Key Techniques and Challenges for Processing of Heart Sound Signals

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Abstract. Recently, new advances and emerging technologies in healthcare and medicine have been growing rapidly, allowing for automatic disease diagnosis. Healthcare technology advances entail monitoring devices and processing signals. Advanced signal processing and analytical techniques were effectively implemented in numerous research domains. Thus, adopting such methods for biomedical signal processing is an essential study field. The signal processing techniques are explicitly applied to heart sound (called phonocardiogram or PCG) signals as part of biomedical signals for heart health monitoring in this paper. The automatic detection of life-threatening cardiac arrhythmias has been a subject of interest for many decades. However, the computer-based PCG segmentation and classification methods are still not an end-to-end task; the process involves several tasks and challenges to overcome. The conducted evaluation scheme of the classifier also has a significant impact on the reliability of the proposed method. Our main contributions are twofold. First, we provided a systematic overview of various methods that can be employed in real applications for heart sound abnormalities. Second, we indicated potential future research opportunities. PCG segmentation

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is critical, and arguably the hardest stage in PCG processing. Basically, basic heart sounds can be identified by detecting the offset R-peak and T-wave in the ECG signal. Unfortunately, utilizing the ECG signal as a reference to the PCG segment is not always an easy operation because: it requires synchronous recording of ECG and PCG signals; precise identification of T-wave offset is often difficult; and ECG-PCG temporal alignment is not always consistent. Using machine learning methods in PCG segmentation involves multiple types and many features retrieved in both univariate or multivariate formats. This leads to selecting the best PCG-segmentation performance feature sets. PCG segmentation approaches that use featureless methods based on powerful statistical models have the potential to solve the problem of feature extraction and minimize the total computational cost of the segmentation approach.

Keywords: Cardiovascular diseases · Machine learning · Bio-signal · PCG · Classifier · Segmentation

1 Introduction

Cardiovascular diseases (CVDs) remain the top leading cause of death worldwide. According to the latest world health organization (WHO) statistics, 17.7 million people die annually from CVDs, approximately 31% of all deaths worldwide. WHO had forecasted that by 2030, almost 23.6 mil-lion people would die from CVDs, mainly from heart disease and stroke [40]. In 2016, WHO and partners launched a new initiative aiming to reduce the global threat of cardiovascular disease, including heart attack and stroke. One of the three main packages aimed by this global initiative is the reduction of heart attacks and strokes can be made through equitable and cost-effective healthcare technical tools. Eventually, for most heart disease cases, the existing approach may come up with a more complex and expensive solution because the patient has already been in a high degree of danger. The heartbeats are generated as a result of systematic electromechanical activity within the heart muscle. Two signals are produced as a representation of the heart's electromechanical activity (see Fig. 1). Electrocardiogram (ECG) is a measure of the heart's electrical activity, whereas a phonocardiogram (PCG) is used to represent the mechanical activity of the heart valves.

Both ECG and PCG are non-invasive tests that play important roles in heart abnormality detection; however, diagnosis based on ECG signal or PCG signal alone cannot detect all cases of heart symptoms. In other words, the ECG signal is assumed to be a more efficient diagnosis tool than PCG. There are heart defects that cannot be detected using ECG but can be detected with PCG; mainly the problems are related to heart valves and heart murmurs. Moreover, PCG could reveal some heart abnormalities before they can be manifested on the ECG graph.

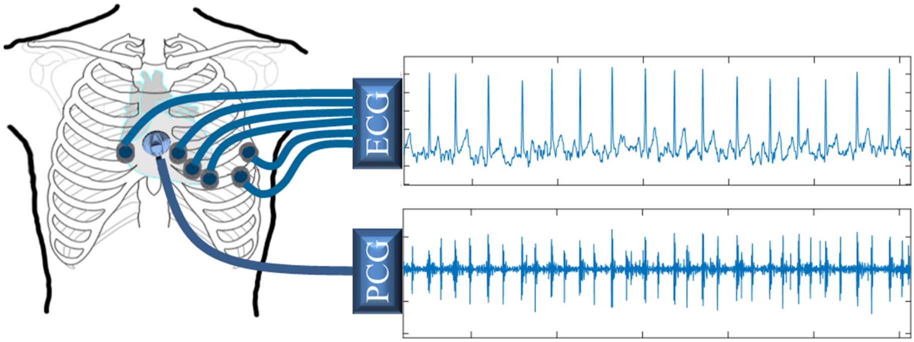

Fig. 1. Example of a single lead ECG recording and single-channel heart sound (PCG) signal. Both signals are recorded using Meditron Welch Allyn digital stethoscope.

2 Background

Throughout this paper, the electrical and mechanical activities are the primary research subjects. Accordingly, a brief review of the heart anatomy and physiology is introduced in this section.

2.1 The Heart Muscle Structure

The cardiovascular system (CVS) consists of the heart, which acts like the blood hub in the human body, and the blood vessels network that distributes the blood to the body organs. The heart is the main station of the CVS, where an exchange of oxygenated (from lungs) and deoxygenated (from body organs) blood happens and redistributed in a cell-to-cell basis in the human body [14]. The four chambers of heart are built from special cells called the cardiomyocytes. Besides the cardiomyocyte cells, the heart also has some unique cells named the cardiac pacemaker cells, which act as an electrical supply for the heart to keep beating.

2.2 Basic Components of PCG

The normal heart contracts periodically, making an average of 70 beats per minute. Each beat is a full cardiac cycle and a result of a series of contractions in different parts of the heart muscle. The human ear translates the two major sounds of the heart as "lub dub" sounds, where the lub sound is the first sound that is caused by the opening and closure of tricuspidmitral valves. On the other hand, the dub sound is a result of the opening and closure of pulmonary-aortic valves. In between these two sounds, the heart normally remains silent or produces a very low sound.

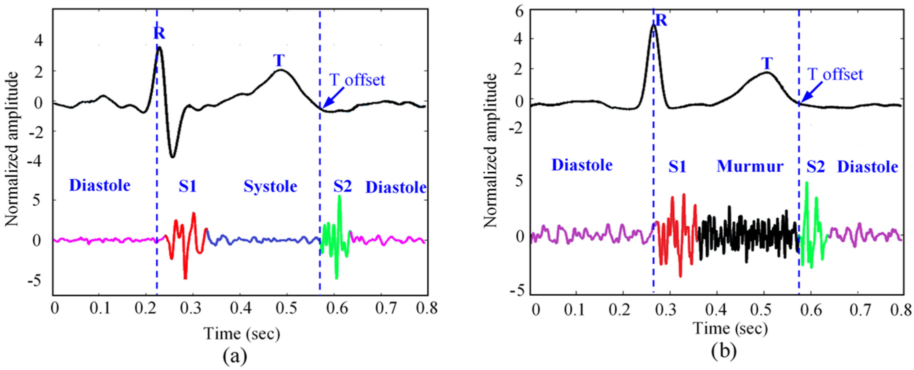

Fig. 2. The heart electromechanical activity in the form of ECG and heart sound (PCG) signals. Show-ing the fundamental heart sound (PCG) components along with the reference ECG graph. (a) Shows an example of normal heartbeat (record a0068 from [9]), (b) shows an example of abnormal heartbeat (record a0002 from [21]).

Figure 2, shows examples of normal and abnormal PCG heart-beats, respectively. A single cardiac cycle is divided into two phases, diastole and systole. The diastole is the period of time when the blood flows from the atria to ventricles; in this case, ventricles are in relaxing mode (not contracting). The systole represents the period of time in which the ventricles contract pushing the blood into the aorta and pulmonary artery. Between these two intervals, the two major sounds of heart (lub-dub), formally known as S1 and S2 sounds, occur. One of the main concerns of the researchers working in this area is to understand the abnormalities of the heart valves in cases where the backflow and the effect of the forward blood movement in the heart cycle stages.

3 PCG Preprocessing

The PCG is an acoustic signal, and it is more likely to be contaminated with various types of surrounding noises, especially in clinical environments. A normal heartbeat contains two fundamental heart sounds, S1 sound and S2 sounds separated by silent intervals. These silent intervals are called systole interval (the interval from the end of S1 to the beginning of S2 sound) and diastole interval (the interval from the end of S2 to the beginning of subsequent S1 sound). For abnormal heartbeats, additional sounds (called murmurs) are manifested in the silent intervals, in which the type of murmur is always referred to as a systolic or diastolic murmur.

During the early stages, the low amplitude murmur sound could be easily buried in noise. The presence of noise will increase the possibility of false alarms occurring in automatic diagnostic systems. Furthermore, PCG may show some innocent murmurs, which leads the primary care physicians and expert cardiologists to misdiagnose the heart status using a simple stethoscope. False alarms must be avoided in any automatic processing of PCG signals. Two possibilities may occur to the patient under test with false alarms. The healthy patient is sent for an echo-cardiogram that is costly and not easy to reach at any time. The pathological patient is sent home without medication or treatment [11].

4 PCG Segmentation

The identification of fundamental components of PCG signals is an essential step towards the automatic analysis of heart sounds. The process involves the localization of the main heart sounds, S1 and S2 sound, followed by boundary detection of these sounds. The segmentation allows the automatic analysis method to explore the intra-beat segments (S1, systole, S2, and diastole) characteristics which could be used for abnormality detection and heart disease diagnosis. Several approached of PCG segmentation have been reported in the literature, which can be grouped into four categories, for example, but not limited to; (1) envelope-based methods, (2) decomposition methods, (3) time-frequency methods, (4) machine learning-based methods. Category (1) and (4) may share a similar methodology; for example, the machine learning approach was built based on envelope features. Some of the recent PCG segmentation will be briefly discussed in this section.

4.1 Envelope-Based Methods

PCG segmentation using the popular envelope-based approach is addressed. The Shannon and Hilbert procedures are two examples of energy envelope-based approaches that are extensively employed. With regard to accuracy of PCG classification, both systems offer advantages and limitations. It is generally difficult for the Shannon type to capture the nuances of PCG signals, but the Hilbert type has many burrs and is unsmooth. As a result, segmentation is a difficult process to complete in the PCG study. Identification of the cardiac cycle is the most critical stage in PCG signal analysis. During a cardiac cycle, the heart produces four different heart sounds. It is the initial (S1) and second (S2) heart sounds that can be heard that are the most basic. With PCG segmentation, the goal is to detect as accurately as possible the positions of S1 and S2, which will allow for the estimation of the cardiac cycle to be performed. The ECG is used by the majority of segmentation algorithms. The ECG and PCG signals are not available at the same time, which is a disappointment. If you use the envelope-based methodology, you compute the energy enveloped by applying the S-transform on the PCG signal, and you can choose between the Shannon or Hilbert types. It is possible that others will employ the empirical wavelet transform for this segmentation as well. As a result, using the energy enveloped model, it is possible to predict the cardiac cycle.

4.2 Decomposition-Based Segmentation Methods

PCG signals are usually segmented based on their time-domain characteristics. Tang et al. [37] proposed a dynamic clustering-based method for segmenting heart sounds. In this method, the short-term cycle frequency spectrum was used to compute the instantaneous cycle frequency (ICF); the ICF was then used to segment the PCG signal into cardiac cycles (heartbeats). These cardiac cycles were then decomposed into 38 time-frequency atoms using Gaussian modulation model. Then compute the weighted density function using Gaussian density kernel estimation to emphasize S1 and S2 sounds in the time-frequency domain. The second-order derivative of the density function was employed to find the peaks (hills) to create dynamic clusters for the involved atoms. Finally, some frequency, timing, and energy constraints were applied for locating the atoms that represent S1 and S2 sounds; other thresholds and level-set method were used to find the boundaries of S1 and S2 sounds. The method was evaluated on a self-collected database containing only 565 cycles in total. Figure 3 shows Example of PCG signal with viola integral envelop. The data was collected using iStethoscope iPhone application.

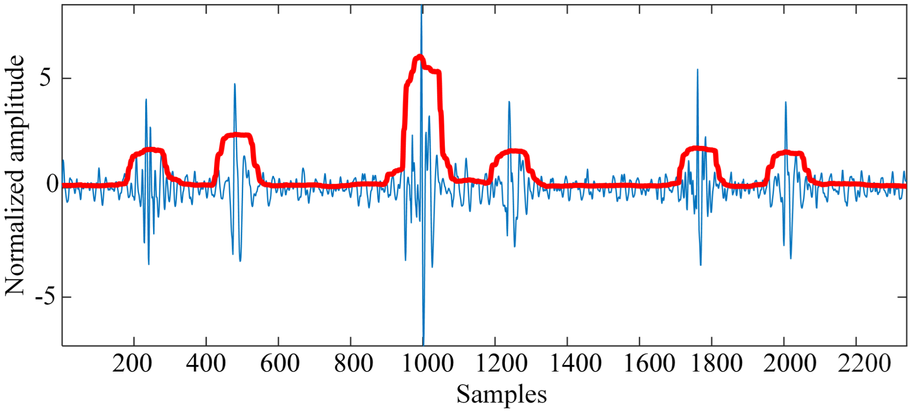

Fig. 3. Example of PCG signal with viola integral envelop. The data was collected using iStethoscope iPhone application.

4.3 Time-Frequency

Time-frequency representation methods also provide some contributions in the direction of heart sounds (PCG) segmentations. Gavrovska et al. [13] presented the use of Wigner-Ville distribution (WVD) for time-frequency representation of PCG signals. Two features (criteria) involved recognizing S1 and S2 viz, the maximum (peak) of the envelope with the detected margins and the duration between current and next candidate sound. Finally, k-mean clustering with city block distance was used to classify the candidate sounds into three classes, S1, S2, and others.

4.4 Probabilistic Models and Machine Learning-Based Methods

Probabilistic and Machine Learning (ML) methods can learn the underlying characteristics of the PCG components; hence, building discrimi-native models that can be used in segmentation, clustering, or classification purposes. Schmidt et al. [34] proposed a breakthrough application of duration-dependent HMM (called DHMM, also known as, hidden semi-Markov model (HSMM)) on PCG segmentation. In standard Markov models, each PCG component is referred to as a state. Some probabilistic rules control the jump from one state to another regardless of the duration of time a particular state remains unchanged. This may lead to rapid jumps between states, hence misdetection of PCG components. Schmidt et al. addressed this problem using labeled S1 and S2 sounds databases; a rough average estimation of the heart sounds duration was found from this database. In the DHMM training phase, multivariate features were extracted from PCG signals including, homomorphic envelogram, STFT energy of band 25–50 Hz, 50–100 Hz and 100–150 Hz.

Springer et al. [36] made extensive attempts and other researches to further improve the performance of HMM for PCG segmentation. Authors investigated the use of different types of features from PCG signals, including Hilbert envelope, DWT-based envelope, and short-time PSD envelope. The procedure is similar to the one using HSMM, except instead of using Gaussian distributions, the emission probabilities of the HMM were derived using SVM. The method was evaluated and compared with [34] on the normal and pathologic database. The performance showed an improvement of 2% when using the modified HSMM. In contrast, the features are not showing a significant improvement in the performance.

5 PCG Feature Extraction

Feature extraction is a fundamental step in PCG signal processing which is carried out to convert the raw data to some distinctive parametric representation. This parametric representation, called a feature, was then used for further analysis and processing [20]. Several methods and approaches are presented in the literature for feature extraction aim to achieve effective PCG classification performance. There is no feature set that can be said to be an optimal representation of the PCG signal diverse characteristics. The review was only conducted on a sample of methods in the literature over the past few years, and it is obvious the wide options of feature extraction methods from PCG signals. However, the MFCC and wavelet transform-based features are the most widely used for HS classifications, and the results presented recently in the literature have demonstrated their effectiveness. Another recently proposed PCG deep feature extraction method [43] is also worth to be further explored and investigated on their effectiveness with more real noisy PCG data, especially pathological PCG data. Some methods may result in a huge number of extracted features, which is impractical and may lead to classification overfitting. Therefore, feature selection or reduction approaches are utilized to solve this issue, some of the previously proposed methods are also reviewed in the following sub-sections. The feature extraction methods from PCG signals can be categorized into four domains: time domain, frequency domain, time-frequency domain, and a mixture of domains. Most of the methods required to perform PCG segmentation prior to the feature extraction process, in which features are extracted from specific intervals within the cardiac cycle or globally from the whole cardiac cycle. A cardiac cycle represents the complete heart mechanical activity in a single heart-beat which consists of S1, S2, and other sounds like S3, S4, and murmurs.

6 Classification Models and Performance Evaluation

Automated PCG analysis has been widely studied during the past few decades. The typical methods for PCG classification can be grouped into six categories: (1) SVM-based classification; (2) Artificial Neural Net-work-based classification; (3) Statistical Tests-based classification; (4) Deep Learning-based classification; (5) Ensemble of classifiers; (6) others including probabilistic and clustering methods. Building on previous review articles, which can be found in [8,21,25] some of the reported studies which involve using a considerable database are discussed briefly in the following sub-sections.

6.1 SVM-Based Classifiers

SVM is the acronynm for a single-layer nonlinear network. It first trans-forms the data into higher-dimensional space using some specialized kernel transformation functions. Then it uses the distance metric to create a boundary between the data groups in which this distance is simultaneously maximized. SVM has been widely used for PCG signal classification and is a well-studied machine learning approach. It has been provided through well-tested libraries and toolboxes, i.e. library of support vector machine (LibSVM) and MATLAB. In addition to linear classification, the SVM has the ability to handle a large number of features by efficiently performing a non-linear classification using what is known as the kernel functions, implicitly mapping their inputs 2D features space into high-dimensional feature spaces enabling accurate classes discrimination. How-ever, SVM has various types of kernel functions, each of which uses some hyperparameters. The kernel function and hyperparameters have to be carefully selected and tuned to achieve the best classification performance.

It is worth to note that, there are three publicly open sources of PCG database; (1) Michigan Heart Sound and Murmur database (MHSDB) was provided by the University of Michigan Health System. MHSDB includes only 23 PCG recordings with a total of 1496.8 s duration. (2) PASCAL challenge database, a total of 832 recordings with varying lengths, between 1 s and 30 s. (3) Physionet CinC challenge 2016 database, contains a total of 3,126 PCG recordings, lasting from 5 s to 120 s. The Physionet CinC is the current largest open source database, which includes clean and very noisy, normal and pathologic, children and adults' recordings. The database comprises of normal and abnormal classes with some PCG recordings labeled as "unsure" which has low-quality heart sounds.

6.2 Artificial-Based Neural Network Based Classifiers

In recent years Machine Learning (ML) techniques have emerged for their notable predictive abilities in a number of fields such as anomaly detection [5,12,41,42], biological data mining [23,25], cyber security [24], disease detection [7,26,29,30,33] and classification [6,10,22,35], earthquake prediction [1,2], elderly care [16,17], elderly fall detection [3,4,27], financial prediction [31], safeguarding workers in workplaces [19], text analytics [32,39], and urban planning [18]. Out of these number of different methods, the artificial neural network technology has been widely adopted for PCG classification. An example is a recurrent neural network (RNN). The RNN is a multilayer neural network in which the output of some or all layers do not only depend on the current input but also the previous output is looped back and reused as extra input. RNNs can be configured in two designs namely, fully connected or partially connected.

6.3 Statistical Tests-Based Classification

There are 2 types of statistical tests-based classifiers, namely the Hidden Markov Model (HMM) and the Gaussian Mixture Model (GMM).

6.4 HMM-Based Classifiers

HMM are the time-averaged signal recorded during each measurement of the heart and is assumed to be representative of some hidden state. This hidden is not directly observed, is assumed to undergo a Markovian process that is governed by statistical models.

6.5 GMM-Based Classifiers

Gaussian Mixture Model is a probabilistic model. The database consisting of abnormalities is assumed to be generated by the Gaussian processes inside the heart having arbitrary stochastic distribution. The classification technique is based on the ECG signal extraction using specific algorithm.

GMM classifier is a basic supervised method which has the ability to automatically cluster the data into a limited set of overlapped clusters. In training, two Gaussian mixtures were used to represent the normal and diseased datasets. The Gaussian parameters (mean, covariance, weights) were estimated iteratively using an expectation maximization algorithm. In testing, the same feature vector from the test ECG heartbeats was used to find the fitted Gaussian parameters, the likelihood was calculated and com-pared with the already built GMM models. The main limitation of GMM based methods is that the number of mixture models must be determined manually, which forces the GMM to cluster the data into a limited number of clusters, which is highly dependent on the correlation of the input data.

6.6 Deep-Learning-Based Classifiers

Over the last few years, deep learning was getting more attention due to its ability to learn and perform classification tasks from raw data directly. Re-cent studies showed that deep learning methods were achieving results that were not possible before, sometimes surpassing human-level performance. PCG classification approach is based on the convolutional neural network (CNN). A CNN is employed as a feature extractor, and features extracted by the CNN are input into a heart-sound classification SVM. Time-frequency features are put into a CNN model to classify normal and abnormal cardiac sounds. Deep-learning architecture has a sequential mode employing a linear layer stack, namely one input layer, and numerous dense layer. Layers' aim is to transform data. PCG segmentation is performed using fixed-length segments with one step from each recording. For each segment, a PSD-based spectrogram was recovered using STFT, and the spectrogram was regarded as the CNN model feature input. The proposed CNN structure consisted of five-layers: input, convolutional with max-pooling, two fully connected layers and output layer. The Physionet training database was first transformed to an overlapped (5-second) PSD spectrograms; the CNN treated these spectrograms as images in the input layer. The CNN model was then trained with stochastic gradient descent using an optimizer, while the output layer contained a single neuron with sigmoid activation function. The system was designed to classify each 5-second segment whether it belongs to a normal or abnormal class.

Ensemble of Classifiers. Homsi et al. [15] used a nesting of three ensemble classifiers: Random Forests (RF), Logit-Boost (LB), and a cost-sensitive classifier (CSC). Each recording in the Physionet database was first segmented by identifying the fundamental heart sounds (S1, systole, S2, and diastole). A total of 131 features were then extracted from time, frequency, wavelet, and statistical domains. The study investigated the tuning of different parameters involved in meta-classifier in an attempt to improve the overall classification accuracy. 10-fold stratified cross-validation was used to partition the Physionet database into train-test sets to evaluate the proposed classification approach. The method achieved a MAcc score of 88.4% on 10-fold test-ing set and MAcc of 84.48% on Physionet hidden test set.

Vernekar et al. [38] proposed a PCG classification method using a weighted ensemble of four XGBoost (extreme gradient boosting) and four ANN classifiers. The Physionet heart sound database was used in this study, ignoring the recordings labeled as noisy. The rest were split into 2615 recordings for training and 296 for validation. The annotations for four heart sound components (S1, systole, S2, diastole), for each heartbeat, were then obtained using Springer's HSMM segmentation algorithm [36]. A total of 108 features were extracted from the time domain, frequency domain, and Markov chain analysis. However, feature importance analysis selected only 36 features to train the classifiers. The proposed method achieved MAcc score of 81.75% on the validation set and MAcc of 77.2% on Physionet hidden test set.

7 Future Work

ECG and PCG are two easy-to-use non-invasive tools for monitoring heart electromechanical activity. Despite the amount of research proposed in the literature, the performance of automatic diagnosis of heart disease is still not satisfying to be implemented in clinical systems. However, the current methodologies could be used in primary healthcare units or at home as the first screening tool and diagnosis tool. This will provide great assistance to help physicians to perform a correct and final diagnosis. The ECG and PCG signals analysis are not end-to-end processing but usually ensembles various methods for each processing step. In general, the state of the art on techniques oriented to the use of neural networks and deep learning should look into for example, classification methods through the use of networks with low computational complexity without domain transformation and with or without feature extraction.

Deep learning methods besides showing promising results also has its disadvantages such as there are numerous parameters of the deep learning model, with a large amount of data to be optimized which can lead to a long execution time and a large training data set required. Moreover, the deep learning modelling needs higher configuration of the computer with powerful CPU and GPU for calculation; hence the model is unsuitable for home computers and microcomputers. Existing deep learning research using only ECG data from multiple perspectives and highlights the present challenges and problems to identify potential future research directions. There are too many different learning architectures that has been used in areas such as disease detection/classification, annotation/localization, sleep staging, bio-metric human identification, and denoising. The deep learning model for disease detection is to map input ECG data to output disease targets through multiple layers of neural networks. Detection of cardiac arrhythmias (e.g., atrial flutter, supraventricular tachyarrhythmia, and ventricular trigeminy) is one of the most common tasks for deep learning models based on ECG signals. However, there are still some unresolved challenges and problems related to these deep learning methods.

Simultaneously analyzing multivariate time series from the same source provides insight into exploring the intersection of underlying dynamics in cardiovascular signals. Simultaneous PCG data recording at multiple auscultation points on the chest area with multiple sensors is more beneficial in terms of diagnostic accuracy since the results from a single HS signal can be cross-referenced with those obtained from other locations. In fact, the introduced SLDS methods in [28] were used for multivariate data analysis and modeling in the literature. Hence, these methods are assumed to provide higher performance if applied to multivariate PCG data, i.e., PCG segmentation application. This research was constrained by using univariate HS data because currently there is no existing clinically approved technology for multivariate HS data acquisition from different heart auscultation points. The recently published benchmark database (Physionet CinC challenge 2016) does not consist of a precise diagnosis of the whole large provided dataset. The accurate automatic diagnostic systems of the multi-class problem are needed, which would help cardiovascular monitoring and pre-screening.

8 Conclusion

In this paper, we provided a systematic overview on the state-of-the-art studies conducted in the last two years on new techniques for classifying cardiac pathologies using ECG/PCG and machine/deep learning techniques from the perspectives of models, data and tasks in real life applications. We found that deep learning methods can generally achieve better performance than traditional methods for ECG/PCG modeling.

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