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A Decision Support System for Cardiac Disease Diagnosis Based on Machine Learning Methods

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Abstract. This paper proposes a decision support system for screening pediatric cardiac disease in primary healthcare centres relying on the heart sound time series analysis. The proposed system employs our processing method which is based on the hidden Markov model for extracting appropriate information from the time series. The binary output resulting from the method is discriminative for the two classes of time series existing in our databank, corresponding to the children with heart disease and the healthy ones. A total 90 children referrals to a university hospital, constituting of 55 healthy and 35 children with congenital heart disease, were enrolled into the study after obtaining the informed consent. Accuracy and sensitivity of the method was estimated to be 86.4% and 85.6%, respectively, showing a superior performance than what a paediatric cardiologist could achieve performing auscultation. The method can be easily implemented using mobile and web technology to develop an easy-to-use tool for paediatric cardiac disease diagnosis.

Keywords. Hidden Markov model, decision support system, heart sound, congenital heart disease screening.

1. Introduction

Rapid progresses in information science initiated a technological leap toward development of the decision support systems by which disease assessment became effectively facilitated. Cardiac disease diagnosis is an important topic that came into this context due to its importance as the statistics show that cardiac disease is still the main factor of human mortality. It has also been reflected on by many researchers that the screening accuracy is not as satisfactory as it could be. The accuracy is low in primary healthcare centers, particularly in children who are sent as a precaution measure to children hospitals or specialized centers for cardiac examination. A great majority of the referred individuals are healthy, but not cleared during the first visit. This comes from the fact that cardiac auscultation is considered as the first screening technique, which is a fairly complicated task; a reliable interpretation of heart sounds needs both the experiences and the expertise. It is well-known that discrimination between normal

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physiological heart sounds from the pathological ones is difficult, especially in pediatric cases, as studies show that as many as 70% of children can have physiological murmurs, while only 0.8% of them are born with congenital heart disease. Consequently, development of a decision support system for improving the screening accuracy can be of a special benefit for the global healthcare system.

Early studies of this topic were initiated in 1990^{th} in which artificial intelligence was employed as the mathematical means of extracting medical information from heart sound [1][2]. Neural networks, as well as the several other statistical techniques, have been well-sounded for the classification purposes [3][4]. Our previous studies have led to innovative methods for processing heart murmurs [5][6][7][8]. We have also developed intelligent method for assessing specific heart diseases [9][10][11]. However, development of a robust system for screening children with mild lesions is still considered as a challenge. One of the related challenges is screening of the abnormalities that may not produce any murmur i.e. bicuspid aortic valve, as most of the existing screening methods are based on the murmur classification.

This paper proposes an original method for developing a decision support system for detecting heart disease in children, even when the abnormality is mild. The main focus of the paper is on the processing method for extracting information from the heart sound time series. We proposed a hybrid method for the classification purpose, based on the encouraging results of our previous studies. The current study tailors the method in a way to include both the first heart sound, and the murmur, to cover a broader patient group. The processing method can be implemented on a portable computer to provide a decision support system for primary healthcare centers.

2. Material and methods

2.1. Data Preparation

Heart sound signals were recorded from the children referrals to the echocardiography lab at the hospital of Children Medical Center, Tehran University of Medical Sciences, Tehran, Iran, using a WelchAllyn Meditron stethoscope in conjunction with a DELL laptop. Each signal contains 10 sec duration of heart sound, recorded at a sampling frequency of 44100 Hz. The informed patient consent was obtained from the legal guardians or from the patients according to the Good Clinical Practice. The study complied with the Declaration of Helsinki and had been approved by the local ethic committee. The patient group was defined as the referrals with Bicuspid Aortic Valve (BAV) and Mitral Regurgitation (MR), against a reference group that constituted of the healthy referrals with or without physiological murmurs, named Innocent Murmur (IM) and No Murmur (NM), respectively. Table 1 lists the patient population

Table 1. Patient population

Heart Condition	Number of Patients	Average Age ± STD (years)
Bicuspid aortic valve (BAV)	20	6.6±1.2
Healthy with innocent murmur (IM)	25	6.7±3.7
Healthy without any murmur (NM)	30	8.6±3.4
Mitral Regurgitation (MR)	15	11.8±4.1

All the referrals were investigated by at least one pediatric cardiologists, and also underwent echocardiography, ECG and chest x-ray as the procedural gold standard of the hospital.

2.2. The Processing Method

The processing method is based on the use of our hybrid method, which is a combination of the Hidden Markov Model (HMM) and support vector machine. The HMM has two states, corresponding to the first heart sound (S1) segment and the systolic period after the S_1 segment (S_{1-2}). A temporal window with fixed length of 50 sec, slides over the signal with an overlapping percentage of 75%, to extract information from the signal. Figure 1 illustrates the state model of the method.

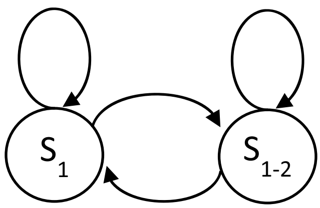

Figure 1. The state model of the method.

Each window is characterized by its spectral contents, using the conventional estimation method, the Priodogram. The Fisher criteria is utilized for finding the most discriminant frequency band, where the spectral contents of the band provide an optimal segregation between the classes [14]. The 8 bands with the highest Fisher value are selected for calculating the spectral energies, which are later mapped to the patterns of numerical symbols, using the Mahalanobis distance. The symbol probabilities are employed as the discriminative features for the classification, which is performed by the support vector machine technique with quadratic kernel. Theoretical foundation for calculating the probability features can be found in [6][8].

2.3. The Statistical Validation

Performance of the method is statistically validated by two different methods, the repeated random sub-sampling (RRSS) and the 5-fold validation method, using the accuracy (I_{ac}), sensitivity (I_{sn}) and specificity (I_{sp}) as the three performance measures:

$$Iac = 100(N_{TP}+N_{TN})/(N_{TP}+N_{TN}+N_{FP}+N_{FN}) \quad (1)$$
$$Isn = 100N_{TP}/(N_{TP}+N_{FN}) \quad (2)$$
$$Isp = 100(N_{TN})/(N_{TN}+N_{FP}) \quad (3)$$

where N_{TP} and N_{TN} are the number of the correctly classified recordings from the abnormal and healthy group, respectively. N_{FP} is the number of the recordings from the healthy group, classified as the abnormal subjects and N_{FN} is the number of the abnormal patient classified as healthy. To apply the RRSS, 50% of the data is randomly selected for training (equally from each class) and the rest for testing the method, after which the performance measures are calculated. This procedure is repeated several times, and the performance measures are calculated accordingly. In a 5-fold validation, each class of data is grouped into 5 divisions, and one division of each class is used for testing and the rest for training the method. This procedure is repeated 5 times, with one single data being used only once for the testing. At the end, the performance measures are calculated.

3. Results and Discussion

The proposed processing method contains two states, including S_1 and $S_{1\text{-}2}$, for the purpose of screening different conditions i.e. bicuspid aortic valve where the murmur might be missing. The method is trained using the dataset, represented in Table 1, and the average values of the probability features are calculated for each class (see Table 2).

Table 2. The average value of the discriminative features for the 4 classes defined in Table 1

Class	F1	F2	F3	F4	F5	F6
BAV	0.86	0.46	0.19	0.48	0.59	0.21
MR	0.34	0.26	0.29	0.27	0.62	
IM	0.11	0.16	0.22	0.18	0.25	0.69
NM	0.09	0.12	0.15	0.13	0.16	0.17

RRSS was applied to the study data, with 100 iterations, and the performance measures were calculated. Table 3 lists the descriptive statistics of the results.

Table 3. Descriptive statistics of the performance measures

Performance Measure	Average (%)	Median (%)	Standard Deviation
Accuracy	86.4	86.7	3.1
Sensitivity	85.6	85.7	5.3
Specificity	87.0	87.3	3.9

To provide a better representation of the misclassification results, the confusion matrix of the RRSS is listed in Table 4.

Table 4. The average value of the discriminative features for the 4 classes defined in Table 1

	Abnormal (System)	Healthy (System)
Abnormal (Actual)	30	5
Healthy (Actual)	7	48

Previous studies showed that the screening accuracy of a typical pediatric cardiologist is below 80%, relying on the conventional auscultation [10][14][15]. As it could be seen from the Table 3, the accuracy of the method is estimated to be 86.4%, which is significantly higher than the accuracy of a typical pediatric cardiologists. It is also shown that the system is sensitive enough to be employed in primary healthcare centers. In our previous studies, we achieved an accuracy/sensitivity rates of 88%/86% by using the previously proposed method [13]. However, adding the patients with BAV diminished the performance by 6%/10%. Using the proposed hybrid model could sustain the discriminative power at 86.4%/85.6%, thus showing effectiveness of the proposed method to extract relevant information from the signals.

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References

[1] J. Semmlow, M. Akay, and W. Welkowitz, "Noninvasive detection of coronary artery disease using parametric spectral analysis methods,"Engineering in Medicine and Biology Magazine, IEEE, vol. 9, no. 1, pp. 33–36, 1990.

[2] E. Ciaccio, S. Dunn, and M. Akay, "Biosignal pattern recognition and interpretation systems. 3. methods of classification," Engineering in Medicine and Biology Magazine, IEEE, vol. 13, no. 1, pp. 129–135, 1994.

[3] C. G. DeGroff, S. Bhatikar, J. Hertzberg, R. Shandas, L. Valdes-Cruz, and R. L. Mahajan, "Artificial neural network–based method of ng heart murmurs in children," *Circulation*, vol. 103, pp. 2711–2716, 2001.

[4] C. N. Gupta, R. Palaniappan, S. Swaminathan, S. M. Krishnan, Neural network classification of homomorphic segmented heart sounds, Appl. Soft Eng. 7 (2007) 286–297.

[5] A. Sepehri, Amir, A. Kocharian, A. Janani, A. Gharehbaghi, An intelligent phonocardiography for automated screening of pediatric heart diseases, Journal of Medical Systems 40 (2015).

[6] A. Gharehbaghi, P. Ask, A. Babic, A pattern recognition framework for detecting dynamic changes on cyclic time series, Pattern Recognition 48 (2015) 696 – 708.

[7] A. Gharehbaghi, A. Sepehri, A. Kocharian, M. Linden, An intelligent method for discrimination between aortic and pulmonary stenosis using phonocardiogram, in: World Congress on Medical Physics and Biomedi- cal Engineering, June 7-12, 2015, Toronto, Canada, volume 51 of *IFMBE Proceedings*, Springer International Publishing, 2015, pp. 1010–1013.

[8] A. Gharehbaghi, P. Ask, E. Nylander, B. Janerot-Sjoberg, I. Ekman, M. Lindén, A. Babic, A hybrid model for diagnosing sever aortic stenosis in asymp- tomatic patients using phonocardiogram, in: World Congress on Medical Physics and Biomedical Engineering, June 7-12, 2015, Toronto, Canada, volume 51 of *IFMBE Proceedings*, Springer International Publishing, 2015, pp. 1006–1009.

[9] A. Gharehbaghi, P. Ask, M. Lindén, A. Babic, A novel model for screening aortic stenosis using phonocardiogram, in: H. Mindedal, M. Persson (Eds.), 16th Nordic-Baltic Conference on Biomedical Engineering, volume 48 of *IFMBE Proceedings*, Springer International Publishing, 2015, pp. 48–51.

[10] A. Gharehbaghi, T. Dutoit, A. Sepehri, A. Kocharian, M. Linde´n, A novel method for screening children with isolated bicuspid aortic valve, Cardiovascular Engineering and Technology 6 (2015) 546–556.

[11] A. Gharehbaghi, I. Ekman, P. Ask, E. Nylander, B. Janerot-Sjoberg, Assessment of aortic valve stenosis severity using intelligent phonocardiography, International Journal of Cardiology 198 (2015) 58 – 60.

[12] P. N. Belhumeur, J. P. Hespanha and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: recognition using class specific linear projection," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, Jul 1997.

[13] A. Gharehbaghi, M. Borga, B. J. Sjöberg, P. Ask, A novel method for discrimination between innocent and pathological heart murmurs, Medical Engineering and Physics 37 (2015) 674–682.

[14] Watrous RL, Thompson WR, Ackerman SJ. The impact of computer-assisted auscultation on physician referrals of asymptomatic patients with heart murmurs. Clin Cardiol. (2008) Feb;31(2):79-83.

[15] R. Watrous, "Computer-aided auscultation of the heart: From anatomy and physiology to diagnostic decision support," in Engineering in Medicine and Biology Society, 2006. EMBS '06. 28t International Conference of the I EEE, 2006, pp. 140–143.