Early Detection of Pediatric Heart Disease by Automated Spectral Analysis of Phonocardiogram in Children

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Abstract

Congenital heart disease is now the most common severe congenital abnormality found in live births and the cause of more than half the deaths from congenital anomalies in childhood. Heart murmurs are often the first signs of pathological changes of the heart valves, and they are usually found during auscultation in the primary health care. Auscultation is widely applied in clinical activity; nonetheless sound interpretation is dependent on clinician training and experience. Distinguishing a pathological murmur from a physiological murmur is difficult and prone to error. To address this problem we have devised a simplified approach to pediatric cardiac scanning. This will not detect all forms of congenital heart disease but will help in the diagnosis of many defects. Cardiac auscultatory examinations of 93 children were recorded, digitized, and stored along with corresponding echocardiographic diagnoses, and automated spectral analysis using discrete wavelet transforms was performed. Patients without heart disease and either no murmur or an innocent murmur (n = 40) were compared to patients with a variety of cardiac diagnoses and a pathologic systolic murmur present (n = 53). A specificity of 100% and a sensitivity of 90.57% were achieved using signal processing techniques and a k-nn as classifier.

Keywords: Phonocardiogram (PCG); Murmur; Cardiac; K-nn Classifier; Pediatric; Wavelet.

1. Introduction

Acoustical vibrations produced by the mechanical action of the heart contain valuable information about the pathological condition of the cardiovascular system. Cardiac murmurs are often the first sign of pathological changes in the heart valves and they are caused by turbulent blood flow or jet flow impinging on and causing vibration of surrounding tissue. Murmurs are critical and must be detected as soon as possible. A heart murmur in pediatrics can be an indicator of congenital heart disease (CHD). Innocent heart murmurs are of no clinical consequence while pathologic heart murmurs indicate congenital heart disease is present [1].

Heart murmurs are an important feature to identify cardiac disorders in childhood, infancy, and especially in newborns. Unrecognized heart disease in newborns carries a serious risk of avoidable mortality, morbidity and handicap.

CHD is the most common congenital disorder in newborns. Unfortunately Iran is one of the countries that is not supporting the screening program for CHD at the moment.

Computer-aided auscultation would allow fast and cheap decisions by using a tool widely known by both physicians and patients: the stethoscope. Since most heart diseases are reflected to the sound that the heart produces, stethoscopes are part of the first line of screening and diagnosis of heart pathologies.

In simple healthcare establishments the heart auscultation is the basic tool for a first screening of patients and deciding which of them should be referred to more complex and costly medical examinations and tests (e.g. based on advanced imaging techniques) and/or specialised cardiologists. Also, many heart diseases cause differentiations of heart sound in much earlier stages before they can be observed in other comparable techniques, such as the Electrocardiogram (ECG). Therefore increasing the accuracy and the whole effectiveness of heart auscultation is of critical importance for improving both the health level of the populations (by diagnosing heart diseases in their early stages) and also the economics of the health systems (by avoiding unnecessary costly medical examinations and tests due to incorrect screening). Furthermore, it should be taken into account that in some circumstances, such as in the developing countries, the auscultation is the only available tool for diagnosis of heart diseases for most of their population.

Cardiac auscultation is one of the most important physical examination and a part of the first medical diagnostic procedures. Many of the heart diseases can be recognized in the primary stage using heart sounds auscultation and therefore are treated earlier. Irregularities detected during auscultation begin the therapy [2].

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Cardiac murmurs occur frequently in healthy children, but it can also be a feature associated to many forms of congenital heart disease. The incidence of heart murmurs in the pediatric population is reportedly as high as 77% to 95%. However, less than 1% of this population has heart disease. Given the prevalence of innocent murmurs and the relatively low incidence of actual heart disease, the primary health care provider may have difficulty determining which patients with murmurs need specialist referral, especially when there are no other signs or symptoms of heart disease. Seven types of innocent heart murmurs are reported in children, i.e. still's murmur, innocent pulmonary flow murmur, innocent pulmonary branch murmur of infancy, supraclavicular bruit, venous hum, mammary souffle, and cardiorespiratory murmur. Generally, clinical history and physical examination are diagnostic for these murmurs.

In studies of patients referred by primary care physicians because of heart murmurs either directly for echocardiography or for evaluation by the cardiologist, only 20% to 30% of the patients have pathology.

Early recognition is an important goal, and equally important is avoiding misdiagnosing a pathological heart murmur in a healthy child without heart disease. To acquire high-quality auscultation skills, requires the guidance of an experienced instructor using a sizable number of patients along with frequent practice. Unfortunately, the interpretation of auscultation findings overall remains prone to error. Imaging technologies can provide more direct evidence of heart disease; however, they are generally more costly.

There is an acute shortage of physicians in developing countries and many rural clinics are run by nurses. Given the high incidence of heart murmurs, automated screening based on electronic auscultation at clinic level would be of great benefit. The main advantages for early recognizing a cardiac disease are that newborns will be seen and assessed earlier and in better clinical conditions. Acceptance will obviously depend on the sensitivity and specificity of the system. Selection of representative data for diagnosis must be relatively simple for the system to be of practical use in rural clinics [3].

Appropriate devices allow nowadays the digitization and storage of heart sounds in digital format, their inclusion in electronic health records, their transmission to other (possibly remote) systems (e.g. using wireless technologies, the Internet, etc.), their presentation on a screen (both in the time and in the frequency domain) and their processing in order to remove noise and other undesirable components. More advanced systems can also perform intelligent processing and provide suggestions of diagnostic nature to the doctor, e.g. concerning the existence of additional sound components, such as the third heart sound (S3), the fourth heart sound (S4), various murmurs, clicks, snaps, etc., or even the existence of particular heart diseases. This combination of the 'traditional' auscultation with the modern information and communication technologies is expected to revitalise the interest in and use of auscultation in the near future [4].

The digital analysis of heart sounds has revealed itself as an evolving field of study. In recent years, numerous approaches to create decision support systems were attempted. Recent advances in digital signal processing have led to a reexamination of the potential role of spectral analysis of heart sounds in cardiac diagnosis [5,6,7,8,9]. In this study, we investigated a new technique for evaluating heart murmurs in children and young adults using automated analysis of the systolic energy content found in digital recordings of cardiac auscultations.

Heart sound features such as spatial loudness, relative amplitude, murmurs, and localization of each component may be indicative of pathology. In this work we build on the "prototypical systole" and then extract two different feature sets that characterize acoustic activity in the systolic phase. One feature set is related to physiological activity of heart sounds. The other is the first three principal components derived from principal component analysis. The objective of our study was to assist the clinician in the detection and evaluation of heart murmurs.

2. Methods

In this sections we will discuss the signal processing stage, signal processing is the most important element of the system, because it provides information useful for diagnosticians. Its purpose is to de-noise and make segmentation of the signal, features extraction and classification between the normal and abnormal heart sound.

2.1 Data Acquisition

The monitoring of sounds heard over the chest walls is known as auscultation, which is usually performed with the stethoscope. The heart sounds signal could be measured in two ways, with analog or digital stethoscope or by phonocardiography. Stethoscope is simple tool to transmit the heart sounds from the chest wall to the ear, but it is not easy to use it correctly. Firstly the human ear is not sufficiently sensitive to determine all frequencies (different level of auscultation skill) and some components of signal can be omitted. Secondly, to make of the diagnosis, a long time-practice and experience of the doctors is required. Also the signal from an acoustic stethoscope has very less sound amplification [2]. Therefore, it was a need to use a device, which could make an automatic recording and interpretation of a signal. Phonocardiography (PCG) is a main tool showing the timings and relative intensities of the heart sounds with graphic recordings on the paper. The digital stethoscopes with suitable software allowing automatic analysis of the signal could be more widely distributed diagnostic tool which has been used in this study.

Fig. 1 shows a simple diagram of a system presented in [2], which consists of an analog part to record signal and with digital to analysis and display waveform. Chest piece is a component of electronic stethoscope. Then signal is recorded by a microphone and by an IC recorder.

It is a possibility to hear it by an earphone or it might be transmitted to the computer. Signal processing is implemented in MATLAB®.

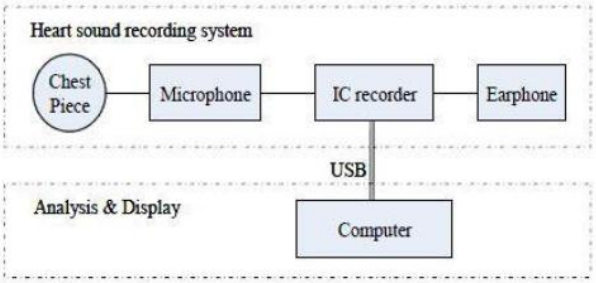

Fig. 1. Schematic diagram of recording and analyzing system [2].

The WelchAllyn Meditron Analyzer, ECG and electronic stethoscope were used during the auscultation. The digital recordings were made at a sampling frequency of 44.1 KHZ, 16 bit precision and saved via USB onto a laptop in the uncompressed WAV file format.

Cardiac auscultatory examinations of 93 children and young adults were recorded, digitized, and stored along with corresponding echocardiographic diagnoses. 40 subjects were diagnosed as normal and the other 53 subjects were found to have one of the pathological cardiac conditions namely VSD, AS and PS. For each patient a 10 second, ECG and heart sound (HS) recording was made at the Apex in the supine position. The sounds recorded on the surface of the body depend on the source location, intensity, and the acoustical properties of the surrounding tissues. It is important that the location of the microphone be specified. The recordings were made by experienced pediatric cardiologists, and in most cases, in a noisy clinical environment. Echocardiography was done on all patients to confirm patient diagnosis.

2.2 Pre-Processing

A signal is a means to convey information. It is sometimes generated directly by the original information source. We may then want to learn about the structure or functioning of the source from the extracted information. The signal available may not yield directly the required information. We then apply some operations on the signal in order to enhance the information needed.

Pre-processing of heart sounds is necessary to obtain consistent useful data for analysis and improve robustness in the presence of noise such as breathing noise, artifacts, voice and external noise.

In the event that the recording environment is not well controlled, noise is coupled to the PCG. To avoid unpredictable effects brought by noise, filtering out the unwanted noise becomes important for later processing. That is the reason why the first step of signal processing consists of filtering heart sounds, since the main spectrum of first heart sound (S1) and second heart sound (S2) stay within the range of 200Hz, We chose the second order filter with a cut-off frequency equals 600Hz in order to save a heart sounds and murmurs bandwidth. In sum, preprocessing was done due to two reasons, first was to eliminate DC values and motion artifacts and the second was to omit redundant high frequency contents.

Heart sounds were down sampled to 2000 samples per second for memory optimization and processing speed. As mentioned above, the significant information of HS signals was contained below 600Hz and no useful information was lost during down sampling. All HSs were filtered using second order, low pass Butterworth filter with cut-off at 600Hz with zero phase delay.

2.3 Heart Sound Segmentation

The first step in the processing is usually that of segmentation. The signal may drastically change its properties during time. We then observe and process the signal only in a finite time window. The length of the time window depends on the signal source and goal of processing. We may use a single window with predetermined length, or we may require some scheme for automatically dividing the signal into varying length segments as we did for this paper.

Since sound pressure level greatly varies subject by subject, the first step in this section was to normalize all HS signals with its norm, for each vector of heart sound, x[n], as shown in Equation (1). This could enable us to compare heart sounds of different patients.

$$x_{norm}[n] = \frac{x[n]}{norm(|x(n)|)} \quad (1)$$

Initially the heart cycle must be segmented into the S1, systolic, S2 and diastolic phases. This is not a trivial task to do in general. In normal patients there is a clear distinction between the lub and dub of the heart sound. In the presence of a systolic murmur, such as generated by aortic stenosis, the boundaries between the end of S1 and the beginning of the murmur, and the end of the murmur and the beginning of S2 can become very obscure.

Frequency differences can assist this segmentation task with S1 and S2 being in the 40 to 80Hz range and murmur being higher, 80 to 150Hz. but is not always the case. Although the fundamental resonances of S1 and S2 are at relatively low frequencies in the audible range, the lub-dub effect can be still heard in the 100 to 200Hz range. An algorithm has been devised that looks for peaks of signal around the probable region where S1 and S2 occur.

Automatic segmentation of the heart signals into individual cycles provide information such as the S1, S2, systolic and diastolic durations. Special algorithms implemented in MATLAB® enable automatic detection of these events. In this research ECG as a reference is used. Another method is to apply a Wavelet multi-resolution analysis [2].

Typically, heart sounds consist of two regularly repeated thuds, known as S1 which is generated by the nearly simultaneous closure of the mitral and the triscupid valve, being followed by the systolic phase, and the second heart sound S2, which is generated by the nearly simultaneous closure of the aortic and the pulmonic valve, being followed by the diastolic phase. Most heart diseases

generate additional components in the heart sound, such as murmurs in the systolic or/and the diastolic phase. The time interval between S1 and S2 is the systole, while the gap between S2 and the next S1 corresponds to the diastole. Therefore a single cardiac cycle or heart beat contains components S1-systole-S2-diastole, as shown in Fig. 2.

A cycle starts just before the R-peak of the ECG and ends before the next R peak. This RR interval was used to segment the heart signal into individual beats. Segmentation of the heart beat was then done to find the first and second heart sound.

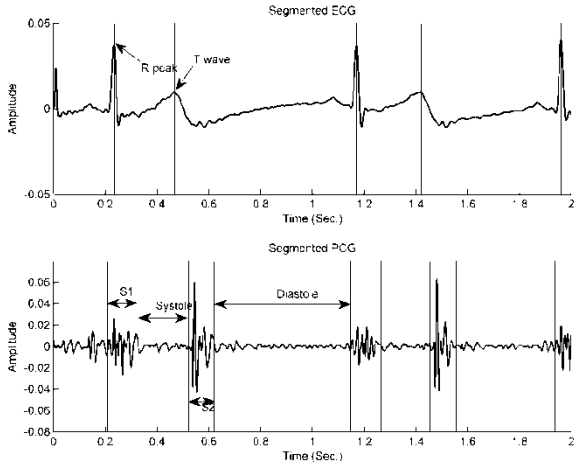

Fig. 2. A normal PCG that we have segmented it by using its corresponding ECG signal.

It should be noted that systolic length may differ in some cases. So in order to distinguish the starting time of S2, we would need to locate the time where T wave occurs in the corresponding ECG signal. S2 start time is the maximum position between the start point of T wave and 100 to 150 ms after that in the HS signal, besed on the RR interval duration.

2.4 Feature Extraction and Selection

Not all the information conveyed by the signal is of interest. The signal may contain redundancies. When effective storing and transmission are required or when the signal is to be automatically classified, these redundancies have to be eliminated. The signal can be represented by a set of features that contain the required information. The most effective feature extraction methods are the time-frequency analysis. Research about time-frequency analysis describe different methods of signal processing from FFT to continuous wavelet transform and the latest method is recognized as the best [2], which we are planning to exploit in the next future. In this study we employ DWT in order to extract features. These features are then used for storage and classification. We construct our diagnostic tool from five functional blocks working in series, as shown in Fig. 3.

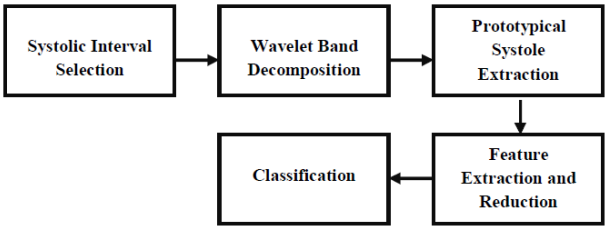

Fig. 3. Sub-Problem decomposition of automated auscultation.

2.4.1 Systolic Interval Selection

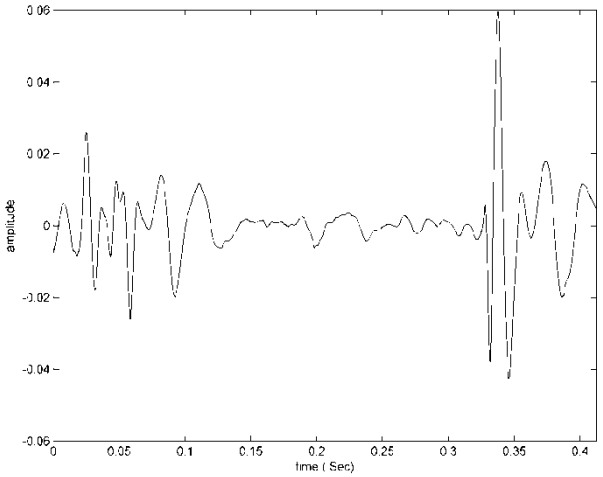

Fig. 4. A sample systole corresponding to a normal HS.

Since our Data set only consists of valvular diseases that take place in the systolic phase of the cardiac cycle, we have extracted only the systolic parts in each beat. Fig. 4 shows the most informative part extracted from the PCG signal shown in Fig. 2.

We have chosen each systole to start with the QRS complex in the corresponding ECG signal and end simultaneously with S2. The reason why we have chosen these two points was the fact that the interval between them contains the most diagnostic information and also these points are easy to locate.

2.4.2 Wavelet Band Decomposition

Since the amplitude of low frequency energy in the recorded signal is generally several orders of magnitude greater than the amplitude of high frequency energy, as shown in Fig. 5, we separate each systolic interval into three bands, approximately corresponding to frequency ranges of 75-150 Hz, 150-300 Hz, and 300-600 Hz.

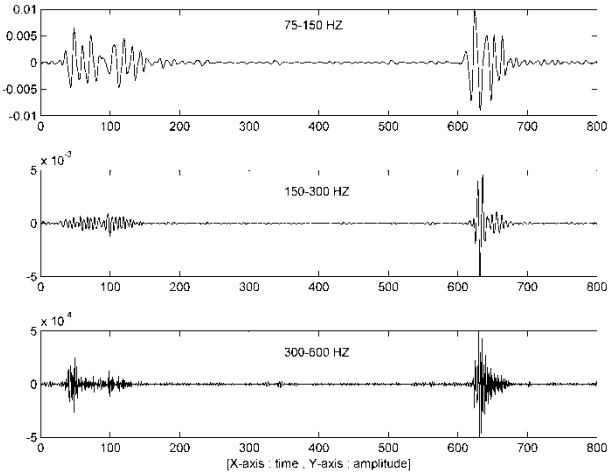

Fig. 5. Variation in amplitude of different wavelet bands.

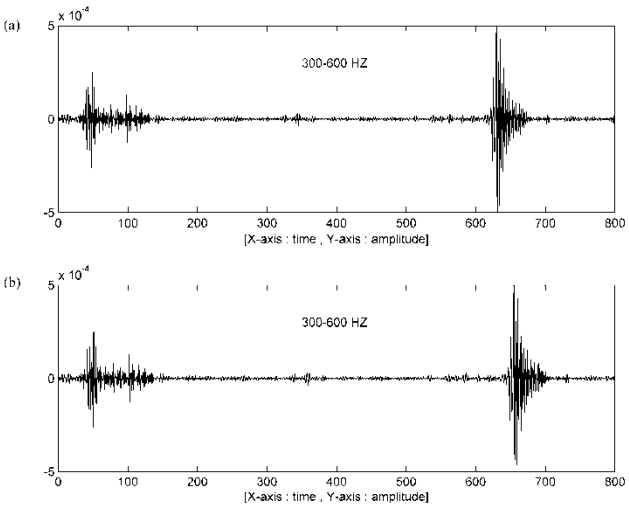

Fig. 6. a) Wavelet band 3 decomposition of a sample systolic interval
b) the same signal after scaling

So that the energy content of any frequency band wouldn't be colored by that of adjacent bands. In order to do so, we use wavelet bands while providing high temporal resolution at high frequencies.

It should be noted that before doing any further processing we should normalize the length of all three bands of each selected systole through scaling step. All three band representations of each systole are stretched to the duration of the longest systole that has been recorded for a patiant. By enforcing a standard length, timing characteristics are viewed as a percentage of systole rather than as a scalar offset from S1. Fig. 6 illustrates how scaling step performs length normalization for band three of the described wavelet bands. We have shown only band three to provide better comparision for readers.

2.4.3 Prototypical Systole Extraction

The time-frequency decomposition provides us with the frequency components for each selected beat. In order to observe the characteristic trends persisting amongst the majority of the beats, we also develop a mechanism to merge information from multiple systolic segments to create a single representative heart-beat for the patient. In other words, we assimilate information from the selected beats to generate the time-frequency decomposition of a hypothetical "typical" beat for the patient.

Like [10], we assimilate information from the selected systoles to generate the time-frequency decomposition of a hypothetical "typical" systole for each patient. The wavelet band decomposition components are time-envelope characterized (see Fig. 7).

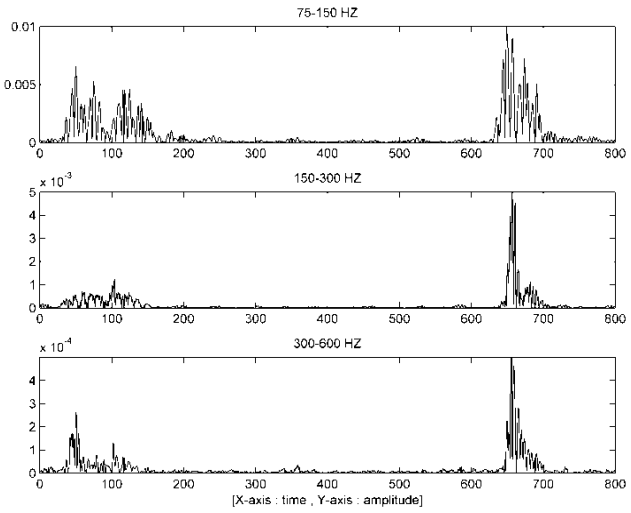

Fig. 7.Time envelope of systolic frequency bands.

We calculate the absolute value at every time instant for the component signals to avoid destructive interference whereby positive and negative values from different systoles may cancel each other. This would lead to the aggregate incorrectly indicating diminished energy content or even the absence of energy altogether, at any time instant.

The step of the prototypical systole calculation can be represented as finding the median four elements along time vector for all of the three bands as in the third block of Fig. 8.

The mean of these median amplitudes is then calculated for each wavelet band. This is illustrated on the last block in Fig. 8 Meaning the end result is a time-frequency decomposition of the prototypical systole.

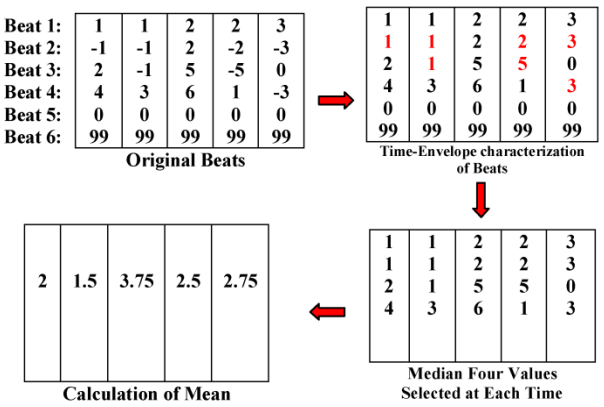

Fig. 8. Prototypical systole construction stages [10].

2.4.4 Feature Extraction

In each band, we record energies from one hundred adjacent bins spanning prototypical systole and normalize by the maximum feature value. This step serves as the basis for our feature set. As it's shown in Fig. 9 when these energy values are plotted in sequence, they would roughly capture the original shape of prototypical systole in a fixed and relatively small number of samples.

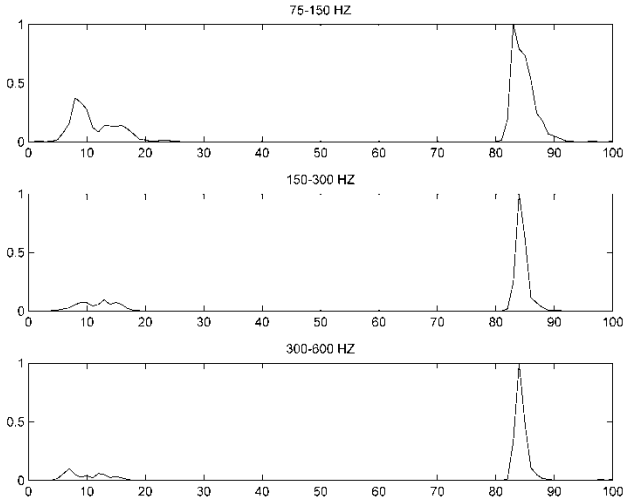

Fig. 9. Energy contents of a windowed sample prototypical systole.

The process of feature extraction would lead to extract some physiological feature from these energy contents for any of the prototype systoles and in all three bands. We have extracted 15 (5*3) features in this step. These features are as follows: energy and width of S2, the height of a possible murmur and the temporal location of its peak and finally mid-systolic energy. In what follows we will see that only four of these features were considered for classification. If too many features are used, the performance of the classifier will decrease as well as recognition rate (due to overfitting). The reason lies in the existence of many different solutions that are consistent with the training examples, but disagree on unseen (test) examples. Hence lack of training data enforced us to choose only some of features.

2.4.5 Principal Components Analysis

Principal component analysis or PCA is a method that has been widely used in several signal processing studies for various reasons, such as data compression or feature extraction or reduction techniques.

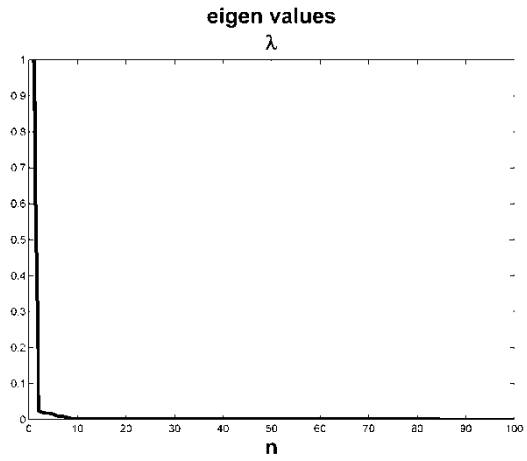

Fig. 10. Eigen values of the covariance matrix (n refers to the n^{th} principle component).

In this study we have used PCA to extract principal components in order to use the first three principle components as our second feature set.

As shown in Fig. 10 the eigen values of the covariance matrix of the input data are in a desending order with a sharp slope after the third principle component. And this is why we have just used three of these components.

Principle component analysis was done to only band three of the signal, which measures energy contents in 100 bins for the prototype systole.

3. Results

In many cases it is required to do an automatic detection of normal and abnormal heart sound. It can be done using methods such as implementation of a neural network, or Hidden Markov Model (HMM). In this study the simple K-nn classifier has been employed because it proved to be efficient and accurate and in some cases better than MLP. Input data set of 93 children recorded HS signals are derived from various sources in digitized sample form, manually recorded with stethoscope on patients, CD-ROM [20], and internet sites, which comprised of 40 normal HSs and 53 patients with a variety of cardiac diagnoses and a pathologic systolic murmur present.

Selecting a wavelet then becomes a process of seeing which wavelet suits the style of the signal to be investigated rather than being constrained by the compression process. To determine that which mother wavelet would best adapt with the prototype systoles we investigated between some common mother wavelets that have been employed in many similar research, namely db4, db2, db10, sym7 and sym8.

A conclusion drawn from the Fig. 11 suggests that there is little difference from a variety of different wavelets when applied to heart sounds, especially when the wavelets visually look closely matched. In sum, there is not much difference in the various mother wavelets, with a slight preference towards the db4 that would best suit to our case.

As it's shown in Fig. 12, the classifier performance will reach to a fixed level for the case when feature vector contains one principal component and four physiological features and at least 55% of the whole dataset is used for training. These results are taken when 55% of total samples are used as the training dataset and 100% of them as the test dataset. Meaning the train and test datasets contain 51 and 93 protypical systoles respectively.

Fig. 12 demonstrates that in order to reach to an optimum condition 55% of the whole databank shold be used for training. In order to increase the performance of our system we have added two more principal components to the input feature vector and increased the percent of training data to 76%. So this new feature vector contains 7 features for each patient.

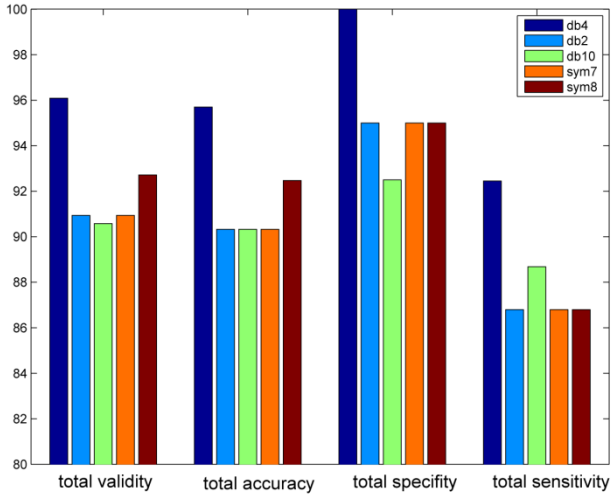

Fig. 11. Total Performane changing mother wavelets.

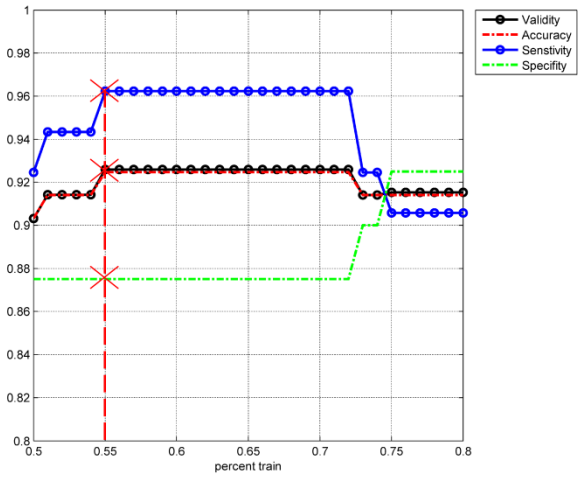

Fig. 12. percent of train databank vs. validity, accuracy, sensitivity and specifity of the classifier.

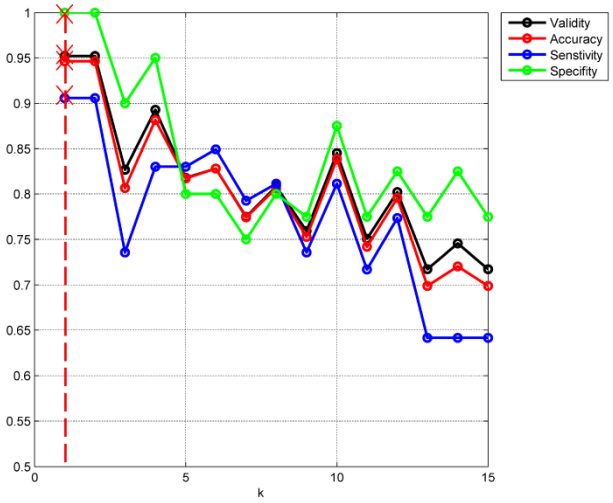

Fig. 13. Number of neighbors vs. validity, accuracy, sensitivity and specifity of the classifier.

After all, the classification was carried out in accordance to tuning of the k-nn classifier. By stepwise increasing of neighbor number, the optimal value of k is determined for the best classifier accuracy. Fig. 13 illustrates the performance of the proposed method for different amounts of k.

This is clearly obvious that the classifier performance decreases as the number of neighbors increases. Therefore, and in order to ensure the computational stability, a value of k=1 was selected. Tabel 1 summarizes the final values related to performance of the proposed method. Amounts related to the crossed points of Fig. 13 are particularly shown in Table 1. G-means metric, which is defined in [21], has been used for evaluating classifiers on imbalanced datasets. We also use this metric to evaluate our classifier. The G-means criterion is represented in Table 1 and is calculated as follows:

$$g = \sqrt{acc+ . acc-} \qquad (2)$$

where *acc+* is sensitivity and *acc-* is specificity.

Table 1. shows that the whole dataset contains 40 prototypical systoles for normal children and 53 for children with CHDs. We used the whole dataset to evaluate the performance of our method. The accuracy and validity of the classifier in this case is higher than 93% which is a significant result.

Table 1. performance of the proposed method.

	Actual Group	
	CHD	Normal
CHD	48	0
Normal	5	40
Total = 93	**Sen** = 90.57%	**Spe** = 100%
	Total Accuracy = 94.62% **Total Validity** = 95.22% **G-means**= 95.17%	

4. Conclusions

In this study, seven features were extracted from the murmurs of four groups of patients. These features were used to train a simple knn classifier. Training set consisted of 30 non-pathological and 40 pathological HSs. The input feature vector contained three features from systole, one feature from the energy of systolic signals, and three features from the PCs which altogether summed up to seven features. Since the number of features used in this study was low, the overall computational time was only a few seconds.

The feasibility of the automatic classification method of phonocardiogram utilizing the k-nn and spectral analysis for early cardiac disease screening has been examined. Based on spectral and timing properties of a child heart sounds signal, we have developed a five step algorithm for a complete automatic detection of pediatric heart disease. In the first step, we have extracted all systolic intervals. In the second and third step, we have used wavelet analysis for the aim of prototypical systole construction. In the two final steps, feature extraction stage and classification were done.

Previous studies present excellent classification results well above 95 % when classifying a number of different heart abnormalities [3,11,12,13,14,15,16,17,18-19].

In this study the classification accuracy was at best 94.62% when classifying VSD, AS and PS. The advantage of our study is that actual clinical data was used. In practice this means that the recordings contained noise such as friction rubs, rumbling sounds from the stomach, breathing sounds from the lungs, background noise from the clinical environment and baby crying sounds. In many other studies, the data is either provided from teaching tapes, [11,12] or from specially selected heart cycles of very high quality and with typical morphology [3,12,13]. Another reason could the choice of the classifier. The choice of an optimal classifier was however not the aim of this paper.

Results show that the algorithm is efficient and could be used as an effective tool for a complete automatic auscultation in a computerized screening of CHDs system. A system based on this approach will be both accurate and robust, while remaining simple enough to be implemented at low cost. Also unlike many other studies the segmanteation step is automatically done without the help of an operator.

Our classifier demonstrated a sensitivity of 90.57% and specificity of 100% for classification of normal and pathological murmurs which is a significant result.

A need for more data is evident for clinical validation. More patients are also needed since a rule of thumb is to use 10 times as many cases as there are features for classification, which is far from reached in the present set-up. Areas for future work include the further development of the system to encompass a broader range of symptoms and pathologies, and an evaluation of the resulting system using a larger and more diverse set of clinical data.

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