Abstract

Heart valve diseases (HVDs) are the primary causes of mortality in developing and underdeveloped countries. Early detection of HVDs is essential to avoid lethal heart diseases due to the disease's progression. Phonocardiogram (PCG) signal provides a non-invasive and cost-effective tool that helps with the preliminary diagnosis of HVDs. However, the raw PCG signals are often susceptible to noise and artifacts. It degrades the signal quality and makes it challenging to diagnose HVDs manually. Furthermore, the wide variabilities in the PCG morphologies due to HVDs exhibit manual examination, often subjective and prone to human error. To address the above challenges, this dissertation focuses on developing automated deep-learning methods for diagnosing HVDs.

First, a novel multi-component oscillatory model is proposed for reliable and accurate HVDs diagnosis. The model captures the morphological variations of the PCG cycles by fitting a half-period sine wave between two successive zero-crossing points. The model parameters, i.e., amplitude and frequency, provide discriminative features to a deep neural network (DNN) classifier to classify the PCG cycles as healthy or pathological. Second, we propose a novel acoustic feature-fusion method using Mel-frequency cepstral coefficients (MFCCs) and linear prediction cepstral coefficients (LPCCs) to classify heart murmurs (HMs). These two features are fused using a hierarchical long-short memory (HLSTM) network to exploit the temporal variation to detect HMs. Further, a self-attention module is introduced to weigh the encoded vectors of the HLSTM network based on their clinical relevance to improve the classification of HMs. Third, we propose a stationary wavelet transform (SWT) to capture the PCG patterns at coarse scales to classify HMs. Then, we propose subband-specific HLSTM networks to exploit the temporal variation across each SWT subband. Further, intra-subband and inter-subband attention modules are proposed to weigh the encoded vectors of HLSTM networks to improve the HMs classification. Fourth, a multi-kernel residual CNN (MK-RCNN) model is proposed to classify the HM severity stages. The multi-kernel CNNs with different filter sizes capture a broad range of features from the PCG segment to capture the HM patterns. The residual learning helps extract deep features from deep CNN layers without degrading the performance accuracy. The efficacy of the proposed methods is verified on various PCG databases. The proposed methods show better performance results compared to the existing baseline methods.

Keywords: Phonocardiogram (PCG), heart valve diseases (HVDs), oscillatory model, hierarchical long short-term memory (HLSTM), self-attention, residual convolutional neural network (RCNN).