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Classification of segmented heart sounds with Artificial Neural Networks

Omer Deperlioglu*[1]

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Abstract: Nowadays heart diseases are the first cause of human deaths. For this reason, many studies have been carried out to reduce early diagnosis and death of heart diseases. These studies are mostly about developing computer-aided diagnosis systems by utilizing the developing technology. Some computer aided systems are clinical decision support systems developed to more easily detect heart diseases from heart sounds. These systems are used in the automatic analysis of heart sounds based on the classification of heart sounds in general. Much of the work done to diagnose heart diseases is to increase the success of classification. Segmentation of heart sound signals is also one of the frequently used methods to increase classification performance. In this study, S1-S2 sounds were segmented using the resampled energy method and the contribution to segmentation performance of the segment was examined. In practice PASCAL Btraining data set which is widely used for heart diseases application is used. The PASCAL Btraining data set contains three different heart sounds such as normal, murmur, and extrasystole. Artificial Neural Networks (ANN) were used to classify these sounds. For the comparison of the obtained results, two classifications were made for the segmented and the non-segmented sounds. As a result of the classification studies, the average all accuracy of classification 84% was achieved in the non-segmented ANN study, and the average all accuracy of classification 88.6% was obtained in the segmented S1-S2 sounds ANN study. Thus, segmentation of heart sounds increased the accuracy of classification by about 4.6%.

Keywords: *Heart sounds segmentation and classification, artificial neural network, re-sampled signal energy, heart sounds.*

1. Introduction

The cardiac auscultation that is performed by the doctors is first diagnosis method for heart conditions. Heart auscultation is a non-invasive, low-cost screening method that is defined as the process of interpreting the heart sounds produced by the mechanical movements of the heart and is used as a basic tool in the diagnosis of heart diseases. Physician experience is also of great importance in examinations made with auscultation. In addition, the fact that heart sounds are variable and complex, not all physicians have the same experience, reveals the need for clinical decision support systems to help diagnose heart sounds. For this reason, many studies on heart sounds have been made. These studies are usually about disease detection by classifying the heart sounds.

Naturally, scientific studies are mostly about increasing the accuracy rate of classification or increasing the performance of classification in classifying heart sounds. In order to increase performance in these studies, different classification algorithms have been used together with different optimization methods [1]. One of these methods is to classify the heart sounds with segmentation of S1 and S2 sounds. For segmentation, the Shannon energy envelope and the use of ECG signals as reference for the detection of peak values of S1-S2 sounds are the most common methods.

The signal analysis approaches of heart sounds are based on temporal segmentation. They define cardiac cycles and S1 refers to the location of primary heart sounds with systolic onset and S2, systolic end. The durations of sounds in S1 and S2 vary and their intensity is explained as a definite indication of heart disease. Determining the exact positions of S1 and S2 sounds is an important process in the analysis of heart sounds. In this way, classification of heart diseases can be made more efficient. The accurate identification of S1-S2 heart sounds is very important for a heart. For this reason, the classification of pathological murmurs can be made by using them [2, 3].

Shankar et al. proposed an algorithm for detection and segmentation of S1 and S2 heart sounds using the Discrete Wavelet Transform and Shannon energy envelop. They used artificial neural network for classification and they tried to detect heart murmur from the heart sounds [4]. Bahekar and his colleagues also used the discrete wavelet transform for detection and segmentation of S1 and S2 sounds in heart sounds. They used adaptive neuro fuzzy inference system (ANFIS) for classification. Sharma and his colleagues also segmented heart sounds using Shannon energy envelope method. They first found envelopes in heart sounds with Shannon energy. Utilizing this, they determined the distance between S1 and S2 sounds and thus performed the segmentation process by fully calculating the systole and diastole intervals in the heart sounds [5]. Sharma, Saha and Kumari proposed a method for calculating heart rhythm variation using phonocardiogram. In this method, the mean heart rate was calculated from the Shannon energy signal and the traits were found using mean, variance and autocorrelation to find the characteristics of the signal [6]. Also, Kumari and Saha have proposed a method of detection of artefact in heart sounds. They used an adjustable Q-wavelet transform and a second difference signal combination with the median filter to detect artefact infected subsequence. At end of the study they have reached 96.98% segmentation accuracy [7]. Choi and Jiang, have

[1] *Computer Tech., Afyon Kocatepe University, Afyonkarahisar – 03200, TURKEY*
* *Corresponding Author: Email: deperlioglu@gmail.com*

made a comparative study about Shannon energy, the envelope information of Hilbert transform, and the cardiac sound characteristic waveform. They said that proposed algorithm provided sufficient performance compared to conventional Shannon envelope and Hilbert envelope algorithms [8]. The algorithm proposed by Saini is an automatic detection of two dominant heart sounds based on a 3-order normalized mean Shannon energy envelope. This proposed automatic detection and analysis algorithm can effectively detect heart sounds S1 and S2 by reducing the effect of noises in heart sounds. Due to the fact that the signal and the envelope calculation was pre-processed, the noises in the heart sounds could be easily suppressed [9].

El-Segaier et al. have used QRS complexes and T waves in ECG signals to find S1 and S2 segments in their studies. They used ECG signals as a reference for segmentation of S1 and S2 sounds [10]. T waves in some ECG signals cannot be clearly selected. For such situations, Carvalho and his colleagues used a new classifier in the selection of S2 sounds for low quality ECG signals. Thus, they tried to come from above the problem of not being classified signals [11]. Many researchers are trying to define the S1 and S2 sounds with a few signal processing and statistical methods to reduce the excessive workload without using the ECG as a reference. Shervegar et al. first filtered the noisy heart sounds using a Chebyshev type I low pass filter. Then, they calculated the Bark Spectrogram. Using the bark spectrogram, they calculated the sound intensity index by taking the average of the amplitudes in all frequency bands. Using the smoothened event detection function, they obtained heart sounds S1 and S2 [12]. Elgendi et al. have developed a Daubechies wavelet algorithm for the automatic detection of S1 and S2 using the wavelet coefficient 'D6' based on power spectral analysis [13].

The purpose of this work is to improve classification performance by easily segmenting without dealing with more complex methods or algorithms. For this, segmentation was done by using re-sampled energy method which is proposed by Deperlioglu [11]. For this, a study was performed using the PASCAL Btraining heart sounds data set. First, samples of heart sounds were arranged and normalized for 8 seconds. After pre-treatment of the heart sound signals, filtering with an elliptical filter was performed. After pre-processing has been completed, S1-S2 sounds are segmented using the resampled energy method [14]. Then, two classifications that include the segmented and non-segmented sounds were performed with artificial neural networks to compare the classification success. These studies are explained in detail in the following sections.

2. Material and Methods

In this study, it is aimed to improve classification performance by segmentation. For this, the block diagram of the process steps was shown in Fig. 1. These processes were explained in detail in the following sections respectively.

2.1. Resampling and Normalization

Classification studies require that all heart sounds should be at the same duration and at the same sampling frequency. If the sounds are recorded in different media with different devices, they are resampled so that they have the same sampling frequency. The sounds used in this study were recorded with the digital stethoscope DigiScope® in the hospital. Therefore, they were not resampled because they have the same sampling frequency. Only, the length of the audio file is arranged as 8 seconds during normalization so that the size of the learning matrix is equal, during

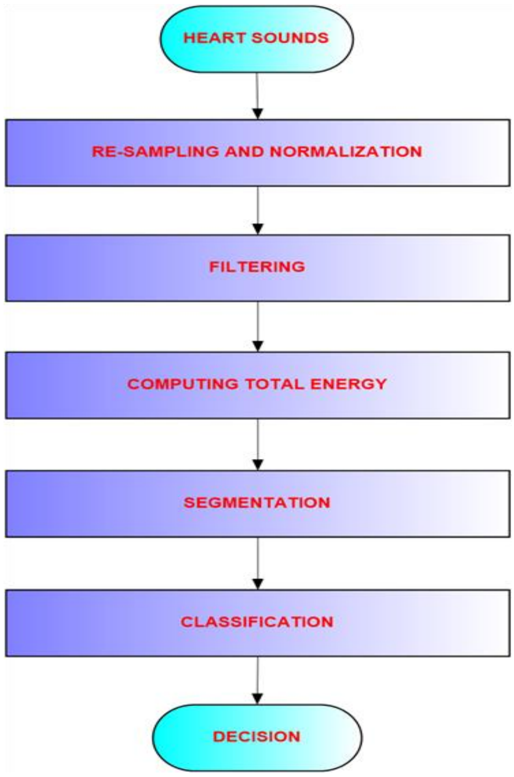

Fig. 1. The block diagram of classification of heart sounds.

the classification process.

After the resampling step, the heart sound signals are normalized to a fixed [-1 1] scale: because heart sounds should be normalized before filtering. Normalization can be performed as in equation (1) [15].

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

Where $x[n]$ is the resampled signal and $x_{norm}[n]$ is the normalized signal. The sample normalization process is shown in Fig. 2.

2.2. Filtering

Heart sounds that provide valuable diagnostic information in clinical examinations are among the most important physiological signals in the human body. However, heart sounds include noises, such as external sounds and lung sounds, caused by signal recording conditions. Noisy heart sound signal negatively affects the diagnosis of the doctor [16].

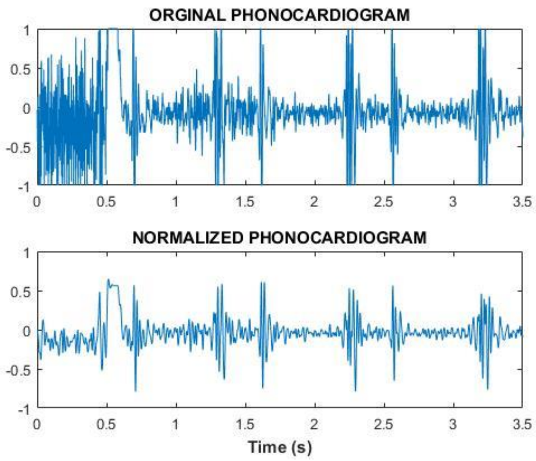

Fig. 2. The sample normalization process.

Digital filters are often used to filter biomedical signal. Digital filtering is defined as the acquisition of desired frequency values according to the characterization of the desired filter in order to improve the signal according to the intended use [17, 18]. Based on the experience gained from previous studies, an elliptic filter was used in this study [14, 19].

2.3. Segmentation of heart sounds

In this study, segmentation was performed using re-sampled energy method. S1 and S2 sounds were selected using the intervals generated by the signal energy.
A short time energy account is used to calculate the energy that the sound signal has at a given time. In this study, a square total energy function was used with resampling of the filtered signal. Sum of square energy can be calculated as Equation 2 [14].

$$E = \sum_{i=1}^{N} x(i)^2 \qquad (2)$$

Where, E is a sum of square energy (the short time energy). x is the audio signal, i is the sampled point, N is the total sampled point number.

2.4. Classification

Artificial neural networks (ANN) was used in this study.

2.4.1. Multilayer feedforward network

The Artificial Neural Network (ANN) is an efficient data processing system compromised by the analogy of centrally based biological neural networks. ANN acquires a large collection of units linked together in a specific way to communicate between units. These units, also called nodes or neurons, are simple parallel processors that operate in parallel. A neural network is an interconnected combination of simple processing elements, units or nodes based on the neuron of a loosely functioning animal. The ability to process the network has been recorded in a number of training examples, either at adaptation or at a combination of weights obtained by the learning process.
Associated memory can be defined as the process of calling patterns or templates stored in a partial or loud version of the original model. Feedforward networks can be used to accomplish this task, but a more powerful tool is provided by the repeating networking class. They may be thought of as not repetitively processing input models to provide new versions approaching a continuously stored memory.
Feedforward network is a non-repeating network with the processing units or nodes in the layer, and all nodes in a layer are linked to the nodes of the previous layers. There are different weights on the connection. There is no feedback loop, the signal input can only flow in one direction. Multilayer feedforward network is feedforward ANN concept with multiple weighted layers as seen Fig. 3. This network is called hidden layers because it has one or more layers between the input and output layers [20, 21].

2.4.2. Bayesian regularization backpropagation

In ANN, some regularization algorithms were developed to solve the problem of extreme compatibility. Levenberg-Marquardt (LM) and Bayesian regularization (BR) of regulating techniques are able to find less mean square errors than other algorithms for approximate problem handling. LM was developed especially for faster convergence in back propagation algorithms. Actually, BR has an objective function involving the sum of the mean squares and the sum of the square weights to minimize the prediction errors and obtain a good generalized model.
Instead of BR or LM, Multilayer Feedforward Artificial Neural Network or Radial Basis Function Artificial Neural Network algorithms can be examined. However, BR and LM are known to perform better than conventional methods in terms of speed and overfitting problems [22].

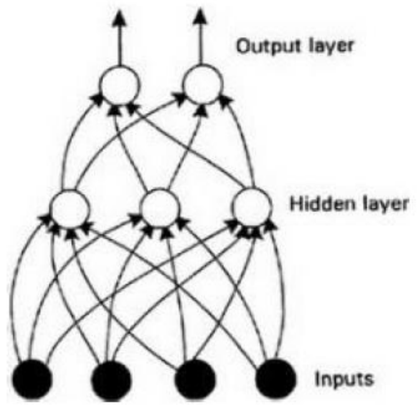

Fig. 3. Multilayer feed forward network [20]

The Bayesian regularization technique updates the weight and bias values according to Levenberg-Marquardt's optimization. With mean square errors, weights are reduced to the greatest together and then the right combination is set to create a generalized network. This process is called Bayesian smoothing [23]. In medical data sets, the best classification performance is obtained from the algorithms used for training of artificial neural networks by Bayesian regulation algorithm [24].

2.5. Performance Evaluation

Accuracy is often used as a measure of performance in the classification of medical data sets. The accuracy rate is used to evaluate the proposed method. This can be calculated as in (3).

$$Ac = \frac{T_P}{T_P + F_P} \qquad (3)$$

In the equation, T_P and F_P represents the numbers of true positives and false positives, respectively.

3. Segmentation of Heart Sounds

In this study, PASCAL Btraining heart sounds dataset was used. Sound files in this dataset are in wav format and they were obtained from a clinic trial in hospitals using the digital stethoscope DigiScope® [25]. In total 192 files of 3 types, as normal, murmur and extrasystole were selected from the Btraining data set. Table 1 shows the general characteristics of the heart sounds files.

Table 1. The general characteristics of the heart sounds files

Category of Sound Files	Duration	Sampling Frequency	Number of Files
Normal	8 second	4000 Hz.	52
Noisy Normal	8 second	4000 Hz.	26
Extrasystole	8 second	4000 Hz.	46
Murmur	8 second	4000 Hz.	52
Noisy Murmur	8 second	4000 Hz.	16
Total			**192**

As shown in Table 1, there are 5 different heart sounds in the data set. These are normal, noisy normal, extrasystole, murmur and noisy murmur. The heart sound diagrams of these sounds were shown in Fig. 4.

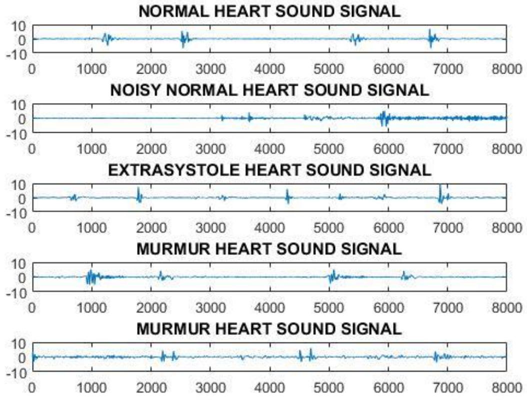

Fig. 4. The heart sound diagrams of selected sound files.

As mentioned earlier, the re-sampled energy method is used for segmentation. The resampling time is selected as 100 milliseconds. After normalization and filtering are done for all files in the data set, segmentation was done. First, the re-sampled energies of every heart sounds were calculated for segmentation. A sample diagram of re-sampled energy of 106_1306776721273_B1.wav file in dataset was given Fig. 5. As seen this figure, the re-sampled energy graphs of heart sounds consist of big, and small triangles. The big triangles correspond to the S1 sounds, and the small triangles correspond to the S2 sounds in the graph. Segmentation can be done easily by taking advantage of the base lengths of these triangles. In other words, by selecting intervals where the energy is different from zero, segmentation of S1 and S2 sounds can be done.

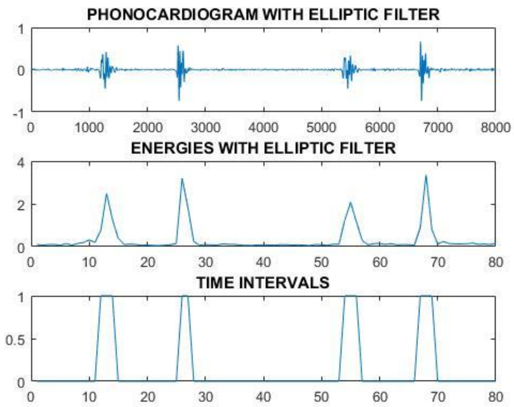

Fig. 5. A sample diagram of re-sampled energy of 106_1306776721273_ B1.wav file

After calculating the resampled energies for each heart sound sample, the segmentation of S1 and S2 sounds was performed. In the classification process, the durations of the S1 and S2 sounds are arranged to be 2 seconds for equalizing the column lengths in the matrix of data set. The segmented diagrams of S1 and S2 sounds obtained from the sample sounds were given in Fig. 6.

4. Classification of Heart Sounds

Multilayer feedforward network was used for classification. There are a number of 16 nodes in the network hidden layer. The Bayesian regularization back propagation used as learning algorithm and the mean square error function also used as a performance algorithm. From a total of 192 samples, 134 samples were used for training data, 29 samples were used for validation data, and 29 samples were used for testing data.

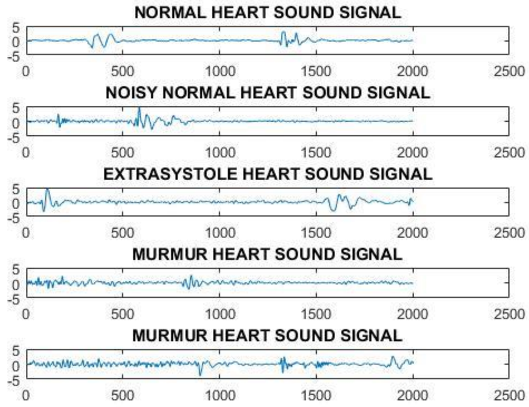

Fig. 6. The segmented diagrams of S1 and S2 sounds obtained from the sample sounds.

Each classification, non-segmented and segmented, was repeated twenty times with randomly selected training, validation, and testing data. The averages of the all accuracy rates obtained at the end of the classification process were taken.

First, a classification study was conducted for the non-segmented data set. The maximum numbers of epoch were selected 1000 and the classification was stopped at the end of 1000 epochs. The sample confusion matrix obtained at the end of the classification is given in Fig. 7. As it is seen from the sample confusion matrix, accuracy of classification 85.9% was achieved in the ANN classification.

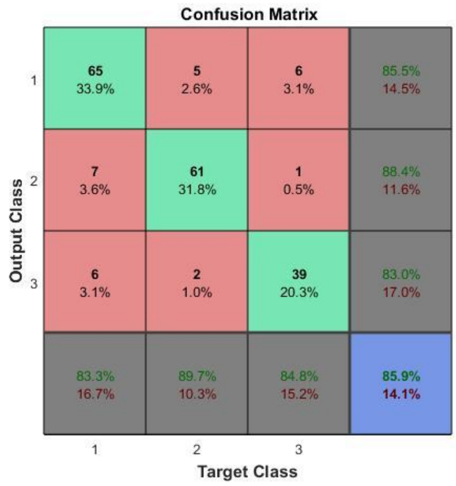

Fig. 7. The Sample confusion matrix of classification of non-segmented dataset

The accuracy rate of the randomly selected training, validation, and testing data was found to be 84% at the end of the twenty times repeated classification process.

In the second application, a classification study was conducted for the segmented data set. The maximum numbers of epoch were selected 1000 and the classification was stopped at the end of 1000 epochs. The sample confusion matrix obtained at the end of the classification is given in Fig. 8. As it is seen from the sample confusion matrix, the sample all accuracy of classification 89.1% was achieved in the ANN classification.

The accuracy rate of the randomly selected training, validation, and testing data was found to be 88.6% at the end of the twenty times repeated classification process.

5. Conclusions

In recent years, automated segmentation and classification of heart sounds has been used in many computer-assisted surveys in clinical practice to accurately detect heart diseases. This is related to a large part of the work. The classification studies on the ring voices are often used to provide the infrastructure for decision support systems. These classification studies are often done to increase the classification success. The segmentation of S1 and S2 sounds in heart sounds, the determination of the peak values of S1 and S2 sounds, the use of different filtering methods, and the use of different classification techniques are the most preferred ways to improve the classification success.

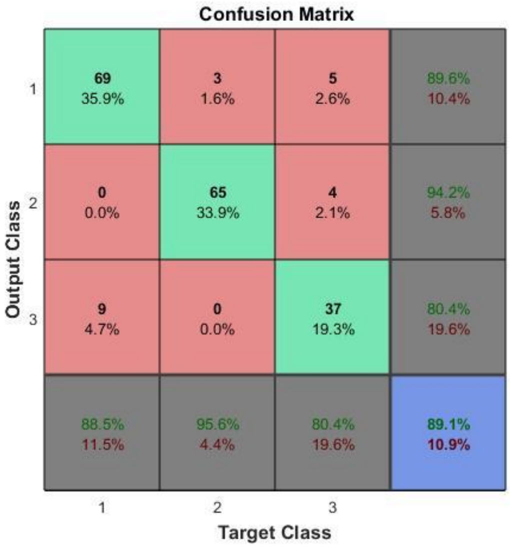

Fig. 8. The Sample confusion matrix of classification of segmented dataset.

In this study, the contribution of classifying of S1-S2 sounds segmented by the re-sampled energy method is examined. First, heart sounds samples were arranged for 8 seconds and normalized. After the pre-processing of the heart sound signals was completed, filtering was performed with an elliptic filter. Three different heart sounds data, such as normal, murmur, and extra systole in the PASCAL Btraining data set were classified. Two classification operations with artificial neural networks were performed with the segmented and non-segmented data set to compare the classification success. As a result of the classification studies, the average all accuracy of classification 84% was achieved in the non-segmented ANN study, and the average all accuracy of classification 88.6% was obtained in the segmented S1-S2 sounds ANN study. Thus, segmentation of heart sounds increased the accuracy of classification by about 4.6%. In studies carried out, it has been seen that segmentation increases the accuracy of classification and contributes to the classification studies efficiently.

In the future works, segmentation times can be adjusted such as only S1 or only S2, or different classification methods can be used to further enhance classification accuracy.

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