Improving the Recognition of Heart Murmur

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***Abstract*—Diagnosis of congenital cardiac defects is challenging, with some being diagnosed during pregnancy while others are diagnosed after birth or later on during childhood. Prompt diagnosis allows early intervention and best prognosis. Contemporary diagnosis relies upon the history, clinical examination, pulse oximetery, chest X-ray, electrocardiogram (ECG), echocardiography (ECHO), computed tomography (CT) and cardiac catheterization. These diagnostic modalities reliable upon recording electrical activity or sound waves or upon radiation. Yet, congenital heart diseases are still liable to misdiagnosis because of level of operator expertise and other multiple factors. In an attempt to minimize effect of operator expertise this paper built a classification model for heart murmur recognition using Hidden Markov Model (HMM). This paper used Mel Frequency Cepestral coefficient (MFCC) as a feature and 13 MFCC coefficients. The machine learning model built by studying 1069 different heart sounds covering normal heart sounds, ventricular septal defect (VSD), mitral regurgitation (MR), aortic stenosis (AS), aortic regurgitation (AR), patent ductus arteriosus (PDA), pulmonary regurgitation (PR), and pulmonary stenosis (PS). MFCC feature used to extract feature matrix for each type of heart sounds after separation according to amplitude threshold. The frequency of normal heart sound (range= 1Hz to 139Hz) was specific without overlap with any of the studied defects (ranged= 156-556Hz). The frequency ranges for each of these defects was typical without overlap according to examined heart area (aortic, pulmonary, tricuspid and mitral area). The overall correct classification rate (CCR) using this model was 96% and sensitivity 98%. This model has great potential for prompt screening and specific defect detection. Effect of cardiac contractility, cardiomegaly or cardiac electrical activity on this novel detection system needs to be verified in future works.**

Keywords*—component; Hidden Markov Model (HMM); Heart Murmur; Mel Frequency Cepestral Coefficient MFCC; Systolic Murmur; Diastolic Murmur; Auscultation Area; ventricular septaldefect (VSD); mitral stenosis (MS); mitral regurgitation (MR); aortic stenosis (AS); aortic regurgitation (AR); patent ductusarteriosus (PDA); pulmonary regurgitation (PR); pulmonary stenosis (PS); Electrocardiogram(ECG); Echocardiography(ECHO); Computed Tomography(CT); Correct Classification Rate(CCR); Artificial Neural Network(ANN); Back Propagation Neural Network (BPNN); Empirical Mode Decomposition (EMD); Support Vector Machines(SVM); Adaptive Neuro-Fuzzy Inference System (ANFIS); MATRIXLABORATORY (MATLAB); Radial Basis Function (RBF)

I. INTRODUCTION

Murmur detection is the cornerstone of diagnosis of congenital heart diseases [1,2]. Efficient detection and delineation of murmurs is important to achieve diagnosis [3]. Research in heart murmur recognition is divided into two domains; (1) heart murmur recognition and (2) suggested method for more accurate murmur recognition. Most of studies in the first domain focused on recognition of mitral regurgitation (MR), mitral stenosis (MS), aortic regurgitation (AR), aortic stenosis (AS), pulmonary stenosis (PS) and normal heart sound [4]. Accurate murmur recognition was reported to vary according to used method, where artificial neural network (ANN) based murmur classification achieved accuracy of 48.5% with recorded signal and 85% with simulated sound. Researchers built a databank with 110 sounds from 28 patients with feature vector extraction from spectrogram using average single cycle. For model testing they used 7 examples for normal sound, 4 examples for aortic stenosis and 4 examples for aortic regurgitation [5]. Back propagation neural network (BPNN) and Hidden Markov model (HMM) were also employed in murmur recognition, with extraction based upon Mel Frequency Cepestral coefficient (MFCC) as a feature. The BPNN overall CCR was reported to be 82.8% and HMM model murmur sounds overall CCR was 94.2% [6]. The recognition using HMM with empirical mode decomposition (EMD) and MFCC yielded overall accuracy equal 98.9% [7]. Other algorithms ANN with back propagation techniques, support vector machines (SVM), ANN with radial basis function and Adaptive Neuro-Fuzzy Inference System (ANFIS) classifiers were also used to recognize four types of murmur aortic regurgitation, aortic stenosis, mitral regurgitation and mitral stenosis with 90% accuracy [8]. SVM also used in heart murmur recognition based on feature extraction including four feature sets, each feature set covered specific domain. They used 3 domains (time domain, frequency domain and statistical domain). They have sensitivity range (86%-100%) [9]. Some research papers suggested new method for feature extraction in presence of murmur; they extracted feature from different features in phonocardiogram (PCG). Each heart signal represented by feature vector contains 7 variables (maximum value amplitude, sum of positive area, absolute sum of negative area, variance, shanon energy, bispectrum and winger bispectrum) [10]. This research aimed at building a novel model with high CCR [11] for detection of the normal heart and with high CCR for murmur recognition using Hidden Markov Model (HMM) and the open source matrix laboratory (MATLAB) as a programming language to build model from scratch. The paper is structured in five main sections: first section subjects and methods, in the second section statistical analysis, in the third section results, in the fourth section discussion and in the final section conclusions.

II. Subjects and Methods

A. Subjects

This research studied 1069 records of heart sounds. The study commenced by April 2015 and ended by November 2015. The records belonged to normal and structurally abnormal hearts. The 1069 records belonged to 824 children whose diagnoses were confirmed by echocardiography devices (SIEMENS acuson CV70 and Vivid S5) and other diagnostic modalities according to clinical decision.

B. Methods

a) Heart Model Creation

Heartbeats were recorded at 16-bit accuracy and 44100 Hz sampling frequency and stored as **wav** format. This research studied 605 heart sounds to build the model, of them 177 (29.3%) were records of normal hearts and 428 (70.7%) were records of structurally abnormal hearts. The structural heart abnormalities studied included VSD, PDA, MR, PS, PR, AR and AS. The records were generated from the known the auscultation areas (Mitral Area, Tricuspid Area, Pulmonary Area and Aortic Area) as shown in figure 1.

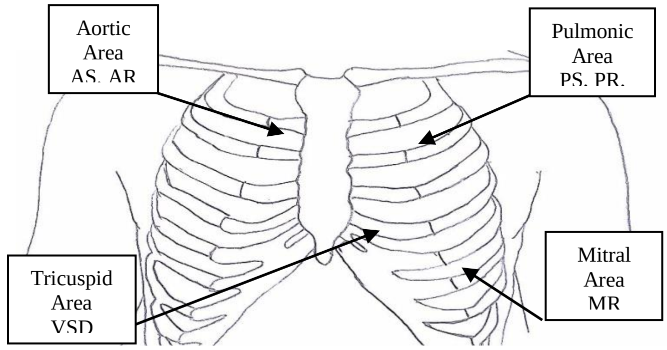

Fig. 1. Auscultation Areas

Heart sounds S1 and S2 were separated from other sounds depending on specific (0.014A amplitude threshold used to separate murmur from the original signal) threshold. Accordingly heart sounds were separated from overlapping

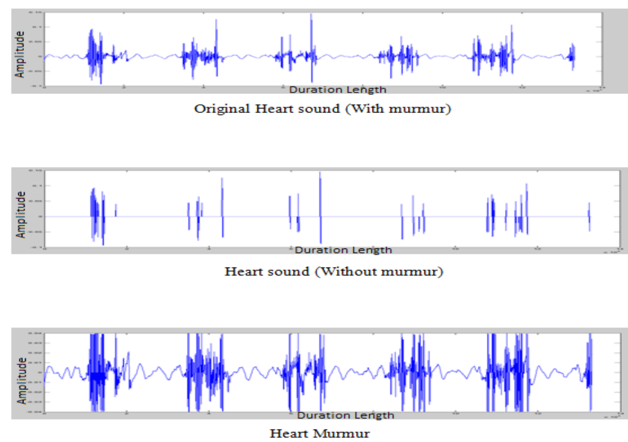

Fig. 2. Heart Murmur Separation

murmurs as shown in figure 2. MFCC feature used to extract feature matrix for each type of heart sounds. MFCC computation display is shown in figure 3. In MFCC computation 13 cepestral coefficients used for each type of heart sound to delineate clearly normal heart sounds frequency.

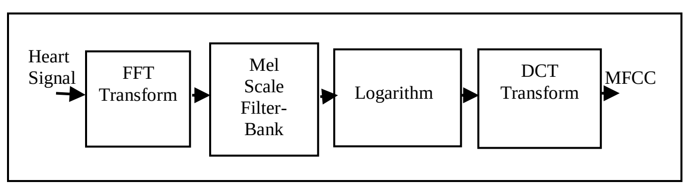

Fig. 3. MFFC Computation Steps

MFCCs computed as follow:

1) Initialize MFCC parameter analysis: frame duration 100 ms, analysis frame shift 99, pre-emphasis coefficient 0.97, number of filter-bank channels 20, number of cepstral coefficients 13, cepstral sine lifter parameter 22, lower frequency limit 130 Hz, upper frequency limit 500 Hz.

2) Preemphasis filtering:

$$y[n] = x[n] - a.x[n-1] \qquad (1)$$

3) Framing and windowing signal. Window size=100, frame shift=99.And we applied hamming window to keep the continuity of the first point and the last point in each frame.

4) Compute fast fourier transform FFT using built in function fft.

5) Apply triangular filter-bank on mel-scale using trifbank function.

6) Apply filter-bank to unique part of the magnitude.

7) DCT matrix computation to eliminate discontinuities.

8) Compute DCT of the log filter-bank FBE. And keep the first 13 DCT coefficients.

Then the heart sounds classified according to HMM model as follows:

1) HMM trained using MFCC feature matrix.

2) Baum-Welch used in HMM to produce new parameter estimates that have equal or greater likelihood of having generated the training data.

3) Viterbi algorithm used to determine the best state sequence that maximizes the probability of generation of the observation sequence (each feature matrix represented one observation).

4) Forward-backward algorithm used to calculate the probability.

5) The heart model isolated HMM model for each auscultation area related murmurs. Auscultation area are divided into 4 areas to increase HMM model accuracy. Figure 4 shows model processing.

6) A heart model guided created by anatomic auscultation areas, to sense frequencies and designate origin of structural abnormality to overcome limitations of frequencies overlap.

7) Frequencies classified as low (1Hz-139Hz) and high (156Hz-556Hz). Structurally normal hearts frequencies were encountered in the low range but never in high range, yet the opposite was not correct, as we encountered low and high frequencies from mild cases of valvular defects. Thus any low frequency was subjected to amplification one fold before designation.

8) Detected signals classified by machine learning into nominal characters denoting specific structural defects.

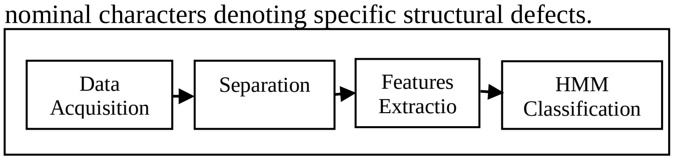

Fig. 4. Heart Model Processing

b) Heart Model Validation:

The created heart machine learning model based on HMM and MFCC used to recognize 464 blinded heart sounds. All validation studies were compared to diagnoses derived from standard echocardiography and other imaging studies.

III. Statistical Analysis

Statistical analysis was conducted using Statistical Package for Social Sciences version 15 (SPSS, Chicago, Ill). Simple frequency, cross-tabulation, descriptive analysis, and tests of significance (t test for parametric data and $\chi 2$ tests for nonparametric numbers N5) were used. Studied heart sounds validation was computed according to CCR [11]. Sensitivity testing was computed for created heart model.

IV. Results

The study was conducted on 1069 records that belonged to 824 children whose diagnoses were confirmed by echocardiography and other diagnostic modalities according to clinical decision. Their ages ranged from 1 week to 14 years (mean±standard deviation=2years 9.5months ±6 months. Of them 458 (55.6%) were males. Table 1 shows different diagnoses of the studied sound records.

A. *Heart Model Creation:*

605 heart sounds were studied to build the model, of them 177 (29.3%) were records of normal hearts and 428 (70.7%) were records of abnormal heart sounds. The structural heart abnormalities studied included VSD, PDA, MR, PS, PR and AS.

Table 2 demonstrates the frequencies of recognized sounds of the aforementioned structural valvular defects, and clearly separates frequencies from structurally normal heart from those of structurally abnormal hearts. We detected general overlap of frequencies between the aforementioned abnormalities, yet this overlap was not recorded on any specific auscultation area according to figure 1.

B. *Heart Model Validation:*

This paper used 464 heart signals covering 100 normal hearts, 62 PS, 56 PR, 46 MR, 64 VSD, 72 PDA, 61 AS and 3 AR to test heart sound recognition using machine learning model based on HMM and MFCC.

TABLE I. Diagnosis of Studied Recorded Signal

diagnoses	**Total Number of Sound Records**		**Machine Learning Model Based on HMM and MFCC Creation**		**Machine Learning Model Based on HMM and MFCC Validation**	
	N	**%**	**N**	**%**	**N**	**%**
PR	146	13.7	90	14.9	56	12
PS	142	13.3	80	13.2	62	13
PDA	152	14.2	80	13.2	72	15.5
VSD	154	14.4	90	14.9	64	13.9
AS	94	8.8	33	5.5	61	13
AR	3	0.2	0	-	3	0.6
MR	101	9.4	55	9.1	46	10
NO	277	26	177	29.2	100	22
Total	1069	100%	605	100	464	100

HMM: Hidden Markov Model, **N**=Total number of heart sounds.

Table 3 demonstrates ages of studied records according to ages.

TABLE II. HEART SIGNAL FREQUENCY RANGE IN HZ

Class	N	%	Frequency Range Min	Max
Normal	177	29.2	1	139
Abnormal	431	70.8	156	556
Tricuspid Area				
VSD	90	14.9	156	164
Mitral Area				
MR	55	9	158	162
Pulmonary Area				
PDA	80	13.2	157	167
PS	80	13.2	156	556
PR	90	14.9	156	200
Aortic Area				
AS	33	5.5	157	176
AR	3	0.1	156	160

Min: Minimum frequency, **Max**: Maximum frequency.

This paper evaluated machine learning heart model based on HMM and MFCC according to sensitivity as shown in table 4 and CCR in table 5.

TABLE III. STUDIED RECORDS ACCORDING TO AGES OF CHILDREN

	Mean age (years)	**SD**(months)	**t -test p =**
Heart Model Creation Group	2.8	7.9	
Heart Model Validation Group	2.82	7.8	0.00072

SD: Standard Deviation.

Finally, mean CCR of machine learning model based on HMM and MFCC was 96% and overall sensitivity was 98%. Machine learning model based on HMM and MFCC training time was 15 seconds and testing time was 3 seconds.

TABLE IV. HEART MODEL IMAGING DETECTED SENSITIVITY

	Machine Learning Model Based on HMM and MFCC detected	**ECHO detected**	**Machine Learning Model Based on HMM and MFCC Sensitivity (TP/(TOP+ FN)) %**	**ECHO detected Sensitivity (TP/(TOP+ FN)) %**
VSD	62	64	96.6	100
PS	62	62	100	100
PDA (Greater than 0.3mm)	72	72	100	100
PR	56	56	100	100
MR	44	46	95.5	100
AS	61	61	100	100
Normal	100	100	100	100

ECHO detected: Echocardiography detected, **TP**= True Positive, **TOP**=Total Positive, **FN**=False Negative.

TABLE V. HEART MODEL CCR

Heart Signal Frequency Range in Hz Min	**Max**	**Heart Signal**	**Cycles**	**Machine Learning Model Based on HMM and MFCC Interpretation**	**Machine Learning Model Based on HMM and MFCC CCR %**
156	164	VSD	64	62	97
156	556	PS	62	59	95
157	167	PDA	72	67	93
156	200	PR	56	52	93
158	162	MR	46	44	96
157	176	AS	61	61	100
1	139	Normal	100	100	100

CCR: Correct Classification Rate, **Min**: Minimum frequency, **Max**: Maximum frequency.

TABLE VI. COMPARISON BETWEEN MACHINE LEARNING HEART MODEL BASED ON HMM AND OTHER MODELS

Ref	**Sound**	**Sensor Type**	**Data Bank**	**Sensor Position**	**Method**	**Results**
Strunic et al., 2007 [5]	AS,AR	Simulator	110	Appropriate Auscultation Area	ANN	Up to 85±7.4% accuracy, 95±6% sensitivity
Zhong et al., 2013 [6]	MR, MS,AS, AR, PS	Not determined	600	Appropriate Auscultation Area	BPNN ,HMM and MFCC	HMM accuracy 94.5% BPNN accuracy 82.5%
Jimenez et al., 2014 [7]	Not determined	Welch Allynr Meditron model	400	Appropriate Auscultation Area	HMM and MFCC combined with statistical moment (EMD)	Accuracy 98.9% and 98.6% sensitivity
Devi et al., 2013 [8]	AS,AR MR, MS.	Not determined	Not determined	Appropriate Auscultation Area	ANN,BPNN,SVM, ANN with RBF ANFIS.	90% and above accuracy
Machine Learning Model Based on HMM and MFCC	VSD, MR, PDA, PS,PR, AS and Normal	hands-free tie-clip electrets (real heart sounds)	1069	Appropriate Auscultation Area	Machine learning Based on HMM and MFCC	CCR 96% And 98% sensitivity

ANN: Artificial Neural Network, **BPNN**: Back Propagation Neural Network**, HMM**: Hidden Markov Model, **MFCC**: Mel Frequency Cepestral coefficient, **EMD**: Empirical Mode Decomposition, **SVM**: Support Vector Machine, **RBF**: Radial Basis Function, **ANFIS**: Adaptive Neuro-Fuzzy Inference System.

V. Discussion

A machine learning model based on HMM and MFCC, covered normal heart sounds and abnormal heart sounds including AR, VSD, MR, PS, PDA and AS. The machine learning model based on HMM and MFCC achieved 98% sensitivity and overall CCR =96%.

This work supports that the HMM as a classifier and MFCC as a feature matrix are widely used for heart sounds classifications, as they have demonstrated their effectiveness, especially if mixtures of features from different domains were employed [12]. The MFCC 13 features coefficients allowed reduction of calculation time and memory that will impact cost of recognition model. Another important point in favor of HMM in heart sound recognition is the ability of easy update.

This machine learning model successfully recognized other types of murmur as VSD, PDA, and PR which were not recognized by others. Table 6 compares all previously reported studies and types of murmur recognized [5-8].

This study comprised the largest reported databank size of real heart sounds (1069 heart sounds), of them 464 heart sounds were for testing and 605 heart sounds were for training. This research did not study simulated heart sounds, while all previous reports used simulated sounds. This research need to emphasize that simulated heart sounds models were not validated against real heart sounds thus the reported accuracy of systems based on simulated heart sounds should be cautiously interpreted [5-8]. The accuracy of this machine learning heart model for recognition of heart sounds has future implications in heart sound recognition using simpler devices compared to the more complex operator dependent ECHO machines, and promises new role in clinical education. Heart sound recognition using HMM model shortcomings is the difficulty of recognizing some mild cases of MR. The number of AR cases were limited thus This paper need to study more cases to enhance machine learning recognition. The study did not address effect of heart contractility, heart rate, conduction defect, hypertrophy and size on accuracy of heart sound recognition.

This paper aim to study effect of combining heart rate sensors with machine learning model on recognition ability and on time of training and computational complexity in future works.

VI. Conclusion

The machine learning model based on HMM as a classifier and 13 MFCC elements and real heart sounds is effective in recognizing VSD, MR, PS, PR, PDA AS and AR. It relies upon separation of murmur from original heart signal using amplitude threshold. It achieved 98% sensitivity and 96% CCR. Real heart sounds recognition sensitivity result is better than simulated heart sounds. Each heart sound should be recorded from specific auscultation area. Heart machine learning model may have the potential to assist clinicians for more accurate diagnosis. This paper used amplitude threshold to separate murmur from original heart sound.

References

[1] Trivedi N, Levy D, Tarsa M, Anton T, Hartney C, Wolfson T, Pretorius DH. Congenital cardiac anomalies: prenatal readings versus neonatal outcomes. J Ultrasound Med 31(3), pp:389-99, 2012.

[2] Rajakumar K, Weisse M, Rosas A, Gunel E, Pyles L, Neal WA, Balian A, Einzig S. Comparative study of clinical evaluation of heart murmurs by general pediatricians and pediatric cardiologists. Clin Pediatr (Phila). 38(9), pp:511-8,1999.

[3] Asprey DP. Evaluation of children with heart murmurs. Lippincotts Prim Care Pract. 2(5), pp:505-13, 1998.

[4] D Kumar, P Carvalho, M Antunes , J Henriques ,M Maldonado, R Schmidt, J Habetha, "Wavelet Transform and Simplicity Based HeartMurmur Segmentation",The Proceedings of The Computers in Cardiology Conference, pp:173:172, Valencia, Spain, 17-20 Sep 2006.

[5] Strunic SL, Rios-Gutierrez F, Flores RA,Nordehn G,Burns S. Detection and Classification of Cardiac Murmurs Using Segmentation Techniques and Artificial Neural Networks. The Proceedings of Computational Intelligence and Data Mining IEEE Symposium on Conference, pp:397-404, Honolulu, USA, 1 March-5 April 2007.

[6] Zhong L, Wan J, Huang Z, Cao G, Xiao B. Heart Murmur Recognition Based on Hidden Markov Model. Journal of Signal and Information Processing.4, pp:140-144, 2013.

[7] Jimenez JA, Becerra MA, Delgado-Trejos E. Heart Murmur Detection Using Ensemble Empirical Mode Decomposition and Derivations of The Mel-Frequency Cepstral Coefficients on 4-Area Phonocardiographic Signals. The Proceedings of The Computing Cardiology Conference,pp:493-496, Cambridge, USA, 7-10 September 2014.

[8] Devi A, Misal A. A Survey on Classifiers Used in Heart Valve Disease Detection. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 2, pp: 609-614, 2013.

[9] D. Kumar, P. Carvalho, M. Antunes, R.P.Paiva, J.Henriques," Heart Murmur Classification With Feature Selection", The Proceedings of The Annual International Conference of The IEEE Engineering in Medicine and Biology Society, DOI:10.1109/IEMBS.2010.5625940, pp:4566-4569, Buenos Aires, Argentina, 31August-4 September2 2010.

[10] Amir Mohammad Amiri and Giuliano Armano,"Segmentation and Feature Extraction of Heart Murmurs in Newborns", Journal of Life Sciences and Technologies Vol 1, pp 107:111, 2013.

[11] Classification accuracy. Centre for Bioscience: The Higher Education Academy. Clustering and Classification methods for Biologists. http://www.alanfielding.co.uk/multivar/accuracy.htm. Accessed on 22/5/2016.

[12] Leng S, Tan RS, Chai KT, Wang C, Ghista D, Zhong L. The electronic stethoscope. Biomed Eng Online. 10, pp:14:66, 2015.