Employment of Multi-Classifier and Multi-domain Features for PCG Recognition

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***Abstract*—In this paper, multi-classifier of K-Nearest Neighbor and Support Vector Machine (SVM) classifiers with multi-domain features are employed, as a proposed methodology for recognizing the normality status of the heart sound recordings (so-called Phonocardiogram - PCG). The PhysioNet/CinC Challenge 2016 offers the dataset used in this paper. Heart sounds are complex signals and required trained clinicians for diagnosis, which motivated us to develop an algorithm for automatic classification of heart sounds into two classes normal and abnormal. Entropy, high-order statistics, Cyclo-stationarity, cepstrum, the frequency spectrum of records, energy, state amplitude, the frequency spectrum of states, and time interval, are the nine-domain features employed. These domain features are extracted to a total of 527 features. These features have been used to train the K-Nearest Neighbor and Support Vector Machine (SVM) classifiers. Fine-KNN classifier outperformed types of SVM classifiers by achieving the accuracy of 93.5% while Cubic-SVM classifier achieved 90.9% which is the highest accuracy of all SVMs. The Fine-KNN classifier and the proposed features are both efficient and significant for PCG recognition.**

***Index Terms*—SVM, KNN, Phonocardiogram, PCG, Heart sound Recognition, Multi-domain features.**

I. Introduction

During the cardiac cycle, the process of recording all the sounds generated by the heart is called Phnocardiography [1]. These sounds are created, due to the interaction between the heart valves and chambers and the blood flow, as a series of mechanical vibrations [2], [3]. They offer significant early hints in the evaluation of the heart disease for extra analytic testing [4]. Moreover, one of the important roles in the detection of heart diseases in advance is achieved by listening to the heart sounds. Therefore, it is almost desirable to exploit the analysis of the heart sounds based computer. In the last 50 years, automated recognition of pathology in heart sounds is an interesting problem. Nevertheless, exact recognition is still a continuous challenge question. From the research view, Gerbarg, et al [5], were the first published in the field of automated heart sound classifications. Abnormal heart sounds seem to have high frequencies as shown in Fig. 1 while normal heart sounds seem to have regular beats as shown in Fig. 2. Fig. 3 shows the difference between normal and abnormal heart sounds. Automated PCG recognition in the clinical application usually involves four steps. These steps are: preprocessing, segmentation, feature extraction, and classification, respectively. Feature extraction and classification methods are extensively examined over the last decades. Feature extraction methods include joint time-frequency domain, complexity-based, frequency domain, and time-domain features while classification methods include clustering such random forest [13], [14], [15], [16] support vector machine [11], [12] and artificial neural networking [6], [7], [8], [9], [10]. In the PhysioNet/CinC Challenge 2016, several methods

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were introduced, such as support vector machine [21], [22] tensor [20].The performance efficiency has been boosted by using FPGA [47]. In the task of heart classification, FPGA was used to speed up the process of classification in real time [48]. Deep learning has shown a great performance in medical image classification [39], [42], [46], [49] as well as heart sound classification [17], [19], [23], [40], [41], [43]. However, Deep learning methods required a lot of data for training and there is a lack of standardized PCG datasets. Machine learning algorithms have shown a great performance in medical images and health care [44], [45]. In general, frequency domain features were employed in these papers [27], [28], [29]. Also, the top general scores of PhysioNet/CinC Challenge 2016 were reported as 89% by Whitaker, et al. [27], 86% by Potes, et al. [28], and 85.9% by Zabihi, et al [29]. The authors of this paper [38][38] enhance their previous work [31] by extracting 515 features for PCG recognition which inspired us to find more features. The PhysioNet/CinC Challenge organizers collected a high number of PCG recording samples from a variety of research groups in the world.

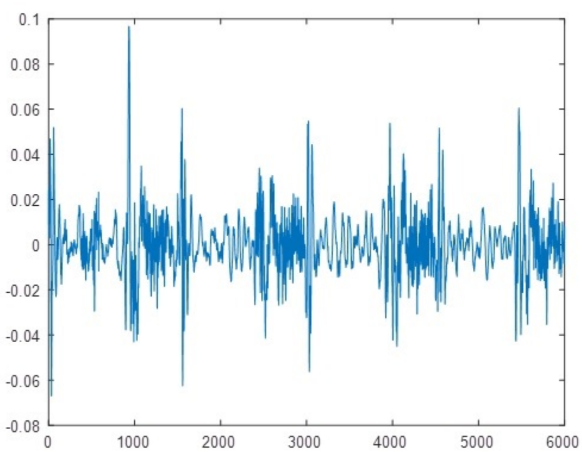

Fig. 1. Abnormal heart sounds.

In our work, the extracted features are from multiple domains, like, entropy, cyclostationarity, frequency spectrum, cepstrum, high-order statistics, energy, state amplitude, and time interval. Then, we trained different KNN and SVM classifiers for automated heart sound classification task.
The contributions of our work are: (i) Extract features from multi-domain. These features used to distinguish between heart sound classes. (ii) Train multi-classifier of K-Nearest Neighbor and Support Vector Machine (SVM) classifiers with a different set of features that we extracted. (iii) We improved the accuracy of heart sound classification and outperformed state-of-the-art methods by achieving 93.5%.

II. METHODOLOGY

Initially, this paper utilized the dataset is offered by the worldwide challenge PhysioNet/CinC 2016, which provided

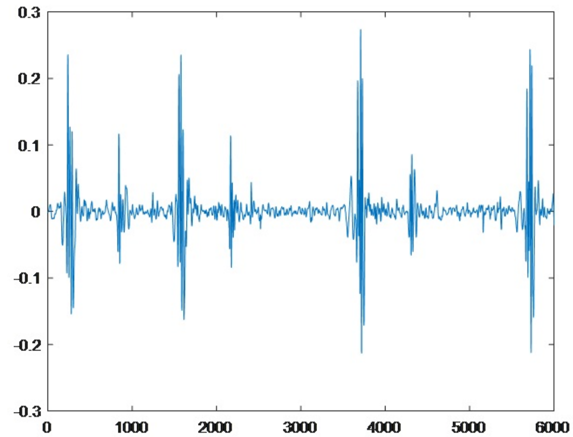

Fig. 2. Normal heart sounds.

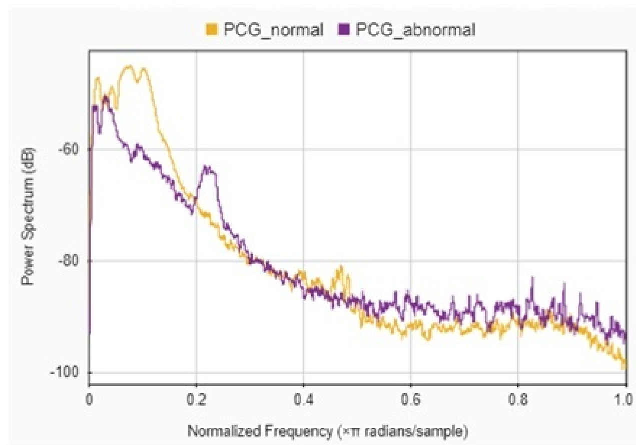

Fig. 3. The difference between Normal and Abnormal heart sounds.

a free download of the dataset from their website [32]. It involved a variety of PCG records of normal/abnormal heart conditions, collected from clinical/non-clinical locations. The dataset includes 3240 PCG records, which have a $'.wav'$ format and enduring 5-120 seconds. Preprocessing is the first step in the process of PCG classification. It involves high-pass filtering to each PCG record. The filter has a cutoff frequency of 10 Hz for removing the baseline drift. Then, the filter output is processed by a spike removal algorithm. Subsequently, the normalization process is applied based on zero mean and unit standard deviation.

The second step is the heart sound segmentation. Each record is segmented into four states by utilizing Springer algorithm, or so-called Hidden Semi-Markov model (HSMM) technique [33]. These four states are S1, systole, S2, and diastole, respectively. The third step is the feature extraction process, which is distributed in nine domains with a total of 527 extracted features. These features are stated in descending order; 320 frequency features, 65 Cepstrum features, 47 energy features, 27 spectrum features, 20 time features, 16 high-order statistics features, 16 entropy features, 12 normalized amplitude features, and 4 Cyclostationary features. Based on the available studies, the entropy and Cyclostationary are original for PCG recognition. The nine domains are listed as follows:

Frequency-domain features: For each cardiac cycle, the frequency spectrum of the state of S1 is estimated by applying a discrete Fourier transform and Gaussian window. Also, for the whole cycles, the mean frequency spectrum is calculated. The spectrum range is 30-790 Hz, with 10 Hz frequency interval. Hence, for the state of S1, 80 features are obtained. The same procedure is applied to the other three states, systole, S2, and diastole. Therefore, for the complete cardiac cycle, the total features are $320 = 80 \times 4$.

Cepstrum-domain features: After calculating the PCG records Cepstrum, the Cepstral coefficients of the first thirteen is considered as features [34]. In addition, a new digital sequence is generated by joining together all the states of S1 from the PCG record. Next, the Cepstrum of the new sequence is computed and again the Cepstral coefficients of the first thirteen are considered as features. The same procedure is applied to the other three states, systole, S2, and diastole. Therefore, additional $13 \times 3 = 39$ features are added. Hence, for the complete cardiac cycle, the total Cepstrum features are 65. It should be noted that the Cepstrum coefficients decompose rapidly. Thus, it is reasonable to consider the features as only the first thirteen coefficients.

Energy-domain features: These features comprise two elements; the energy ratio of one state to another and the energy ratio of a band-pass signal to the original signal. The first element is obtained between any two states, which gets 20 features. In Eq 1 , the energy ratio of S1 state to the whole cycle is:

$$\boldsymbol{energy_{ratio_{S1_{cycle}}}} = \frac{\sum_n |\boldsymbol{S1_i(n)}|^2}{\sum_n |\boldsymbol{c_i(n)}|^2}, \quad \boldsymbol{i = 1, \ldots, N} \qquad (1)$$

Where n = discrete time index, and N = number of cycles in PCG record. Note that the standard deviation and the average energy ratio are considered as two features. Considering the second element, a range of frequency bands are investigated (actually 27 bands). The starting value is 10 Hz and the bandwidth is 30 Hz. More specifically, the starting band is (10-40) Hz and the 27th band (last band) is (790-820) Hz. The murmurs frequency is less than 800 Hz as the previous studies disclosed. So, in this domain, the maximum frequency investigated for reflecting the murmurs properties is 820 Hz. Note that the frequency band less than 200 Hz represents the normal heart sound signal. If this frequency band contains murmurs, then, it can be extended to 800 Hz. Hence, the energy ratio indicates the distribution of the signal energy on the length of the frequency band. And these features are very useful for discriminating the presence of murmurs in the PCG records. The total is 47 proposed features.

Spectrum-domain features: Initially, Fast Fourier Transform is applied to each PCG record. As mentioned in (c), there are 27 frequency bands. Therefore, there are 27 features for each PCG record in this domain. These features are valuable for discriminating the presence of murmurs in the PCG records, because murmurs, in general, have a high frequency as compared to the normal PCG records.

Time-domain features: After the completion of the segmentation process, each PCG record is partitioned into several parts (states). These states are in sequence S1, systole, S2, diastole. Next, the time interval measuring is applied to each state by computing the time difference between the starting of each state with the starting of the next state. The time interval of the whole cycle is calculated as the time difference between the starting of two neighboring S1 states. From the heart physiological point of view, these time intervals have several physiological significances. The total is 20 features.

High-order statistics features: A measure of the real-valued random numbers around its average with an asymmetry probability distribution is called Skewness, as in probability theory and statistics. Skewness is a three-order statistics, while Kurtosis is a four-order statistics. Kurtosis is defined as a measure of real-valued random numbers concerning the 'tailedness' of the probability distribution. Both measures are taken into consideration.

Entropy features: The complexity of a random sequence can be measured by fuzzy measure entropy (FuzzyMEn) or Sample entropy (SampEn) [36], [37]. Each state is segmented by Springers algorithm for measuring its complexity using both Fuzzy measure and Sample entropy. Next, the standard deviation and the average are utilized as features. References [36] and [37] have a detailed algorithm for calculating the fuzzy measure and sample entropy.

Normalized amplitude features: According to the physiological conclusions in heart sound amplitude, there is an effective relation between the heart hemodynamics and the amplitude [1], [3]. Hence, it is valuable for extracting features from the heart sound amplitude. Also, there is not an absolute amplitude, as a reference, for eliminating the difference between records and objects.

Cyclostationary features: This domain contains four features. The first feature represents the mean value cyclostationary degree. It shows the degree of signal repetition. Ref. [35] involves the definition of the "cyclostationary degree". This feature has an infinite value if the actions which happened during heart beating were accurately cyclic. While it has minor value if the actions are arbitrarily alike. The PCG signal is uniformly partitioned into subsequence. Next, the mean value and the standard deviation are evaluated. Hence, the first two features are obtained. The third feature is the mean value of the sharpness degree. It represents the peak sharpness of the cycle frequency spectral density. So, as the peak be sharper, the feature is greater. In a similar manner, for each PCG subsequence, the feature can be evaluated, and after that, the mean value and the standard deviation are obtained.

The last step is the classification process. Typically, the signal quality classification is categorized into two-class process namely normal and abnormal classes. We divided the data into 70% for training and 30% for testing. We have trained different KNN and SVM classifiers. Both KNN and SVM classifiers have shown outstanding results in several tasks for binary classification. KNN is classifying objects based on closest training examples in the feature space. An object is classified by a majority of its neighbors. We have trained four types of KNN classifiers namely Cubic KNN, Cosine KNN, Weighted KNN, and Fine KNN. A support vector machine (SVM) is a hyperplane that separates two different sets of samples with the maximum distance of hyperplane to nearest samples from both sets. Four types of SVM classifiers which are Linear SVM, Quadratic SVM, Medium Gaussian SVM, and Cubic SVM have been used to classify heart sound.

III. Experimental Results

The classification performance was evaluated using the challenge score (MAcc) defined as the arithmetic mean of sensitivity and specificity [32]. We consider binary classification into 'normal', 'abnormal' ignoring the quality of labels. We trained and tested different types of SVM and KNN classifiers as reported in Table I. 30% of the dataset used for testing. Fine-KNN achieved the highest accuracy of 93.5% while Weighted KNN achieved the second highest accuracy of 92.2%. Cubic SVM scored the third highest accuracy of 90.9% which is higher than Cubic KNN, Cosine KNN. 90.5% and 90.7% are accuracies of Cubic KNN, Cosine KNN, respectively. Lastly, linear SVM, Quadratic SVM, Medium Gaussian SVM achieved the lowest accuracies of 87.1%, 89.9%, 90.4%, respectively. Fine-KNN outperformed different methods that applied to The PhysioNet/CinC Challenge 2016 dataset as shown in Table 2. The experiment has been done using Matlab2018a and the processor specifications used in this experiment are Intel (R) Core TM i7-5829K CPU @ 3.30 GHz, the RAM was 16 GB and the GPU was 8 GB.

TABLE I
EXPERIMENTAL RESULTS OF KNN & SVM CLASSIFIERS

Classifier	MAcc(%)
Linear SVM	87.1
Quadratic SVM	89.9
Medium Gaussian SVM	90.4
Cubic SVM	90.9
Cubic KNN	90.5
Cosine KNN	90.7
Weighted KNN	92.2
Fine KNN	93.5

IV. Conclusion & Future Work

In this paper, we extracted features from multiple domains, i.e., time interval, state amplitude, energy, high-order statistics, cepstrum, frequency spectrum, cyclostationarity, and entropy with a total of 527 features. These features used to train different KNN and SVM classifiers. The results show the overall score reaches 93.5% using Fine-KNN with proposed features, which is superior to the previous best classification methods. Furthermore, the KNN classifier has a very good performance with even a small number of features for training and has stable output regardless of randomly selected features for training. As a future work, we aim to compare the performance of machine learning methods as applied in this paper to performance of deep learning model. We also aim to classify heart beats in real time using FPGA.

TABLE II
COMPETITIVE RESULTS

Methods	MAcc(%)
B. M. Whitaker [27]	89
Potes, et al [28]	86
Zabihi, et al [29]	85.9
Fine KNN	93.5

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