000B pulse wave sensor, silver chloride-based flexible electrode to collect ECG analog signal	Sanuki et al. (2017)
	4-LED PPG sensor, ECG sensor	Li et al. (2008)
	Two sets of PPG sensor for finger and wrist	Myint et al. (2014)
	BP waveform sensors on finger, BCG sensor, ECG sensor	Kim et al. (2015)
	Webcam for acquiring photoplethysmograph waveform	Patil et al. (2017)
	ABP signal	Hemberg et al. (2013)
	Three PPG pulse sensors into a pair of glasses	Holz and Wang (2017)
	PPG sensor	Zhang et al. (2017b)
	Arterial waveforms measurement through camera	Yoshizawa et al. (2013), Kyal and Mestha (2014) and Greneker (1997)
	EBI (Electrical bioimpedance), ICG (Impedance cardiography)	Kumar and Anand (2006)
Mobile ECG monitoring system	ECG sensors in clothing	Lin et al. (2013)
Heart rate measurement	Gyroscope sensor to measure HR	Mohamed and Youssef (2017)
	Pulse sensor	Kirtana and Lokeswari (2017)

Table 1 Sensors in healthcare applications (continued)

Area	*Sensors and signals*	*References*
WiFi-based breathing estimator	RSS signal	Abdelnasser et al. (2015)
Respiration monitoring during meditation	Accelerometer and gyroscope sensors, RIP (respiratory inductance plethysmography) sensor	Hao and Chan (2017)
Conversation detection using a mobile respiration sensor	RIP bands, analog-to-digital (A-D) converter in field AutoSense chest sensor	Bari et al. (2018)
Sleep mode/period/stage /respiration rate/posture	Phone sensors.	Hao et al. (2013)
	PSG (Polysomnography) signals, RE signals	Long et al. (2017)
	EDA (electrodermal activity) signals during PSG accelerometer	Hwang et al. (2017)
	Ear-EEG sensor.	Nakamura et al. (2017)
	Accelerometer, pulse oximeter	Sun et al. (2017)
	Pressure sensor.	Zhu et al. (2006)
Respiratory pattern variability	Respiratory flow signals using a pneumo-tachograph connected to an endotracheal tube	Chaparro et al. (2011)
Non-contact respiration monitoring	Camera, zephyr wearable device(breathing pattern) and an oxyconmetabolic analysis instrument.	Shao et al. (2014)
Food intake detection	Accelerometer on chest, COTS pulse oximeter	Brugarolas et al. (2015)
	Acoustic sensors: throat microphone	Bi et al. (2016)
Heart sound-based authentication	Microscope and gyroscope	Shao et al. (2014)
Activity time series classification	Accelerometers and gyroscopes, ECG	Rav et al. (2017)
	Accelerometer, gyroscope	Jain and Kanhangad (2018) and Cornacchia et al. (2017)
Remote lung function assessment	Using Kinect V2 RGB-D sensor	Soleimani et al. (2017)
Jaundice detection	Uses digital photographs of the eyes and two accessories 3D-printed box and a pair of glasses	Huang et al. (2018)
Analytics for sports	Accelerometer, gyroscope, and magnetometer	Jain and Kanhangad (2018)
Assessment of fatigue and drowsiness	Stonyman vision chip produced by Centeye, Inc. as its imager3mW and has a resolution of 112x112 pixels	Rostaminia et al. (2017)
Computer vision syndrome, dry eyes	Infrared reflectance sensor	Dementyev and Holz (2017)

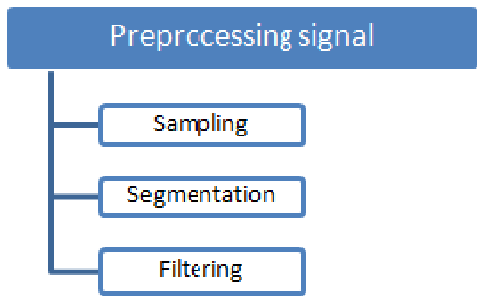
Table 1 Sensors in healthcare applications (continued)

Area	*Sensors and signals*	*References*
Emotion	EEG and ECG signals	Holz and Wang (2017), Abdelnasser et al. (2015), Nakamura et al. (2017), Shao et al. (2014) and Katsigiannis and Ramzan (2018)
	Smartphone typing.	Ghosh et al. (2018)
	Biopac MP150-laboratory sensor and Empatica E4-wearable sensor	Ragot et al. (2018)
	Shimmer GSR sensors equipped with a 3-D accelerometer, GSR	Guo et al. (2013)
Depression	Fitbit, smartphone location	Lu et al. (2018)
Stress	Accelerometers, audio recorder, GPS, Wi-Fi, call log and light sensor	Gjoreski et al. (2015)
	Accelerometer	Garcia-Ceja et al. (2016)
	Pulse sensor	Pandey (2017)
Stress	Microphone sensor, GSR sensor	Lu et al. (2012), Bakker et al. (2011), Sano and Picard (2013) and Setz et al. (2010)
Mood	Microphone audio, light sensor, GPS, WiFi, phone call, SMS, APP log, accelerometer, compass, gyroscope, screen	Zhang et al. (2017a)
Stress office syndrome	Microcontroller At Mega 328 cortex accelerometer ADXL345 EEG NeuroskyMindwave, sensor.	Reanaree et al. (2017)
Mental workload	E3 (Empatica), emWavePro (HeartMath), Biopatch	Lo et al. (2017)
Fall detection	InfraRed integrated systems (IRISYS) thermal imaging sensors	Sixsmith and Johnson (2004)
Glucose monitoring	Implanted	Lucisano et al. (2017)
Critical illness for pneumonia detection	Pulse oximetry, phoneoximeter	Sano and Picard (2013)
Thermal camera for body temperature detection	Facial recognition technology with two infrared cameras and regular video cameras	Thermal Camera for Body Temperature (2021)

4 Signal pre-processing

The raw signal data acquired from sensors are pre-processed and transformed into a form which can be used for feature extraction. Acquired analog signal data is to be converted into digital data. Signal pre-processing techniques sampling, segmentation and filtering are applied to signals. Figure 2 shows the basic signal pre-processing techniques. Sampling is acquiring data at specified time stamp (Park et al., 2015). It is performed for converting continuous time signal to discrete time signal and window size considers the number of signal samples and duration. Table 2 shows signal sampling performed and the accuracy achieved for some healthcare applications.

Figure 2 Signal pre-processing techniques (see online version for colours)



Segmentation is splitting the signal cycle. There are various segmentation techniques used in research projects as shown in Table 3 like string matching (SM), sliding window and bottom-up (SWAB), reference-based windowing (RbW), dynamic windowing (DWin), top down (ToD), Bottom up (BUp), symbolic aggregate approximation (SAX), fixed size non-overlapping sliding window (FNSW), fixed size overlapping sliding window (FOSW) and variable size sliding window (VSW). These methods are different in their online and offline behaviour. Online methods work before the complete data is available and offline methods work on entire dataset.

Table 2 Signal sampling

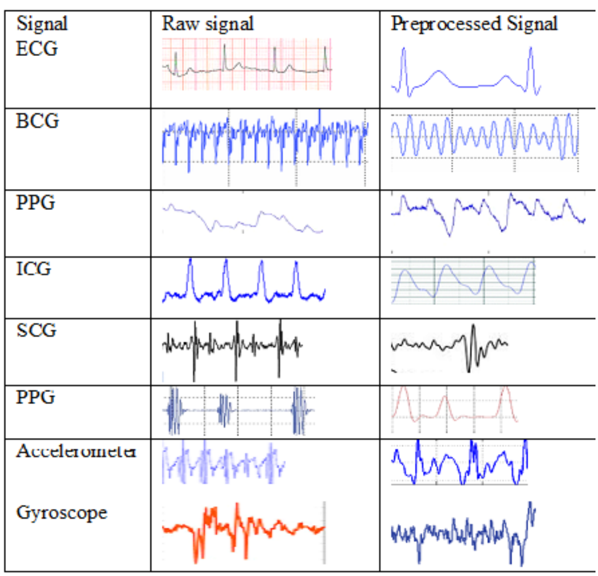
Task	*Window size*	*Sampling rate*	*Accuracy*	*References*
EDA measurements	70 mm * 70 mm * 20 mm	32 Hz	Correlation: 99%	Bersch et al. (2014)
Multi-sensor device for biofeedback and data acquisition	4 cm * 4 cm	4Hz		Tseng et al. (2014)
Human emotions (GSR sensor)	65 mm * 32 mm * 12 mm	10 Hz	80%	Guo et al. (2013)
Distinguishing stress by EDA	4,167 mm	16 Hz	82.8%	Setz et al. (2010)
Wearable mobile ECG sensor (electrocardiogram monitoring system)	4 cm * 2.5 cm * 0.6 cm	512 Hz	99.51%	Zena and Gillies (2015)
Wireless, portable capacitive ECG sensor	45 mm * 60 mm * 9 mm	500 Hz		Nemati et al. (2012)
HR monitoring in ear canal	15 mm * 17 mm	100 Hz	Sensitivity: 97.25%	Park et al. (2015)

Table 3 Signal segmentation methods

Segmentation method	*References*
FNSW	Pietka (1988) and Keogh et al. (2001)
FOSW	Pietka (1988) and Keogh et al. (2001)
SWAB	Keogh et al. (2001)
SM	Pietka (1988)
RbW	Chu (1995)
ToD	Keogh et al. (2001)
BUp	Keogh et al. (2001)
SAX	Pietka (1988)
DWin	Kozina (2011)
VSW	Ortiz et al. (2011)

Filtering is applied to remove undesired signals according to their frequency. Filtering is very effective when frequency spectra of signal and interference are different. A signal can be denoised using thresholding technique which removes noise part. Figure 3 shows multiple raw biosignal waveforms and the signals after performing pre-processing which makes signal noise free.

Figure 3 Raw signals and pre-processed signals (see online version for colours)



In recent works on sensor based healthcare monitoring systems various signal filtering techniques used are shown in Table 4. From the study (Tobola et al., 2015) on sampling rate impact on classification accuracy, it is observed that finite impulse response (FIR) filters are important for biomedical signals because of its linear phase (Tobola et al., 2015). It keeps signal shape undistorted. It shows quadratic behaviour with sampling rate. Infinite impulse response (IIR) filter is less dependent on sampling rate compared to FIR filter and shows linear behaviour. Short-time Fourier transformation (STFT) filter, median filter are performing good with linear and logarithmic behaviour. So sampling rates can be reduced for them. It is also observed that Kalman-based filters need high sampling rate thereby increasing (Tobola et al., 2015) computational load. Chebyshev II filter (Liang et al., 2018) proved better than Butterworth filter which is used widely for PPG signal filtering since it has excellent frequency selectivity passband with no equal ripple which maintains valuable information. New advance filters can be identified to be used in this domain sensor to get good signals and at the same time reducing sampling rate, energy consumption and improving classification accuracy.

Table 4 Signal filtering methods

Signal filtering methods	*References*
Smoothed butterworth low pass filter	Kim et al. (2015), Long et al. (2017), Hwang et al. (2017), Sun et al. (2017), Shao et al. (2014) and Bong et al. (2013)
Local mean removal	Mohamed and Youssef (2017)
Amplification	Lin et al. (2013), Bi et al. (2016) and Li et al. (2018)
Averaging filter	Reddy and Rao (1994), Bari et al. (2018) and Hwang et al. (2017)
Exponential moving average filter	Kim et al. (2015) and Dementyev and Holz (2017)
Band pass filter	Holz and Wang (2017), Abdelnasser et al. (2015), Nakamura et al. (2017), Shao et al. (2014) and Katsigiannis and Ramzan (2018)
Kalman filter	Sun et al. (2017)
TV filter	Sun et al. (2017)
Notch filter	Katsigiannis and Ramzan (2018) and Li et al (2018)
Linear phase FIR filter	Katsigiannis and Ramzan (2018)
High and low pass filter	Myint et al. (2014), Abdelnasser et al. (2015), Long et al. (2017) and Hwang et al. (2017)
Trimmed mean filter	Abdelnasser et al. (2015)
Empirical cumulative distribution function (ECDF)	Radu et al. (2017)
Peak detection	Sanuki et al. (2017) and Li et al. (2008)
Splin fitting method	Long et al. (2017)
Moving average centreline curve	Bari et al. (2018)
Box filter, mean filter	Rostaminia et al. (2017) and Dementyev and Holz (2017)
Bilateral filtering	Chaparro et al. (2011)
Bandpass hamming since linear phase FIR filter, notch filter	Katsigiannis and Ramzan (2018)
Fast Fourier transforms, high pass filter	Sano and Picard (2013)
Median filter	Rostaminia et al. (2017), Dementyev and Holz (2017), Guo et al. (2013) and Madhan Mohan and Nagarajan (2017)
Chebyshev II filter	Liang et al. (2018)

5 Feature extraction

Key features can be extracted from signals in different domains like time domain, frequency domain, time frequency domain and sparse domain. In time domain, features are extracted in specific time window with N discrete time samples (Prahallad, 2011). Different time domain feature extraction methods are (Krishnan and Athavale, 2018) AR modelling, cepstrum analysis, linear predictive coding (LPC), morphology feature extraction, kernel-based modelling. Time series extraction methods are used for waveform data (Park et al., 2015). The most basic time domain features include mean, median, variance, standard deviation, RMS (root mean square), kurtosis, skewness, inter-quartile range (Politi et al., 2014). AR modelling is sensitive to artefacts (Kevric and Subasi, 2017).

Frequency domain signals helps in identifying artefact frequencies. Mostly Fourier transforms gives information about frequencies present in the signal in ratios and helps in extracting useful hidden information for pattern recognition and classification (Prahallad, 2011). Discrete Fourier transform (DFT), discrete cosine transform (DCT), fast Fourier transform (FFT), spectral estimation and Hillbert transform are common frequency domain methods (Krishnan and Athavale, 2018).

Time frequency domain features extracts low level features. Sometimes multiple signal components overlap with varying discriminative characteristics, in that case time frequency domain features are used (Rangayyan and Krishnan, 2001; Umapathy et al., 2005, 2002; Thayilchira and Krishnan, 2002). Time frequency feature extraction methods are SIFT, discrete wavelet transform (DWT), continuous wavelet transform (CWT), indirect Fourier transform (IFT), wavelet packet transform (WPT), ambiguity function, Ramanujan Fourier transform (RFT) and non-negative matrix factorisation (NMF) (Krishnan and Athavale, 2018).

Table 5 Feature extraction techniques

Feature extraction techniques	*References*
IFT	Rav et al. (2017)
FFT	Mohamed and Youssef (2017), Abdelnasser et al. (2015), Long et al. (2017), Sun et al. (2017), Rav et al. (2017) and Radu et al. (2017)
DWT	Kachuee et al. (2017), Abdelnasser et al. (2015) and Bong et al. (2013)
CWT	Sanuki et al. (2017) and Li et al. (2018)
ITD, EMD	Kevric and Subasi (2017)
Mexican Hat wavelet	Sanuki et al. (2017)
FT	Zhang et al. (2017b) and Rav et al. (2017)
WT	Kumar and Anand (2006), Zhang et al. (2017b) and Zhu et al. (2006)
db3 wavelet decomposition	Bi et al. (2016)

In sparse domain compressive sensing techniques are used which compresses signals at reduced rates and extracting useful pattern from signal which can be helpful in reconstruction (Foster et al., 2014). Nonlinear non-stationary signals can be constructed as meaningful information, sparse in nature which is decomposition domain feature extraction. The methods are empirical mode decomposition (EMD), intrinsic timescale decomposition (ITD), singular value decomposition (SVD) and tensor analysis. Much of the huge data these days is redundant (Tosic and Frossard, 2011) and sparse in nature and needs sparse domain feature extraction methods. They use sparse representations, compressive sensing methods for feature extraction (Krishnan and Athavale, 2018). Different feature extraction domains and the methods under them are shown in Figure 5. Table 5 shows various feature extraction techniques used in the recent work.

As an example, time domain (Dargie and Denko, 2010) features for accelerometer are mean, zero crossing rate, maxima/minima, cross correlation, autocorrelation, linear correlation coefficient, standard deviation. Frequency domain data from accelerometers can be extracted by first segmenting into certain time window. Each segment is then transformed into frequency spectrum with FFT. Then calculate energy for each frequency band around interested frequency and form a feature vector. It can contain features like mean, correlation, spectral roll-off, spectral centroid, spectral flux, band energy, maxima (Dargie and Denko, 2010). Figure 4 shows feature extraction for accelerometer signal in frequency domain.

Figure 4 Feature extractions for accelerometer signal in frequency domain (see online version for colours)

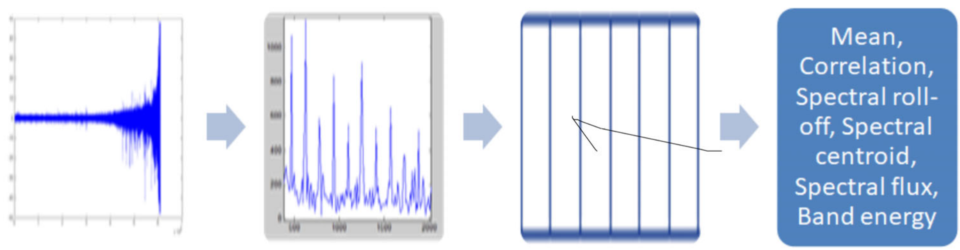
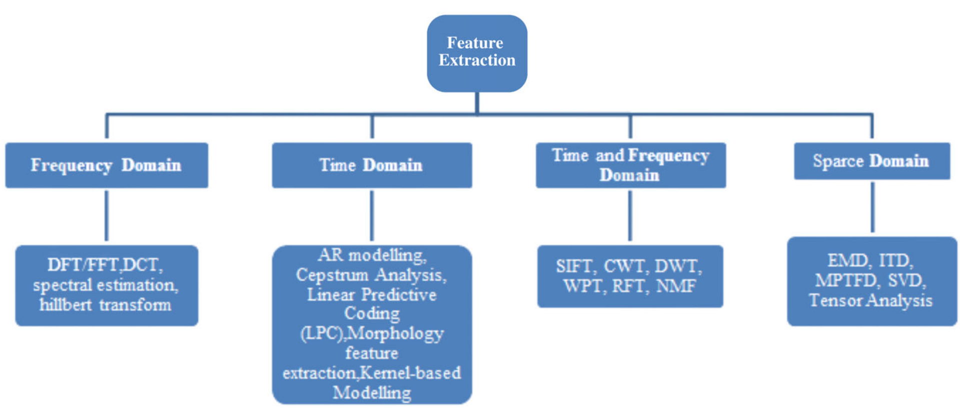


Figure 5 Feature extraction classification techniques (see online version for colours)



6 Dimensionality reduction

After feature extraction data need to be further reduced by applying reduction techniques, resulting in reduced feature vector. There are two main strategies for dimensionality reduction (Krishnan and Athavale, 2018). One is feature projection which generates reduced feature set as the best combination of original features (Zecca et al., 2002). Principal component analysis (PCA) is the most traditional linear dimensionality reduction technique, other nonlinear methods are ICA (independent component analysis), kernel PCA (KPCA), quadratic discriminant analysis (QDA), linear discriminant analysis (LDA), local linear embedding (LLE), hessian LLE can be used as feature projection method which projects data onto the eigen vectors of the covariance matrix (Bishop, 1995). It is observed that most nonlinear techniques do not outperform PCA (Van Der Maaten et al., 2009). Figure 6 shows dimensionality reduction techniques chart and Table 6 shows techniques used in recent works. There are many other dimensionality reduction methods available like Isomap (Lim et al., 2003), Gaussian process latent variable model (GPLVM) another version of kernel PCA is defined over high dimensional data space. Kernal PCA has a problem of selection of kernel function so, maximum variance unfolding (MVU) (Weinberger et al., 2007) formerly known as semidefinite embedding) solves this problem by learning the kernel matrix (Van Der Maaten et al., 2009), diffusion maps (Xu and Wunsch, 2007), local tangent space analysis (LTSA) (Zhang and Zha, 2004) can also be applied.

Figure 6 Dimensionality reduction techniques (see online version for colours)

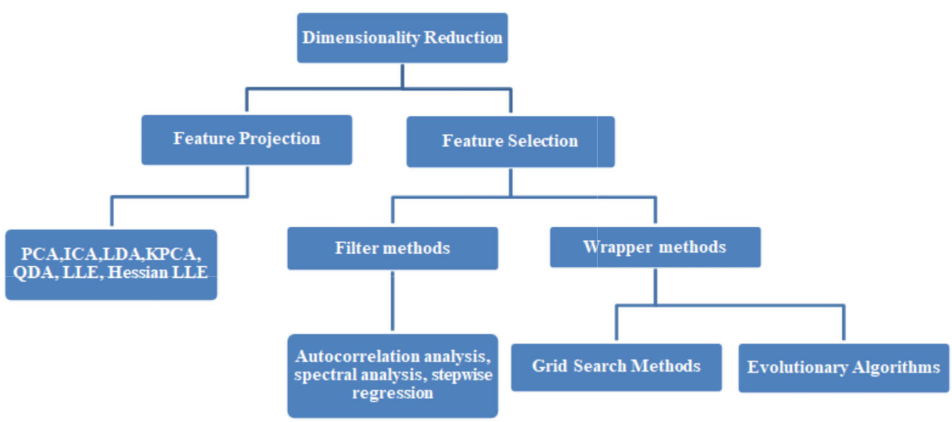


Table 6 Dimensionality reduction techniques

Dimensionality reduction techniques	*References*
PCA	Kachuee et al. (2017), Prathyusha et al. (2012) and Madhav et al. (2012)
Genetic algorithm	Miao et al. (2017)
ICA	Patil et al. (2017)
LDA,QDA	Elgendi (2016)
kernel PCA	Van Der Maaten et al. (2009)
LLE, hessian LLE	Bakir (2017)

Another method is feature selection which selects the best subset of the original feature vector (Zecca et al., 2002). Feature selection approaches can be categorised into filter methods and wrapper methods (Van Der Maaten et al., 2009; Zhang et al., 2014).

Filter methods extracts features from the data without any learning involved. These methods are computationally efficient, faster compared to wrapper methods as they do not consider classifier in account which (Zhang et al., 2014) can be a disadvantage. They are of two categories multivariate and univariate (Zena and Gillies, 2015). Multivariate methods can find relationships among features and univariate methods consider every feature separately. Different filter methods are autocorrelation analysis, spectral analysis, stepwise regression.

Wrapper methods uses learning techniques to evaluate which feature is useful and can identify feature dependencies. They are of two categories, deterministic and randomised wrapper (Zena and Gillies, 2015). Deterministic wrappers uses sequential forward selection approach which adds all possible features one by one by hill climbing approach (Zena and Gillies, 2015), grid search method (Crone and Kourentzes, 2010) and evaluate them. Features with best classification accuracy are added permanently. Randomised wrappers uses exhaustive search to find best feature subset which can be time consuming (Reunanen, 2003), e.g., genetic algorithm, evolutionary algorithms, stimulated annealing. They find smaller set of features considering optimisation criteria.

7 Machine learning techniques

After feature reduction, the reduced feature vector can be used for model formation. Different machine learning techniques are applied to create the model, which is tested and validated with the dataset and then used for classification and prediction for biomedical applications. As there are huge numbers of machine learning techniques available for applying to biomedical system. Table 7 shows the machine learning techniques used in such systems.

Table 7 Machine learning techniques

Machine learning techniques	*References*
Regression	Kumar and Anand (2006), Myintet al. (2014), Chaparro et al. (2011) and Li et al. (2018)
Regularised linear regression	Reddy and Rao (1994)
Regression	Ansermino et al. (2010), Kumar and Anand (2006), Myintet al. (2014), Chaparro et al. (2011) and Li et al. (2018)
Multivariate linear regression	Rav et al. (2017)
Logistic regression (LR)	Bari et al. (2018), Chaparro et al. (2011), Shao et al. (2014), Rostaminia et al. (2017) and Pandey (2017)
L2-regularised logistic regression	Ghosh et al. (2018)
LR, DT regression, nonlinear (AdaBoost, RF) regression	Kachuee et al. (2017)
Logarithmic model, exponential arterial elasticity model least square method	Kim et al. (2015)

Table 7 Machine learning techniques (continued)

Machine learning techniques	*References*
Support vector machine (SVM)	Jain and Kanhangad (2018), Li and Fernando (2016), Reddy and Rao (1994), Kachuee et al. (2017), Sanuki et al. (2017), Nakamuraet al. (2017), Chaparro et al. (2011), Shao et al. (2014), Rav et al. (2017), Katsigiannis and Ramzan (2018), Ghosh et al. (2018), Ragot et al. (2018) and Pandey (2017)
Hidden Markov models (HMM)	Jain and Kanhangad (2018) and Bi et al. (2016)
Gaussian Markov model (GMM)	Jain and Kanhangad (2018) and Lu et al. (2012)
Download	Li and Fernando (2016) Sun et al. (2017), Brugarolas et al. (2015), Bi et al. (2016), Garcia-Ceja et al. (2016) and Radu et al. (2017)
Source	
PDF	
Actions	
Copy Project Word Count	
Sync	
Dropbox	
Git	
GitHub	
Settings Compiler TeX Live version main document spell check auto-complete auto-close brackets code check editor theme overall theme keybindings font size	
Font family line height PDF	
Viewer help	
Show hotkeys documentation	
Contact Us	
Paper	
Editor mode.	
32	
Decision tree-based algorithm	
Naive Bayes (NB)	Sun et al. (2017), Garcia-Ceja et al. (2016), Pandey (2017) and Neitzel et al. (2017)
Bayesian network (BN)	Sun et al. (2017)
Random forest (RF)	Sanuki et al. (2017), Sun et al. (2017), Ghosh et al. (2018) and Radu et al. (2017)
Linear chain conditional random field model	Bari et al. (2018)
Artificial neural network (ANN)	Jain and Kanhangad (2018), Reddy and Rao (1994) and Tosic and Frossard (2011)
Deep neural network (DNN)	Rav et al. (2017)

Table 7 Machine learning techniques (continued)

Machine learning techniques	*References*
Autoregressive models (AR), autoregressive moving average models (ARMA), autoregressive models with exogenous input (ARX)	Chaparro et al. (2011)
DBSCAN clustering	Li et al. (2018)
Multimodal deep learning	Radu et al. (2017)
Time series regression model, pooled panel data regression model, pre clustered personalised regression mode, SVM, DT, RF	Li and Fernando (2016)
Incremental merge segmentation algorithm	Sano and Picard (2013)

Machine learning techniques use training data for discovering hidden patterns, build model and then use the best model to diagnose diseases. Some well known algorithms like SVM, random forest, hidden Markov model, Bayesian network, Gaussian network are used extensively these days. In the recent work it is seen that SVM is used extensively because of its performance but it is a black box if not used carefully can create false discovery. Selection of number of attributes is important because it may lead to overfitting. Choice of attributes is also very important as the classifier we are building must use relevant features, ideally should be independent and should not contain confounding variables.

8 Research challenges and future directions

In biomedical health monitoring systems, various signal processing methods used in the research work are shown in the paper. For revolutionary application development in this domain involve research challenges and can be improved by incorporating changes in the system development which are discussed as follows:

1. Sampling rate: selection of sampling frequency is challenging. Sampling rate is tried to keep as high as possible to capture all relevant frequencies. Higher sampling frequencies results in an increased rate of computational load and higher energy consumption. Undersampling can lead to loss of information and oversampling can generate noise. Higher sampling rate is difficult to achieve for that resampling can be performed (Orfanidis, 1995). So appropriate sampling rates along with next other parameters selection is required to achieve good accuracy of results. Computational complexity can be evaluated for signal processing algorithms and its relationship with sampling rate is determined to decide the sampling rate for the application (Tobola et al., 2015).
2. Window size: difficult to choose window size and can be chosen manually based on sinusoidal features in the signal like frequency, peak amplitude, phase trajectories. It can also be decided based on classification method going to be used in the system. It is important for improving accuracy of predictions. Shibli Nisar and Tariq (2016) has proposed a method which can adaptively selects window size from narrow band

signal without prior information about the input signal and can be applied in biomedical signal analysis domain.

3 Segmentation method: segmentation method selection is challenging as it is splitting the signal cycle and choosing the actual points in real stream data (Orfanidis, 1995). Selection of all above discussed parameters sampling frequency and segmentation with proper window size and its effect on classification accuracy is one of the most discussed topics in biomedical engineering. Best parameter selection is needed to get best classification accuracy. Investigations shows that in parameter selection for signal data pre-processing, choice of classification method is most important parameter followed by segmentation method, window size and finally sampling frequency (Bersch et al., 2014). New advance online segmentation methods can be used for improving accuracy of results.

4 Filtering method: another important parameter is filtering method selection as it improves signal quality that is removal of noise in the signal. Andreas Tobola et al. (2015) have given Bachmann-Landau notation which is used to compute the computational complexity of the filtering algorithm so that the sampling rate can be decided. Aim is to reduce it for low battery consumption and can be reduced for low computational complexity algorithms. So that the filtering algorithms show linear, quadratic, cubic and logarithmic dependency with sampling rates and accordingly the algorithms can be chosen. Filtering algorithms with linear behaviour with sampling rate can work best for the biomedical system. New advance filters can be also be identified to be used in this domain, to get good signals and at the same time reducing sampling rate, energy consumption and improving classification accuracy. Many advanced signal processing techniques like adaptive ltering, EMD, ICA or time-frequency analysis can be used to improve SNR (signal to noise ratio).

5 Extraction method: real world biomedical applications comprise of multi model components and signals are nonlinear, non-stationary. Most of the feature extraction methods used so far works well with non-stationary data with windowing approach which may lead to loss of information, low signal to noise and distortion ratio (SNDR). Therefore it challenging to use appropriate feature extraction technique and has a huge research directions for implementing them in building wearable systems in the world of biomedical signal processing.

For improvement on feature extraction methods, intelligent methods could be developed which can make use of streaming or on the fly approaches for extracting features by using sparse representation in signal acquisition process and signal compressive approaches. This will make system faster and also sparse representation will make system consume less memory space. Real world biomedical signals are nonlinear and non-stationary and contain multimodel components and multi domain (local and global) features and methods should be developed to handle it. Deep learning approaches can also be used for good results for feature extraction by using cascaded wavelets (Krishnan and Athavale, 2018). Practically a feature extraction method should be with low computation cost and robust enough to handle changed device or signal source. Deep neural networks can be used to handle it. New nonlinear modelling techniques should also be explored for promising results.

Intelligent feature extractor can be used with minimum redundancy and maximum representation which can eliminate need for separate feature selection. These extracted features can be coupled with clinical features and metadata also for better pattern learning. Domain expert's knowledge and experience in feature extraction design can play important role in smart system building as feature selection or extracted features are the basis for pattern generation.

6 Dimensionality reduction: after extracting features processing is required to reduce volume. It is observed that nonlinear techniques of dimensionality reduction like ICA, KPCA, LDA, QDA, LLE and hessian LLE do not outperform linear methods like PCA. The novel method can be developed which should give optimised results and should be computationally feasible. Choice of attributes for dimensionality is important as they should be medically relevant features. Also above all conventional methods of dimensionality reduction assumes signal to be under normal distribution and noiseless but in practice signal corruption problems might be inefficient, so sparse representation along with PCA, ICA conventional approaches can prove best for this problem.

7 Classifiers: typical biomedical system includes less number of subjects and the classifiers need to be developed on larger datasets. Classifiers often use entropy or wavelet coefficient of biomedical signal for training, hence the classifier should be trained on medically relevant features and huge dataset for better pattern learning.

Also extensive validation of the work is of high importance for improving the quality of biomedical application by improving the accuracy of the classifier used. The classifier performance can be improved by choosing all above appropriate parameters. Data exploration analysis techniques can be also be used for selection of attributes which can ultimately affect classifier performance. Deep learning approach can generate features automatically with less human intervention and can also be used as trainable classifier as well.

8 Machine learning techniques: today when there is a need for building revolutionary biomedical applications in healthcare it is challenging to make use appropriate advance machine learning approaches. Deep learning approaches holds promising future. Deep learning approach in biomedical signal processing is done mostly on brain encoding and anomaly classification (Min et al., 2016) to diagnose disease, so having scope for exploring it for many more applications in this domain. Although deep learning can suffer problems of imbalance data, interpretation of results, selection of architecture and hyperparameters (Min et al., 2016) still if these parameters are chosen appropriately can generate outstanding results.

In terms of learning methodology semisupervised and reinforcement learning's are also eye capturing. Semi supervised learning's are using both labelled and unlabeled data and can be used in wearable healthcare applications for learning the user pattern and labelling the missing events or labels. Reinforcement learning resembles human behaviour learning and has a great promise in artificial intelligence (Arel, 2012). Currently this approach is limited to robotics (Cutler and How, 2015) and game playing (Silver and Huang, 2016).

Machine learning and data analytics techniques are evolving highly which can give interesting human health patterns and analytics. There is a need to develop innovative healthcare systems, collect huge data over time for valuable knowledge generation using advanced techniques like deep learning, time series methods. So more research and development efforts are needed to healthcare automation. Overall biomedical signal processing system with best performance and reliability is the future although they have challenges in making use of these systems in terms of accuracy of results, speed of results and privacy of the information collected for the patient.

9 Conclusions

In this paper we have presented a survey on sensor based health monitoring systems. The biological signals generated from the sensors can be used for monitoring physiological parameters of the body. This paper focuses on recent healthcare applications developed and the non-invasive, wearable sensors used. The generated signals are noisy and needs pre-processing before feature extraction. This paper gives the complete activity flow of biomedical signal processing systems at one place by categorising and enlisting the signal pre-processing techniques like sampling, segmentation, filtering, features extraction, data reduction and machine learning techniques applied in the recent works, giving research challenges and future directions for utilising new techniques for further improvement in building biomedical health monitoring systems.

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