GU J Sci 31(1): 112-124 (2018)

Gazi University

Journal of Science

http://dergipark.gov.tr/gujs

Automated Auscultative Diagnosis System for Evaluation of Phonocardiogram Signals Associated with Heart Murmur Diseases

Ayşe ARSLAN[1], Oktay YILDIZ[2,*]

[1]*Yıldırım Beyazıt University, Department of Computer Engineering, Ankara, Turkey*

[2]*Gazi University, Department of Computer Engineering, Ankara, Turkey*

Article Info

Received: 26/09/2017
Accepted: 28/12/2017

Keywords

Computer-Assisted Diagnosis
Phonocardiography
Heart Sounds
Classification

Abstract

Cardiac auscultation that is a commonly used method to diagnose heart murmurs caused by cardiac disorders. Taking into account that this method is quite subjective and time consuming, the computerization of diagnosis process would significantly enhance clinical auscultation. Development of automated auscultative diagnosis systems, which provide more objective and reliable results, would be beneficial to reduce the classification errors for the cardiac disorders.
The presented study uses a combination of Mel–frequency cepstral coefficient (MFCC), BaumWelch parameter re-estimation and Hidden Markov Model (HMM) to diagnose and categorize heart murmurs. Classification experiments were conducted on the 84 high-quality heart sound data made up of 6 different types of murmurs. From this, average correct classification rate of 98.8% was achieved when the HMM has 5 states and frame size is 25ms. This study shows that, a highly successful automated auscultative diagnosis system working on less feature can be developed as a supportive diagnostic tool for health-care professionals.

1. INTRODUCTION

The heart is one of the vital organs and cardiovascular diseases may lead to fatal consequences. Abnormal heart sounds called murmur may be the precursor of many serious heart diseases. A heart sound-phonocardiogram signal consists of two consecutive primary activities; S1 and S2. Secondary signal activities between S1 and S2 are known as abnormal sounds (S3, S4, murmurs, clicks, etc.) [1]. Pathological heart anomalies can be detected by analyzing phonocardiogram characteristics such as localization, amplitude, frequency.

Heart diseases are one of the major causes of deterioration in the heart sound generally. Murmurs can be identified by the characterization of the abnormal heart sounds. Murmurs actually indicate various heart diseases depending on characteristics. The identification of heart diseases with high accuracy and reliability would provide benefit for the early diagnosis of serious heart discomforts.

The diagnosis process of heart sounds consists of these steps; first one is listening the heart sound with a stethoscope and second one is making a decision based on the past experience [1]. Cardiac auscultation still remains a common method in evaluation of cardiac functions and the detection of the cardiac abnormalities presence. However, this method is not objective and accuracy of results directly depends on the expertise, interpretation and perception ability of physicians.

Today, the use of two diagnostic methods are widely preferred in clinics: Electrocardiogram and Echocardiography. Electrocardiogram brings along high cost and long-term diagnostic process while Echocardiography cannot provide an effective outcome for all patients [2]. With these reasons, it would

*Corresponding author, e-mail: oyildiz@gazi.edu.tr

be desirable to improve a computer-aided automated auscultation system that can be helpful to obtain more objective and reliable diagnostic results and heart sound identification.

Taking into account that development of successful decision support systems would be quite helpful in clinics, especially in homecare, in rural areas where there are the lack of physicians and modern techniques, a lot of studies have been carried out to produce more stable and accurate diagnostic systems that support clinicians in auscultation process. Such automated diagnostic systems can be used as diagnostic tool by inexperienced physicians or cardiology students can benefit from these systems using as training tool.

In this study, a HMM-based diagnostic system providing automated heart disease identification with high achievement is proposed. There are similar studies on the classification of murmur sounds in the literature. However, there are no studies that have developed a model distinguishing between 6 different types of murmurs 100% succesfully. The main difference of this system from the others that providing higher accuracy with less feature. In the work performed, the Baum-Welch algorithm is applied on the feature vector obtained by MFCC technique to obtain unknown HMM parameters in the best way. These parameters, which are reduced to the smaller size instead of the whole feature vector, improve the classification performance and reduce the working time. In this way, a real-time diaagsosis system can be developed and used in clinics to be helpful to the doctors with another supportive decision tools if required. In addition, used data set is recorded with high quality stethescopes, and their quality is proven with various studies for filtering and noise cleaning. This study shows that, when such a data set recorded with high quality stethoscope is used, automatic murmur diagnostic systems with 100% high success can be developed and can be used in real life. Here, it appears that the device used plays an active role in the acquisition of phonocardiogram data. The HMM classifier has been found to be a very successful classifier in cases where the data set is composed of well-filtered, well-segmented and labeled data.

The paper is structured as follows: in Section 2 problem definition, the phonocardiogram data set and methodology are described while Section 3 explains pre-processing, feature extraction, model training and testing phases. The same section presents system performance results and compares this performance to the performance of a number of alternative approaches obtained in the previous similar studies. Finally, Section 4 includes conclusion and discussion of the findings.

2. METHODOLOGY

2.1. Heart Sounds and Murmur

Biomarkers received from the patient with the aid of a converter (electrode) can be interpreted with pre-processing, signal processing and classification techniques (Figure 1). S1 determines the beginning of systole; while S2 determines the end of systole and the beginning of diastole in a cardiac cycle. Additional sounds such as S3; S4; systolic click; ejection click may be included in this cycle in case of occurrence of various heart diseases, because these diseases generate abnormal sounds by reflecting on the heart sound.

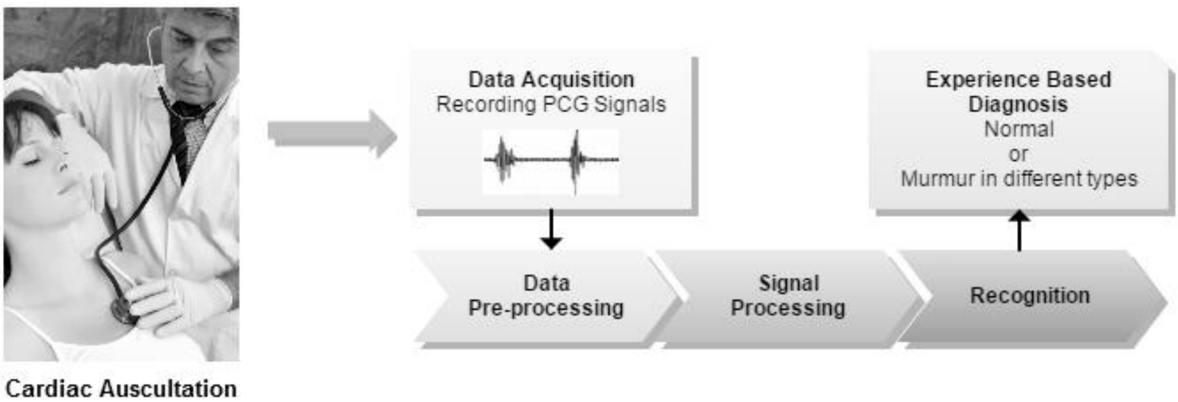

Figure 1. *Decision making process of biologic markers*

Abnormal heart sounds may refer to different heart diseases according to their characteristics. Murmur is a widely seen disease that can be identified just by analysis of these abnormal sounds. Normal and abnormal phonocardiogram signals are illustrated in Figure 2. Many of systolic murmurs are innocent, but diastolic murmurs usually indicate a heart problem. Murmurs can be classified as following [3]: systolic murmurs (early systolic (ES), late systolic (LS), holo systolic (HS)), diastolic murmurs (early diastolic (ED), middle diastolic (MD), late diastolic (LD)), sistolo-diastolic murmurs, continuous murmurs, ejection murmurs.

A well-trained physician can understand whether the murmur is innocent by listening to the heart of patient with a stethoscope. The intensity, duration and severity of the sounds are used for making a more informed decision about murmurs and their types. However, the human ear is insufficient for the exact diagnosis of some cardiac diseases in the analysis of phonocardiogram signals by auscultation.

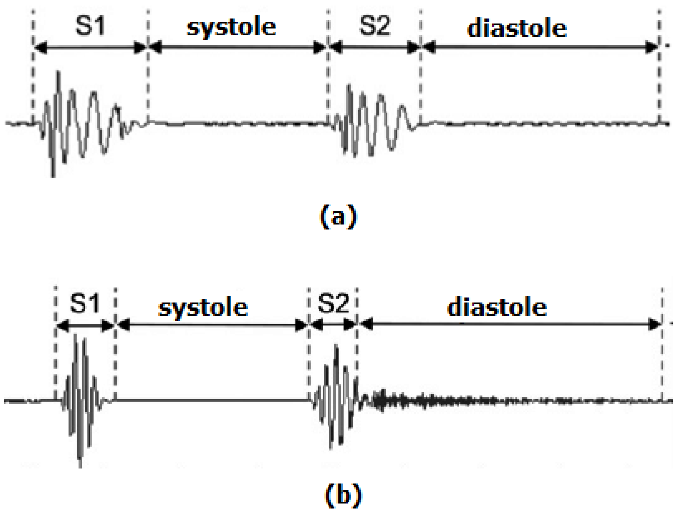

Figure 2. *Characteristics of heart sounds obtained from phonocardiogram signals of normal patient (a) and patient with murmur (b) [2].*

The intensity and duration of the intensity are critical information for the identification of murmurs. ED begins with S2 or right after while MD begins with S2 and reaches to S1, and these murmur sounds are often difficult to hear clearly because of being soft murmur and having a low amplitude. MS is seen shortly after S1, LS begins shortly after S1 and reaches to S2. MS has a fast-changing amplitude while LS is usually formed of soft and high-toned sounds. HS begins with S1 and has approximately uniform intensity throughout systole. In a normal heart, noises except from S1 and S2, S3 and S4 sounds must not be heard [4, 5].

2.2. Phonocardiogram Dataset

Phonocardiogram dataset is public to the use of researchers [6, 7], and can be accessed from internationally recognized medical equipment company [8]. It consists of 5 different degrees of murmur and regular phonocardiogram records received from 84 different patients with the help of a powerful electronic stethoscope.

2.3. Murmur Diagnosis System

Data pre-processing

According to literature, pre-processing techniques have a impact on recognition performance directly [8]. After recording, the data passed through pre-processing stage that includes data selection and segmentation. In the initial case, the recorded raw data composes of long-term phonocardiogram signals. By applying segmentation, murmur signal parts included in these signals are extracted under the supervision of experienced physicians and each of them is labeled with the appropriate murmur type. All data in different murmur types which will be used in the training phase are recognized and labeled.

Feature Extraction

Feature extraction process is detection of feature vectors that can characterize murmur sounds in the best way. The MFCC uses the Mel scale cepstral analysis that has similar frequency response of the human ear [9]. The MFCC algorithm and flowchart are illustrated in Figure 3 and Figure 4 in order [10].

```
Algorithm 1: MFCC feature extraction algorithm pseudocode
input : signal (Phonocardiogram signal)
output : MFCC ( MFCC of phonocardiogram signal)
function MFCC (parameters)
  Initialize parameters;
  Split into frames phonocardiogram signals;
  Apply Hamming windowing to frames;
  Get spectrum by applying Fast fourier transform to all frames;
  Determine matrix for a mel-spaced filterbank;
  Transform spectrum to mel spectrum;
  Obtain MFCC vector for each frame by applying discrete cosine transform;
end function
```

Figure 3. *Pseudo code of the MFCC algorithm used in the study.*

Frame blocking provides that sound signals are divided into short time intervals and framed [11]. The appropriate values of frame length and shifting value can be determined by trial and error method depending on the properties of the used signals. In the literature, frame length has been proposed varying between 20 and 30 ms for especially phonocardiogram signals and successful results have been observed [7, 12, 13].

Windowing is applied to minimize discontinuities located at the start and end points of the each frame. Hamming windowing function is one of the most used windowing functions:

$$Y(m) = X(m)\, W_n(m), \qquad 0 \leq m \leq N_m\text{-}1 \tag{1}$$ [10]

In Equation 1, *X(m)* input signal, *Y(m)* output signal, $W_n(m)$ represents the hamming window applied to the input signal, N_m is the number of samples within each window. $W_n(m)$, the Hamming function is shown in Equation 2.

$$W_n(m) = 0.54 - 0.46\, cos\, (2\pi m \,/\, (N_m - 1)), \qquad 0 \leq m \leq N_m\text{-}1 \tag{2}$$ [10]

Fast Fourier transform is used to transform the samples time domain into frequency domain. Fast Fourier transform formulation implemented on N_m samples is given in Equation 3. D_k is the given array (frame), D_m is the obtained complex numbers.

$$D_m = \sum\nolimits_{m=0}^{N_m-1} \left(e^{-\frac{j2\pi km}{N_m}} D_k \right) \qquad k = 0,1,2,\ldots, N_m\text{ -}1 \tag{3}$$ [10]

Equation 4 is used to convert the frequency to mel-frequency where *f* is frequency in hertz, *M* represents the mel frequency.

$$M = 2595\, log\, (1 + f/700) \tag{4}$$ [10]

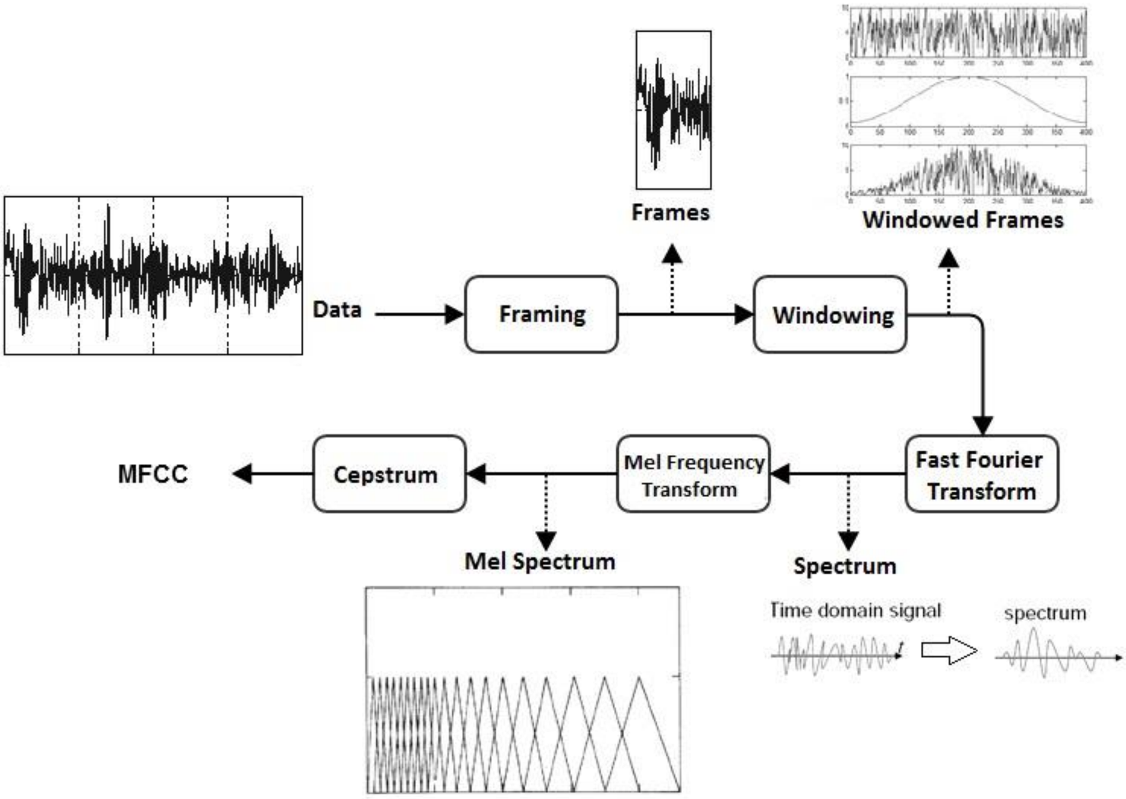

Figure 4. *The flow procedure of the MFCC feature extraction used in the study.*

Finally, work space is transformed from frequency domain to time domain by performing inverse Fourier transformation on all frames, and thus the *MFCC* values are obtained as seen Equation 5. *m* shows the number of coefficients, ($log\ D_k$) shows the log-energy output of the *kth* filter. *MFCC* feature vectors are obtained for each frame in selected *MFCC* size.

$$\mathrm{MFCC} = \sum_{k=1}^{k} (\log D_k) \cos[\mathrm{m}(\mathrm{k} - 1/2)\, \pi/k\,] \qquad \mathrm{m}=0,1,\ldots,\mathrm{k}-1, \qquad (5)[10]$$

Classification

HMM is a well-structured statictical learning and classification approach that can decide based on the probability weights defined by a probability distribution between states and transitions [11]. Unknown HMM parameters can be obtained by applying the Baum-Welch algorithm on MFCC feature vector and performing maximum likelihood parameter estimation. Classification performance is improved by using smaller feature vector instead of the entire feature vector.

$q_t = S_i$ expression indicates that system is in case of S_i at t time and the system is always

in one of N different cases ($S_1, S_2,..,S_N$). In Equation 6, the probability of passing from a state to another state depends on what the previous state is.

$$P(q_t=S_j \mid q_{t-1}=S_i,\ q_{t-2}=S_k,\ \ldots) \qquad (6)$$

In Equation 7, a state at time $t + 1$ depends only on the state at time t in the first-degree Markov model.

$P(q_{t+1}=S_j|q_t=S_i,q_{t-1}=S_k,\ldots)=P(q_{t+1}=S_j|q_t=S_i)$ (7)

N, the number of states in the model: $S=\{S_1,..S_N\}$

M, is the number of obtained different observations: $V=\{v_1, \ldots v_M\}$

A, state transition probability matrix: $A=[a_{ij}],a_{ij}=P(q_{t+1}=S_j,|q_t=S_i)$ (8)

B, observation probability matrix: $B=[b_j(m)]$, $b_j(m)=P(O_t=v_m|q_t=S_j)$ (9)

π, the initial state probabilities vector: $\pi=[\pi_i]$, $\pi_i=P(q_t=S_i)$ (10)

After determining *N* and *M* system parameters, $\lambda = (A, B, \pi)$ expression creates HMM.

3. EXPERIMENTAL STUDY

3.1. Training

The used data set that does not contain incorrect or noisy data, thus, no filtering processes were required and only segmentation was implemented in the pre-processing stage. Manual segmentation and labeling were implemented on phonocardiogram data in consultation with a experienced physician as ED, HS, MS, LS, MD and normal. Examples of murmur segments obtained with segmentation process are shown in Figure 5.

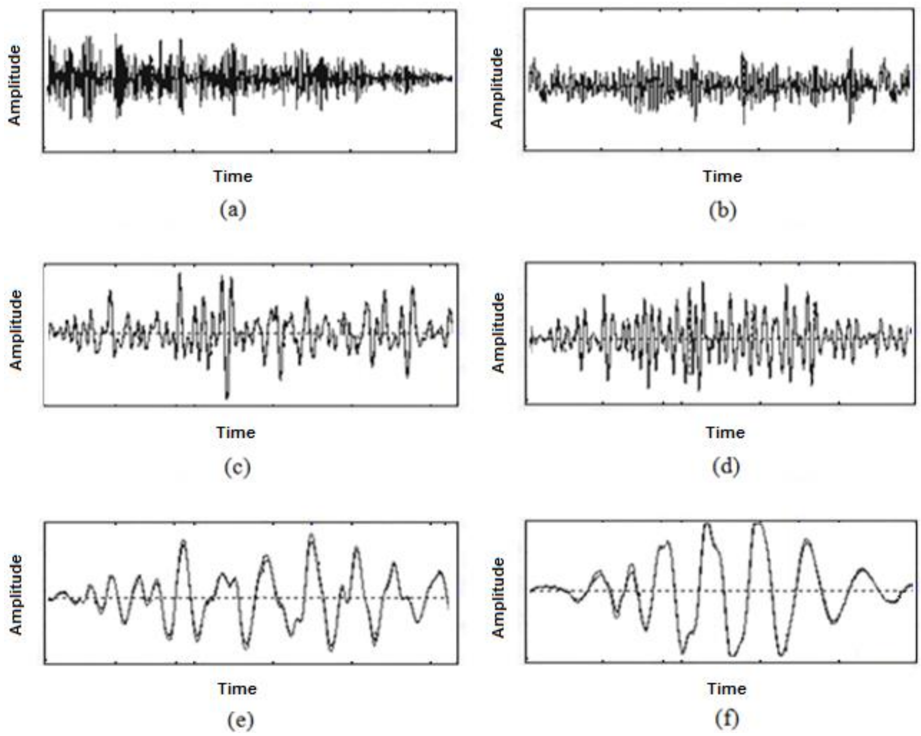

Figure 5. *Obtained phonocardiogram datas with segmentation (a) ED, (b) HS, (c) MS, (d) LS, (e) MD, (f) Normal.*

The feature vector of each data were extracted using MFCC. 22.050 Hz signals were framed in 25 ms length, the shifting value was selected as 1/3 ~ 1/2 of the frame size. Each frame was multiplied by

Hamming windowing function. Fast Fourier transform was applied on these signals for conversion from the time domain to the frequency domain.

The response of the calculated spectrum at mel scale was found. Transformation to the time domain was made on obtained mel spectrum by applying the discrete cosine transform. The number of coefficients extracted from each frame was defined as 22.
Principal parameters to give the HMM classifier model were determined by applying Baum Welch algorithm on the extracted features. Unknown HMM parameters were obtained both more correctly and in the smaller size. Storing compact parameters instead of all feature vector increases the classification performance.

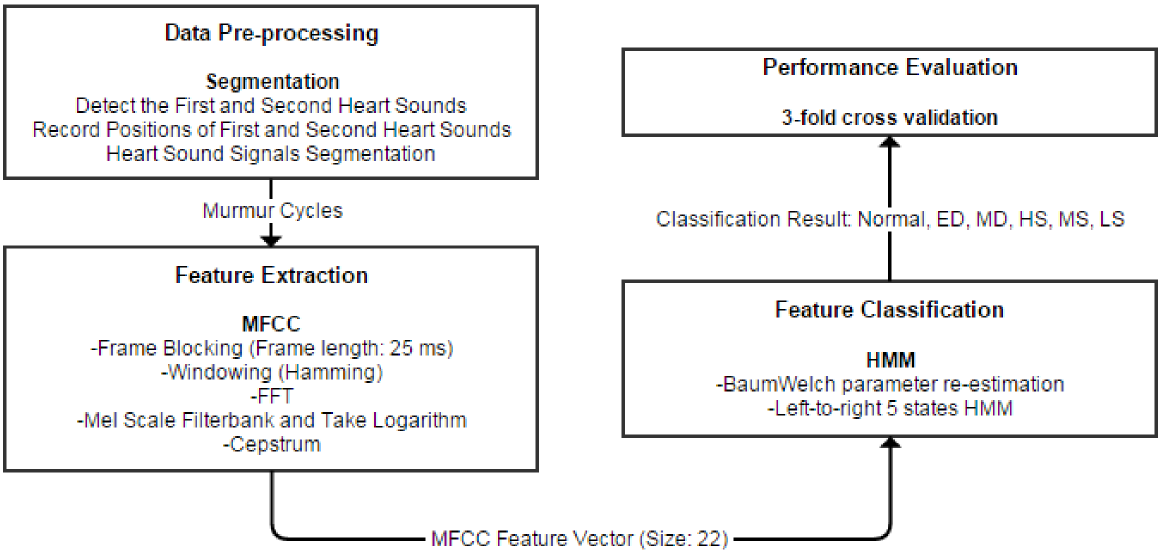

Figure 6. *The flowchart of the study to classify different types of heart sounds.*

The classifier model was generated by left to right HMM by assigning probabilities to the transitions between consecutive segments appropriately to train system by using the 2/3 of data set and conducted murmur classification process was performed as seen in Figure 6.

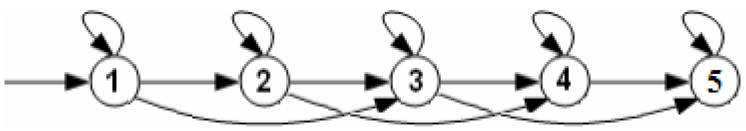

Figure 7. *5-states Hidden Markov Model.*

Different situations of a murmur segment from start to end point generate states of HMM state machine and the number of states was selected as 5 in this study (Figure 7).

3.2. Test and Validation

Test and validation of the implemented system were performed by k-fold cross validation technique. In 3-fold cross validation, 15 samples labeled as ED, LS, HS, MD, and normal separately were divided into 3 subsets, so each of subset had 5 samples. 10 samples were used for training, the remaining 5 samples were used for testing. The classification process was repeated 3 times so that each subset was used in testing and the others were used in training. 11 samples labeled as MS divided into subsets, 8 samples were used for training, the remaining 3 samples were used for testing. As an important point, there has been no change in performance when the 3-fold and 5-fold cross validation is applied. It is seen that the feature vector size representing phonocardiogram signals has an important effect on classification performance. Thus, the obtained performances in different vector sizes, frame length, shifting value and k value in k-fold cross validation were analyzed and compared by repeating experimental study. A comparative evaluation of results based on feature vector size is presented Table 2.

Table 1. *Performance evaluation of system with 3-fold cross validation.*

Type of Diseases	**Results of 3-fold cross validation Test Data Feature Vector Size (n)**		
	n =2	n =12	n =22
Early Diastolic	14/15	15/15	15/15
Late Systolic	15/15	10/15	14/15
Holo Systolic	13/15	15/15	15/15
Mid Diastolic	12/15	15/15	15/15
Mid Systolic	9/9	9/9	9/9
Normal	15/15	15/15	15/15
Total	78/84 (92.9%)	79/84 (94.1%)	83/84 (98.8%)

4. RESULTS AND DISCUSSION

We investigated a HMM-based diagnostic system providing automated heart disease identification with high achievement in this study. The main purpose of this system that providing higher accuracy with less feature than the previous studies.

Early identification of cardiovascular diseases is a famous one of medical research interests. The machine learning algorithms have been implemented successfully with the purpose of the heart sound identification and classification [14-35]. There are available successful studies in which hybrid classifiers were used and highly significant results were obtained [2, 20]. Artificial Neural Networks (ANN) is one of the commonly used techniques for classification of phonocardiogram signals [14-22]. High achievements have been obtained in the phonocardiogram signal segmentation and classification problems with HMM [23-27]. A study that used Mel Frequency Cepstral Coefficients (MFCC) feature extraction and HMM classification techniques to develop automated auscultation system showed that the performance of auscultation varies depending on the localization and the most appropriate region is tricuspid region with 90.2% accuracy [27]. Support Vector Machines (SVM) and Dynamic Time Warping (DTW) and k-nearest neighbor (k-NN) algorithms are also famous classifiers used in the classification of cardiac diseases [28-33].

In the traditional auscultation method, physicians need the advanced training and perception skills to become capable to discriminate objectively all the characteristics of heart sounds in an reproducible way and to make a decision depending on them accurately. However, especially junior health care physicians who have poor auscultation skills or are not experienced and well-trained for cardiology.

In this study, we report on implementation of a real-time diagnostic tool to detect various murmur diseases automatically. This is significant because the traditional auscultation is quite subjective, time consuming and dependent entirely on perception of physicians, therefore the enhancement of diagnosis techniques would contribute significantly to clinical cardiovascular analysis. The main novelty of this system is providing higher accuracy despite the less feature usage than the previous studies. The number of features, definition of actual model parameters and their impact on performance are critical points to be implement a real time system. Most of the previous research on the automated classification of heart sound signals focused on feature extraction and learning algorithms, while impact of data set quality and accurate model parameters identification have not been sufficiently explored yet. In this study, a reliable data set taken from patients with a robust and sensitive electronic stethoscope is used. This study clearly shows that successful automatic auscultative diagnostic kits can be developed by working on the ideal phonocardiogram signals and by implementing computational techniques with correct parameters to be used in real life. Taking into account that many studies were conducted to diagnose heart murmurs, but this problem is still not clarified sufficiently and need better performance results to be implemented in real cardiology treatments, this study would serve a reliable diagnostic auscultative tool with higher accuracy.

Table 2. *A comparative results between the developed system and the previous studies*

Authors	Scope	Method	Accuracy rate
Ping et al. [36]	Contiuous Murmur (CM), Diastolic Murmur (DM), Systolic Murmur (SM), Normal	Feature Extraction: •Time Domain(TD) •Short Time Fourier Transform (STFT) •MFCC Classification •HMM	Sensitivity: TD: 0.83 STFT: 0.93 MFCC: 0.97 Specifitiy: TD: 0.84 STFT: 0.94 MFCC: 0.96
Carlos et al. [37]	Segmentation of heart sounds	Feature extraction •MFCC Classification •HMM	Frame error rate: Training records: 0.053±0.021 Remaining records: 0.12±0.084 Model error rate: Training records: 0.031±0.011 Remaining records: 0.096±0.061
Hang et al. [38]	Normal sound (NM), Innocent Murmur (IM), Splitting (SPI), Mitral Value Prolapse (MVP), Gallop (GAL), Ventrical Septal Defect (VSD), Aortic Stenosis (AS), Mitral Stenosis (MS), Pulmonic Stenosis (PS), Coarctation of Aorta (CA)	Feature extraction •MFCC Classification •HMM	95.08% maximum correct classification rate
Juan et al [6]	Holo Systolic Murmur (HS), Mid Systolic Murmur (MS), Normal	Classification •ANN.	96.7% average classification rate
Chauhan et al [39]	Continuous murmur (CM) Systolic murmurs (SM) Diastolic murmurs (DM)	Feature extraction •MFCC Classification •HMM	95.7% (CM) 96.25% (SM) 90% (DM)
Kwak et al [2]	Normal Abnormal	Feature extraction •MFCC Classification •HMM	98.7 (normal) 97.5 (abnormal)
Our study	**Early Diastolic Murmur (ED), Holo Systolic Murmur (HS), Mid Diastolic Murmur (MD), Mid Systolic Murmur (MS), Late Systolic Murmur (LS) Normal**	**Feature extraction •MFCC Classification •HMM**	**98.8% Average classification rate**

5. CONCLUSION

Today, cardiac auscultation is still a common technique for the diagnosis of heart diseases. Accurate diagnosis and timely taken measures have a great importance in the early treatment of heart diseases that may have mortality risk and this dependent on the experience and perception skills of the physicians directly. Development of a computer-aided diagnosis system that can assist to physicians in auscultation process can be beneficial by providing highly accurate, quickly and cost-effectively remote diagnosis. Most of the previous research on the automated classification of heart sound signals focused on learning algorithms, while impact of data set quality and feature vector has not been sufficiently explored yet.

In this study, a computer-aided automatic murmur diagnosis system was implemented on a reliable data set with higher accuracy than previous studies despite the less feature usage. The system can automatically diagnose murmur diseases just by listening phonocardiogram signals with an electronic stethoscope from healthy and sick peoples that have different degrees of murmur. In implemented system, classification of phonocardiogram signals is carried out with 98.8% success when size of feature vector, n is selected as 22, 94.1% when n is selected as 12, 92.9% when n is selected as 2 (Table 1). Another important point is obtaining the actual parameters of HMM by applying Baum-Welch algorithm and reducing MFCC feature vector to improve system performance.

The obtained results show that some important criterias for high achievement of automatic murmur diagnosis system such as working on phonocardiogram signals that are filtered from noise and other factors, successful segmentation and labeling, definition of HMM parameters accurately. With the developed system, ED, HS, MD, MS and normal murmurs with 100%, LS murmur with 93.3% success can be recognized by a reliable computerized recognition system. Thus, it is clearly seen that successful automatic auscultative diagnostic kits can be developed by working on the ideal phonocardiogram signals and implementing computational techniques with correct parameters to be used in real life.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

[1] Debbal, S.M., Bereksi-Reguig, F., “Computerized heart sounds analysis”, Computers in biology and medicine, 38(2), 263-280, (2008).

[2] Kwak, C., Kwon, O.W., “Cardiac disorder classification by heart sound signals using murmur likelihood and hidden Markov model state likelihood”, IET signal processing, 6(4), 326-334, (2012).

[3] Eroğlu, A.G., “Üfürümlü çocuğa yaklaşım”, Turkish Pediatrics Archive, 44(2), (2009).

[4] Topol, E.J., Califf, R.M., “Textbook of cardiovascular medicine”, Lippincott Williams & Wilkins, (2007).

[5] Abbas, A.K., Bassam, R., “Phonocardiography signal processing”, Synthesis Lectures on Biomedical Engineering, 4(1), 1-194, (2009).

[6] Liu, J., Liu, W., Wang, H., Tao, T., Zhang, J., “A novel envelope extraction method for multichannel heart sounds signal detection”, 2011 International conference on computer science and information technology, IPCSIT, 51:630-638, (2012).

[7] Arslan, A., Yildiz, O., “Cardiac arrhythmia analysis using Hidden Markov Model and murmur diagnosis”, Signal Processing and Communications Applications Conference (SIU), 2014 22nd. IEEE, (2014).

[8] 3M littman heart sounds data set information, Available: http://www.littmann.com/wps/portal/3M/en_US/3M-Littmann/stethoscope/littmann-learning-institute/heart-lung-sounds/, (2015).

[9] Ellis, D., Mandel, M., "Automatic analysis of heart sounds using speech recognition techniques", Speech Communication 48.9, 1162-1181, (2005).

[10] Gupta, S., Jaafar, J., Ahmad, W.F.W., Bansal, A., "Feature extraction using MFCC", Signal & Image Processing, 4(4), 101, (2013).

[11] Schafer, R.W., Rabiner, L.R., "Digital representations of speech signals", Proceedings of the IEEE, 63(4), 662-677, (1975).

[12] Vyas, G., Kumari, B., "Speaker recognition system based on MFCC and DCT", International Journal of Engineering and Advanced Technology (IJEAT), 2(5), 145-148, (2013).

[13] Verma, S., Kashyap, T., "Analysis of heart sound as biometric using MFCC & Linear SVM classifier", International Jornal of Advanced Research in Electrical and Electronics and Instrumentation Engineering, 3(1), (2014).

[14] Gupta, C.N., Palaniappan, R., Swaminathan, S., Krishnan, S.M., "Neural network classification of homomorphic segmented heart sounds", Applied soft computing, 7(1), 286-297, (2007).

[15] Abdel-Motaleb, I., Akula, R., "Artificial intelligence algorithm for heart disease diagnosis using phonocardiogram signals", Electro/Information Technology (EIT), 2012 IEEE International Conference, IEEE, (2012).

[16] Babaei, S., Geranmayeh, A., "Heart sound reproduction based on neural network classification of cardiac valve disorders using wavelet transforms of PCG signals", Computers in Biology and Medicine, 39(1), 8-15, (2009).

[17] Martínez-Alajarín, J., López-Candel, J., Ruiz-Merino, R., "Classification and diagnosis of heart sounds and murmurs using artificial neural networks", International Work-Conference on the Interplay between Natural and Artificial Computation, Springer, Berlin, Heidelberg, (2007).

[18] Uğuz, H., "A biomedical system based on artificial neural network and principal component analysis for diagnosis of the heart valve diseases", Journal of medical systems, 36(1), 61-72, (2012).

[19] Sinha, R.K., Aggarwal, Y., Das, B.N., "Backpropagation artificial neural network classifier to detect changes in heart sound due to mitral valve regurgitation", Journal of Medical Systems, 31(3), 205-209, (2007).

[20] Phatiwuttipat, P., Kongprawechon, W., Tungpimolrut, K., Yuenyong, S., "Cardiac auscultation analysis system with neural network and SVM technique", Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2011 8th International Conference, IEEE, (2011).

[21] Rios-Gutierrez, F., Alba-Flores, R., Strunic, S., "Recognition and classification of cardiac murmurs using ANN and segmentation", Electrical Communications and Computers (CONIELECOMP), 2012 22nd International Conference, IEEE, (2012).

[22] Salman, A.H., Mengko, T.R., Mengko, R.K.W., Langi, A.Z.R.," Review of digital heart sound classification methods via Artificial Neural Networks", Instrumentation, Communications, Information Technology, and Biomedical Engineering (ICICI-BME), 2013 3rd International Conference, IEEE, (2013).

[23] Zhuravlev, Y.I., “Pattern recognition and image analysis”, MAIK Nauka/Interperiodica, (2005).

[24] Schmidt, S.E., Toft, E., Holst-Hansen, C., Graff, C., Struijk, J.J., “Segmentation of heart sound recordings from an electronic stethoscope by a duration dependent Hidden-Markov model”, Computers in Cardiology, IEEE, (2008).

[25] Ricke, A.D., Povinelli, R.J., Johnson, M.T., “Automatic segmentation of heart sound signals using hidden Markov models”, Computers in Cardiology, IEEE, (2005).

[26] Malayath, N., Hermansky, H., “Data-driven spectral basis functions for automatic speech recognition”, Speech communication, 40(4), 449-466, (2003).

[27] Kamarulafizam, I., Noor, A.M., Harris, A.A., Oemar, H., Yusoff, K., “Classification of heart sound based on multipoint auscultation system”, Systems, Signal Processing and their Applications (WoSSPA), 2013 8th International Workshop, IEEE, (2013).

[28] Sengur, A., “Support vector machine ensembles for intelligent diagnosis of valvular heart disease”, Journal of medical systems, 36(4), 2649-2655, (2012).

[29] Markaki, M., Germanakis, I., Stylianou, Y., “Automatic classification of systolic heart murmurs”, Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference, IEEE, (2013).

[30] Chatunapalak, I., Phatiwuttipat, P., Kongprawechnon, W., Tungpimolrut, K., “Childhood musical murmur classification with support vector machine technique”, Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2012 9th International Conference, IEEE, (2012).

[31] Kumar, D., Carvalho, P., Antunes, M., Paiva, R.P., Henriques, J., “Heart murmur classification with feature selection”, Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference, IEEE, (2010).

[32] Fu, W., Yang, X., Wang, Y., “Heart sound diagnosis based on DTW and MFCC”, In Image and Signal Processing (CISP), 2010 3rd International Congress, IEEE, (2010).

[33] Shen, C.H., Choy, F.K., Chen, Y., Wang, S., “A modular approach to computer-aided auscultation: Analysis and parametric characterization of murmur acoustic qualities”, Computers in biology and medicine, 43(6), 798-805, (2013).

[34] Bilge, H.Ş., Verim, V., “Ultrason görüntülerinde prostat sınırının bulunması”, Gazi Üniversitesi Mühendislik-Mimarlık Fakültesi Dergisi, 22(3), (2007).

[35] Yıldız, O., Bilge, H.Ş., Akcayol, M.A., Güler, İ., “Meme Kanseri Sınıflandırması için Veri Füzyonu ve Genetik Algoritma Tabanlı Gen Seçimi”, Gazi Üniversitesi Mühendislik-Mimarlık Fakültesi Dergisi, 27(3), (2012).

[36] Wang, P., Lim, C.S., Chauhan, S., Foo, J.Y.A., Anantharaman, V., “Phonocardiographic signal analysis method using a modified hidden Markov model”, Annals of Biomedical Engineering, 35(3), 367-374, (2007).

[37] Lima, C.S., Cardoso, M.J., “Phonocardiogram segmentation by using hidden Markov models”, Proceedings of the Fifth IASTED International Conference on Biomedical Engineering; 2007 Feb 14-16; Innsbruck: Austria, (2007).

[38] Wu, H., Kim, S., Bae, K.," Hidden Markov Model with heart sound signals for identification of heart diseases", Proceedings of 20th International Congress on Acoustics (ICA), Sydney, Australia, (2010).

[39] Chauhan, S., Wang, P., Lim, C.S., Anantharaman, V., "A computer-aided MFCC-based HMM system for automatic auscultation", Computers in Biology and Medicine, 38(2), 221-233, (2008).