STUDY OF TWO FEATURE EXTRACTION METHODS TO DISTINGUISH BETWEEN THE FIRST AND THE SECOND HEART SOUNDS

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Abstract: Most of the existing methods for the segmentation of heart sounds use the feature of systole and diastole duration to classify the first heart sound (S1) and the second heart sound (S2). These time intervals can become problematic and useless in several clinical real life settings which are particularly represented by severe tachycardia or in tachyarrhythmia. Consequently with the objective of development of a robust generic module for heart sound segmentation we propose to study two methods of extraction based on Singular Value Decomposition (SVD) technique to distinguish S1 from S2. A K-Neirest Neighbor (KNN) classifier is used to estimate the performance of each feature extraction method. The study uses a database with 80 subjects, including 40 cardiac pathologic sounds which contain different systolic murmurs and tachycardia cases. The first and the second proposed method reached 96 % and 95% correct classification rates, respectively.

1 INTRODUCTION

One of the first and most important phases in the analysis of heart sounds, is the segmentation of heart sounds. Heart sound segmentation partitions the PCG signals into cardiac cycles and further into S1, systole, S2 and diastole. In the classic approach (Ahlstrom, 2008), the segmentation algorithms can be divided into 3 parts; the first one is the localization method which consists of finding S1 and S2 without distinguishing the two from each other, the second part consists of estimating the boundaries of located sounds and the third part aims at distinguishing between S1 and S2 which is the main purpose of this paper.

Most of the existing methods in the literature use the systole and diastole duration (systole regularity) as a criterion to discriminate between S1 and S2 (Liang et al., 1997), (Dokur et al., 2007) and (Yan et al., 2009), to name a few. These methods do not perform well for all types of heart sounds, especially in the presence of high heart rate or in the presence of arrhythmic pathologies (figure 1). To deal with this problem, an unsupervised method for the discrimination of S1 and S2 using the high frequency information obtained from the Shannon energy of the detail coefficients of wavelet analysis was proposed (Kumar et al., 2011) which uses the fact that S2 in general contain higher frequency than S1. However this criterion cannot be generalized on all real life cases because some medical even normal conditions are characterize by S2 frequency content lower than S1 frequency content.

With the objective of development a generic auto-analysis module, and without any previous information about the subject, we present in this paper a supervised approach to classify S1 and S2.

Two feature extraction methods are presented. Both of them are based on the Singular Value Decomposition (SVD) technique. The first method applies the SVD technique on the S-matrix calculated by the S-Transform time-frequency method. The second one proposes the use of the Empirical Mode Decomposition (EMD) technique and the Shannon energy of the intrinsic mode functions (IMF) before applying the SVD technique. The K-Neirest Neighbor classifier is used to estimate the performance of each feature extraction method.

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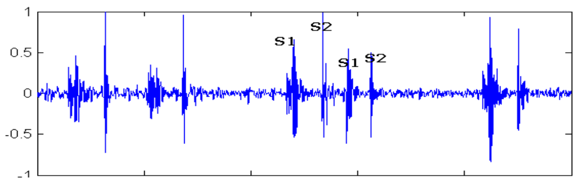

Figure 1: Example of an arrhythmic subject.

This paper is organized as following: sections 2.1 and 2.2 describe the dataset used in this study and the acquisition and pre-processing of PCG signals, respectively. In section 2.3 the localization and the boundaries detection algorithms are presented briefly, section 2.4 describes the feature extraction methods. The results and discussion are presented in section 3, while section 4. consists in conclusions.

2 MATERIAL AND METHODS

2.1 Data Set

Different cardiologists equipped with a prototype electronic stethoscope with a Bluetooth standard communication module, have contributed to a campaign of heart auscultation in the Hospital of Strasbourg. In parallel, 2 prototypes have been dedicated to the MARS500 project, promoted by ESA, in order to collect signals all two months from 6 volunteers (astronauts) in a confinement experience lasting 520 days and transmitted to IBMP station in Moscow as a real telemedicine investigation. The use of prototype electronic stethoscopes by different cardiologists makes the database rich in terms of qualitative diversity for the collected sounds and create the condition for a real life database.((.n more realistic.))

The dataset contains 80 subjects, including 40 cardiac pathologic auscultation sounds which contain different systolic murmurs and tachycardia and or arrhythmia cases. Each recorded auscultation corresponds to one patient. The length of each recording lasts between 8 and 12 seconds which represents generally the time of tolerated apnoea.

2.2 Acquisition and Pre-processing of PCG Signals

The sounds are recorded with 16 bits accuracy and 8000Hz sampling frequency in a wave format, using the software “Stetho” developed under Alcatel-Lucent license. The original signal is decimated by factor 4 to 2000 Hz sampling frequency and then the signal is filtered by a high-pass filter with cut-off frequency of 30 Hz to eliminate the noise collected by the prototype stethoscope. The filtered signal is pre-filtered reverse direction so that there is no time delay in the resulting signal. Then, the Normalization is applied by setting the variance of the signal to a value of 1.

2.3 Localization and Boundaries Detection of Heart Sounds

In this study, the localization of heart sounds is established by using the SRBF method based on S-transform and radial basis functions (RBF) neural network (Moukadem et al., 2011). The boundaries of the heart sounds are determined by the first local minima before and after the located sound.

The results were visually inspected by a cardiologist and erroneously extracted heart sounds were excluded from the study.

2.4 Classification of S1 and S2

The initial component of S1 is related mitral and tricuspid valve closure, due to contraction of ventricles, thus identifying the onset of ventricular systole and the end of mechanical diastole. The S2 is produced by the aortic and pulmonic valves closing when left ventricular pressure decreases under diastolic aortic pressure. The vibrations of S2 occur at the end of ventricular contraction and identify the onset of ventricular diastole and the end of mechanical systole (Felner, 1990). These physiological differences lead to different time and frequency content behaviour between S1 and S2.

Two feature extraction methods for distinguishing between S1 and S2 are examined. The feature extraction process extracts a feature vector per extracted sound H_i and each of these vectors is averaged across available extracted sounds from each subject. So from each subject in the database, we obtain one S1 feature vector and one S2 feature vector to use in the training and classification process.

2.4.1 Feature Extraction using the s-Transform

The SVD technique is a powerful tool to represent the time-frequency matrix in a compact manner. Hassanpour et al. proposed a feature extraction method based on SVD technique to classify EEG seizures (Hassanpour et al., 2004). The advantage of this approach, that it incorporates information from the eigenvectors, which contains relevant information about signal. Following this approach, this study proposes a feature extraction method for S1 and S2 classification.

The time-frequency analysis is performed by the S-Transform (Stockwell et al., 1996). The S-matrix S_i of the extracted heart sound H_i is decomposed by the SVD technique as follows:

$$S_i = UDV^T \tag{1}$$

Where $U(M\times N)$ and $V(M\times N)$ are orthonormal matrices so their squared elements can be considered as density function (Hassanpour et al., 2004) and $D(M\times N)$ is a diagonal matrix of singular values. The columns of the orthonormal matrices U and V contains in this case the time and frequency domain information, respectively. The eigenvectors related to the largest singular values contain more information about the structure of the signal. The first left eigenvector and the first right eigenvector that correspond to the largest singular values are used for the feature extraction process. The histogram (10 bins) for each related distribution function is calculated based on the density function.

Five feature vectors obtained by this method are tested in the classification process; the eigentime histogram vector U_1 (T-Features), the eigenfrequency histogram vector V_1 (F-Features), the singular values vector D_1 (SV Features) and the time-frequency vector $U_1\&V_1$ (TF Features). All vectors have a length of 10 features except the time-frequency vector that has a length of 20.

2.4.2 Feature Extraction using the EMD

In this study, a new feature extraction method based on EMD technique and Shannon energy is proposed for S1 and S2 classification. The EMD method decomposes a time series signal into IMF modulating both in amplitude and frequency (Huang et al., 98).

The initial signal $H_i(t)$ can be represented as follows:

$$H_i(t) = \sum_{j=1}^{n} IMF_j(t) + r_n \tag{2}$$

Where $r(t)$ is the residual signal. The feature extraction method consists to calculate the Shannon Energy of each IMF vector, as follow:

$$SE_i = -\sum_{k=1}^{N} IMF_i^2(k).\log(IMF_i^2(k)) \tag{3}$$

Where $i = 1,\ldots,4$ and N is the number of samples of IMF_i the Shannon energy is smoothed by using a median filter, and the feature vector is obtained by applying the same SVD approach used in section 2.5.1 at each calculated IMF (Figure 2). For each extracted heart sound the first four IMF is calculated. The others IMF don't contain relevant information about S1 and S2. Five feature vectors obtained by this method are tested in the classification process; FV1 (that correspond to IMF1 signal), FV2, FV3, FV4 and FV (that correspond to the average of calculated FVs). The length of each vector is 10.

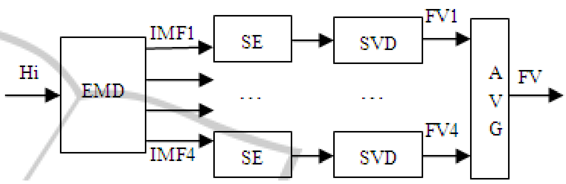

Figure 2: Feature vector (FV) of Heart Sounds (Hi) extracted using EMD and Shannon Energy (SE) before applying the SVD technique.

3 RESULTS AND DISCUSSION

A 3-Neirest Neighbor (KNN) classifier is used to evaluate the performance of the nine feature vectors obtained by the two methods and the 5-fold approach is used for cross validation. The choice of KNN classifier was based on its simplicity of and its robustness to a noisy training data. Other classifiers can be tested and compared but it is not the main goal of this study.

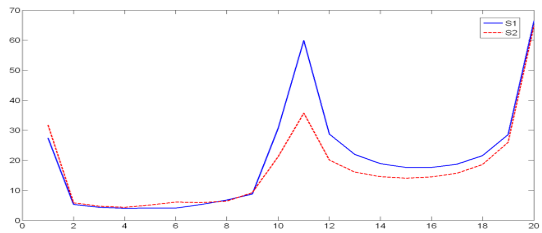

Figure 3: Average of TF Feature vectors for S1 (solid line) and S2 (dashed line) obtained by the S-transform based method.

The eigenfrequency feature values (first ten values, figure 3) of S2 are slightly higher than S1 in all of the cases except the 2 last. However, S1 eigentime feature values (last ten values, figure 3) are significantly higher than S2 eigentime feature values. This explains why we obtain a higher classification rate with eigentime feature compared to eigenfrequency feature when they are tested separately (Table1). The singular values are almost

Table 1: Sensitivity and specificity for the nine extracted feature vectors evaluated by a KNN classifier.

KNN	T-Features	F-Features	SV Features	TF Features	FV1	FV2	FV3	FV4	FV
Sensitivity	92%	81%	60%	95%	88%	81%	82%	65%	94%
Specificity	92%	88%	65%	97%	91%	97%	94%	95%	97%

indistinguishable from each other and it is shown by the low classification rate for the SV features (Table1). In most cases seen in the medical field, S2 has a higher frequency than S1. This is due to the fact that S2 is the heart sound associated with the closure of the aortic valve in a context of high left ventricular pressure, the mitral closing occurring at low left ventricular pressure (S1). However, as we mentioned before, this criterion cannot be generalized on all real life cases because some medical conditions are characterized by S2 frequency content lower than S1 frequency content. Hence, the importance of time-frequency based features approach, especially in a generic module.

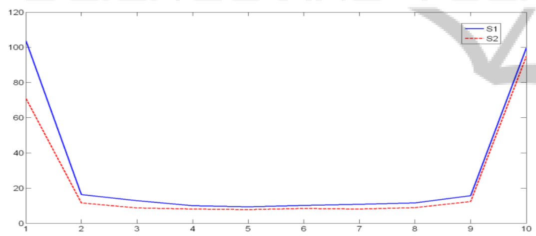

Figure 4: Average of feature vectors (FV) for S1 (solid line) and S2 (dashed line) obtained by the EMD based method.

For the EMD based method, the feature vector of S1 is always higher than the feature vector of S2 (figure 4). This can be explained by the fact that EMD technique performs a multi resolution analysis which reflects the richness of the signal at different frequency bands. Moreover, it is known from a physiological point of view, that S1 in general is more complicated than S2, so it is not surprising that the average of the first four IMF gives higher values for S1. We note here that FV1, the feature vector that correspond to the IMF1 gives the best results, in term of sensitivity, compared to other IMFs when they are tested separately (Table 1).

4 CONCLUSIONS

Two feature extraction methods based on the SVD technique are presented in this study for the classification of S1 and S2. Before applying the SVD technique, the first method calculates the time-frequency matrix of segmented heart sound by applying the S-transform and the second method calculates the Shannon energy of the first four IMF obtained by the EMD algorithm. Each feature vector extracted by these methods is evaluated by applying a KNN classifier. These methods are tested on a dataset that contains 80 subjects, including 40 cardiac pathologies sounds which contain different systolic murmurs and tachycardia cases.

The objective of this paper is to find suitable features for classification of S1 and S2 without using the systole regularity criterion. The results obtained by the proposed approaches are very promising; the TF Feature vector obtained by the S-transform based method reaches 96 % correct classification rate, and the FV feature vector obtained by the EMD based method reaches 95% correct classification rate. Both methods are suitable for the main purpose of this study. More robustness tests against noisy signals, algorithms complexity, facility of implementation and more signals, would contribute to choosing the adequate method in the aim of developing a generic tool for the automatic heart sounds analysis.

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