Proc of the 4th Annual IEEE Conf on Information Technology Applications in Biomedicine, UK (24-26 April 2003, Birmingham, UK)

USING DECISION TREE ALGORITHMS AS A BASIS FOR A HEART SOUND DIAGNOSIS DECISION SUPPORT SYSTEM

A. Ch. Stasis [1], E. N. Loukis [2], S. A. Pavlopoulos [1], D. Koutsouris [1]

[1] Biomedical Engineering Laboratory, National Technical University of Athens, Athens, Greece

[2] Dept. of Information and Communication Systems Engineering, University of Aegean, Samos, Greece

Abstract- **In this study, Decision Trees Algorithms were used with promising results in various critical problems, concerning heart sound diagnosis. In general this diagnostic problem can be divided in many sub problems, each one dealing either with one morphological characteristic of the heart sound or with difficult to distinguish heart diseases. The sub problems of the discrimination of Aortic Stenosis from Mitral Regurgitation and the discrimination between the second heart sound split, opening snap and third heart sound, are used as case studies. Using signal-processing methods, we extracted the heart sound feature vector. Relevance analysis was performed using the Uncertainty Coefficient. Then for each heart sound diagnosis sub problem, a Specific Decision Tree (DT) was constructed. Decision Tree pruning was also investigated. Finally, a General Decision Support System Architecture for the Heart Sound Diagnosis problem, is proposed. The partial diagnosis, given by these DT, can be combined using arbitration rules to give the final diagnosis. These rules can be implemented by another DT, or can be based on different methods, algorithms, or even on expert knowledge. All these can lead to an Integrated Decision Support System Architecture for Heart Sound Diagnosis.**

Keywords - **Heart Sound Diagnosis; Decision Trees; Decision Support Systems; Data Mining; Data Distillation**

I. INTRODUCTION

New technologies like Echocardiography, CT, and MRI provide more direct and accurate evidence of heart disease than heart auscultation, but they are costly, large and operationally complex, so these technologies are not suitable for use in rural areas, in homecare and generally in primary healthcare [1]. Although heart sounds can provide low cost screening for pathologic conditions, the internal medicine and the cardiology training programs underestimate the value of cardiac auscultation and the new clinicians are not well trained in this field [2]. Therefore efficient Decision Support Systems would be very useful for supporting clinicians to make better heart sound diagnosis especially in primary healthcare.

In this study the general heart sound diagnostic problem is divided in simpler sub problems, each one dealing either with one morphological characteristic of the heart sound or with difficult to distinguish heart diseases. For each sub problem a Specific Decision Tree is constructed. In this paper two heart sound diagnosis sub problems are presented i.e. the problem of distinguishing the Aortic Stenosis (AS) from the Mitral Regurgitation (MR) and the problem of discrimination between the Opening Snap (OS), the Second Heart Sound Split (A2_P2) and the Third Heart Sound (S3), using only heart sound signals.

In particular the first goal of this work is to evaluate the suitability of various Decision Tree structures for these important diagnostic sub problems. Among the evaluated structures are included both fully expanded Decision Trees Structures and pruned Decision Trees Structures. The second goal is to evaluate the diagnostic abilities of the investigated heart sound features for Decision Tree - based diagnosis. In both the above evaluations were also examined the generalization capabilities of the implemented Decision Tree structures. Generalization is a very important issue due to the difficulty and the tedious work of having in the training data set adequate data for all possible data acquisition methods. The third goal of this work is to suggest a way of selecting the most appropriate Decision Tree structures and heart sound features in order to provide the basis of an effective Decision Support System. Finally a new architecture is proposed. This architecture is based on the idea of the consistent diagnosis between the partial diagnoses made from each Specific Decision Tree, for each sub problem.

II. METHODOLOGY

A. Heart sound selection

Cardiac auscultation and diagnosis are quite complicated, depending not only on the heart sound but also on other factors. There is also a great variability of the quality of the heart sound affected by mans factors associated with the acquisition method. Some important factors are: the kind of stethoscope used, the sensor that the stethoscope has, the mode that the stethoscope was used (i.e. bell, diaphragm, extended), the way the stethoscope was pressed on the patients skin (firmly or loosely), the medicine that the patient used during the auscultation (i.e. vasodilators), the patient's position (i.e. supine position, standing, squatting), the auscultation areas (i.e. apex, lower left sternal border, pulmonic area, aortic area), the phase of patients' respiration cycle (inspiration, expiration), the filters used while acquiring the heart sound (i.e. anti-tremor filter, respiratory sound reduction, noise reduction). The variation of all these parameters leads to a big number of heart sound acquisition methods. A heart sound diagnosis algorithm should take into account this variability of the acquisition method, and also be tested in heart sound signals from different sources and recorded with different acquisition methods. For this purpose we tried to collect heart sound signals from different heart sound sources ([hs1], [hs2], [hs3], [hs4], [hs5], [hs6], [hs7], [hs8], [hs9]) and create a "global" heart sound database. The heart sound signals were collected from educational audiocassettes, audio CDs and CD ROMs; they had already been diagnosed and related to a specific heart disease and their morphology had been also recognized. For the first sub problem we chose 41 heart sound signals with AS systolic murmur and 43 ones with MR systolic murmur and for the second one, 46 heart sounds containing A2_P2, 36 containing OS, and 53 containing S3.

B. Heart sound preprocessing

The sets of the chosen heart sound signals in a first phase were pre-processed in order to detect in each signal the cardiac cycles, i.e. detect the first (S1) and the second (S2) heart sound, using a method that was based on the following steps:

a) The wavelet decomposition described in [3] (the only difference being, that we kept the 4th and 5th level detail, i.e. frequencies from 34 to 138Hz).

b) The calculation of the normalized average Shannon Energy ([4]).

c) A morphological transform action that amplifies the sharp peaks and attenuates the broad ones ([5]).

d) A method, similar to the one described in [4] that selects and recovers the peaks corresponding to S1 and S2 and rejects the others.

e) An algorithm that determines the boundaries of S1 and S2 in each heart cycle.

f) A method that distinguishes S1 from S2 similar to the one described in [6].

In a second phase from each transformed (being processed in the first phase) heart sound signal we extracted the standard deviation of the duration of all the heart cycles it includes, the standard deviation of the S1 peak value of all its heart cycles, the standard deviation of the S2 peak value of all its heart cycles, and the heart rate. These were the first four scalar features (F1-F4) of the feature vector of the heart sound signal. In a third phase the rest of the features were extracted: for this purpose we calculated for each heart sound signal two mean signals for each of the four structural components of the heart cycle, namely two for the S1, two for the systolic phase, two for the S2 and two for the diastolic phase. The first of these mean signals focused on the frequency characteristics of the heart sound; it was calculated as the mean value of each component, after segmenting and extracting the heart cycle components, time warping them, and aligning them. The second mean signal focused on the morphological time characteristics of heart sound; it was calculated as the mean value of the normalized average Shannon Energy Envelope of each component, after segmenting and extracting the heart cycles components, time warping them, and aligning them. Then each of these two S1 mean signals was divided into 8 equal parts. For each part we calculated the mean square value and this value was used as a feature in the corresponding heart sound vector. In this way we calculated 8 scalar features for S1 (F5-F12), 24 scalar features for the systolic period (F13-F36), 8 scalar features for S2 (F37-F44) and 48 scalar features for the diastolic period (F45-F92). The systolic and diastolic phase components of the above first mean signal were also passed from four bandpass filters: a) a 50-250Hz filter giving its low frequency content, b) a 100-300Hz filter giving its medium frequency content, c) a 150-350Hz filter giving its medium-high frequency content and d) a 200-400Hz filter giving its high frequency content. For each of these 8 outputs, the total energy was calculated and was used as a feature in the heart sound vector (F93-F100). With the above three phases of preprocessing every heart sound signal was transformed in a heart sound vector (pattern) with dimension 1x100.

Finally these preprocessed data feature vectors were stored in a database table. Each record of this table describes the feature vector of a heart sound signal and has 102 attributes. One attribute for the pattern identification code, named ID (used as the primary key of this database table), one attribute that is used for characterization of each heart sound according to the specific sub problem, named PartDiag (Partial Diagnosis) and 100 attributes for the above 100 heart sound features (F1-F100).

C. Decision Tree construction

Before constructing and using the Decision Tree algorithms to classify the heart sounds, a Relevance Analysis of the features was performed. Relevance Analysis aims to improve the classification efficiency by eliminating the less useful (for the classification) features and reducing the amount of input data to the classification stage.

In this work we used the value of the Uncertainty Coefficient ([7]) of each of the above 100 features to rank these features according to their relevance to the classifying (dependent variable) attribute, which in our case is the PartDiag attribute. In order to compute the Uncertainty Coefficients, the 100 numeric attributes were transformed into corresponding categorical ones. The algorithm that has been used for optimizing this transformation for the specific classification decision is described in [8]. Then for each of these 100 categorical attributes its Uncertainty Coefficient was calculated as described in [7] and the decision trees were constructed according to the method described in [8] and [9], using as splitting index the entropy index. A separate Specific Decision Tree was constructed for each sub problem, using as training set the half of the heart sounds records of our heart sound database. Fig.1 shows a Specific Decision tree structure for the problem of discrimination of AS from MR.

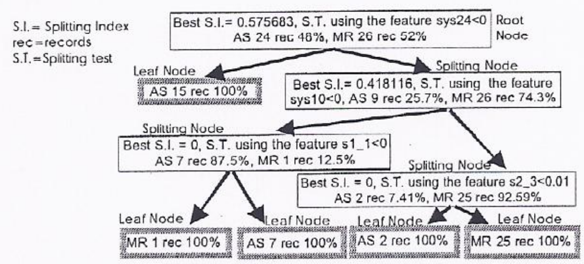

Fig. 1. A Specific Decision Tree structure, constructed for the sub problem of discriminating AS from MR.

D. Decision Tree pruning

The expansion of a Decision Tree can continue, dividing the training set in to subsets (corresponding to new child nodes), until we have subsets-nodes with "homogeneous" records having all the same value of the classification attribute. Although theoretically this is a possible scenario in practical situations usually leads to a Decision Tree structure that is over-fitted to the training data set and to the noise this data set contains. Consequently such a Decision Tree structure has not good generalization capabilities (=high classification accuracy for other test data sets). Stopping rules have been therefore adopted in order to prevent such an over-fitting; this approach is usually referred to as Decision Tree Pruning ([10]). A simple stopping rule that has been examined in this work was a restriction concerning the minimum node size. The minimum node size sets a minimum number of records required per node i.e. if a node has less records than a percentage of the initial training data set records then the expansion stops from that node.

III. Results

The relevance analysis results are related to the sub problem and the specific classifying attribute i.e. the PartDiag attribute in the case of discrimination of AS from MR has two possible values, namely AS or MR, while for the sub problem of discrimination between A2_P2, OS and S3 has three possible values. In both cases the most relevant features according to the Uncertainty coefficient and the classifying attribute were the frequency features (i.e. High and Medium Frequency Energy in both systolic and diastolic phase, etc) and the morphological features that describe the S1 (i.e. s1_1...s1_8), the S2 (i.e. s2_1...s2_8). Especially for the discrimination of AS from MR sub problem the systolic phase features (sys1, ... sys24) were also valuable.

The constructed Decision Trees were used to classify the heart sound records that were not used during construction i.e. the test set records. The same procedure was repeated for various combinations of test and training sets, for having better statistical estimation of the results. We remarked, that for all the examined cases and sub problems, the classification accuracy was the same, either using the 100 heart sound features, or using the 15 most relevant out of the 100 features. This is very important because using relevance analysis we can choose the most relevant features and reduce the computational complexity of a specific sub problem without worsening the classification accuracy. The Decision Tree Pruning did not improve the classification results significantly. In order to confirm statistically the above mentioned conclusions, statistical t-tests were performed. The average classification accuracy, for the discrimination of AS from MR sub problem, of all the examined cases was 88% while for the discrimination between A2_P2, OS, and S3 sub problem was 68,5%.

IV. Discussion

An effective Decision Support System, assisting the clinician to make better diagnosis, should provide reliable and consistent diagnostic suggestion, especially to unknown and new examined cases. Considering the approach used in this paper, an effective Decision Support System for the heart sound diagnosis should consider all the partial diagnoses, made for each specific sub problem, and suggesta final diagnosis. So the clinician can have the final diagnosis and the justification of this final diagnosis. The justification will be based on the partial diagnoses. The proposed architecture for such a Decision Support System consists of a first stage with various Partial Diagnosis modules and a second stage with an arbitration module. The arbitration module decides, whenever inconsistent suggestions appear, which of the suggestions should be accepted and which of them should be rejected and finally, combines all the accepted suggestions to the final diagnosis. The arbitration rules are defined, considering the heart sound diagnosis problem and the type of the available partial diagnoses, proposed by the Partial Diagnosis modules. The arbitration module can be another Decision Tree, or can be based on different methods, algorithms, or even on expert knowledge. This Architecture leads to an Integrated Decision Support System for Heart Sound Diagnosis.

Some additional Partial Diagnosis modules for specific sub problems, that can be solved with Decision Trees and with the appropriate features are: the detection of systolic murmur and /or diastolic murmur, the determination of the type of the murmurs (crescendo, decrescendo), of the frequency content (low, high, medium), the detection of Mid-systolic click, of arrhythmia, of premature ventricular contraction, the discrimination between heart diseases with similar heart sound signals, between the 4rth heart sound, ejection clicks and the first heart sound split etc

Fig.2 shows a Decision Support System architecture, for heart sound diagnosis that is based on Decision Trees (DT) and therefore is named Multiple Decision Tree Architecture.

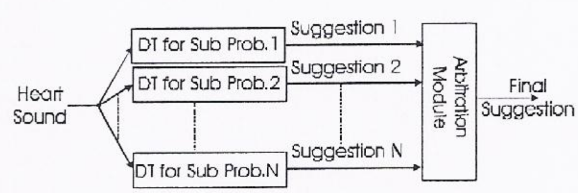

Fig. 2. Multiple Decision Tree Architecture for the Heart Sound Diagnosis Problem.

V. Conclusion

Initially a number of Decision Tree structures have been evaluated for the discrimination between OS, A2_P2 and S3 and the discrimination of AS from MR, which are regarded to be difficult sub problems in heart sound diagnosis. Heart sound diagnosis is very important especially in homecare, in rural areas and generally in the primary healthcare. The main criterion for this evaluation was the classification accuracy of the test data set. The most important conclusions from this work are the following:

- The Decision Tree algorithms can be used successfully as a basis for a Decision Support System, which will assist the young and inexperienced clinicians to make better heart sound diagnosis. In this way the unnecessary patient transfers to Hospitals and the redundant examinations can be reduced.
- Using Relevance Analysis we can determine a small critical subset, from the initial set of features that contains most of the information required for the discrimination. In

this way the required computational effort for constructing, training and using Decision Trees significantly decrease.

- For the examined sub problems, the Classification Accuracy and the Generalization capabilities of the Decision Tree structures remained the same with pruning, according to statistical hypothesis testing.
- The generalization capabilities of the Decision Tree based methods were found to be satisfactory. This is very important, due to the difficulty and the high cost of having enough training data for every possible case. The Decision Tree structures were tested on various training and test data set and the Classification Accuracy was found to be consistently high.
- The general heart sound diagnosis problem can be divided into a number of simpler problems. All these simpler problems can be solved by separate specialized Decision Support Systems, which can be based on different methods, algorithms and features. The partial diagnosis given by these Decision Support Systems can then be combined to give a total diagnosis. The combination of all these Decision Support Systems can lead to an integrated Decision Support System architecture for Heart Sound Diagnosis.

Further research is required for the evaluation of the Multiple Decision Tree Architecture and forthe development of a systematic arbitration rule design methodology. The selection of the most appropriate Decision Tree structure for achieving the best Classification Accuracy for a specific problem is also an open research subject.

Acknowledgment

The authors would like to thank Prof. B. Theothoulidis, Dr George Koundourakis, and Neurosoft S.A. for their support and provision of Envisioner, a data-mining tool that was used to execute algorithms related to the Decision Trees.

References

[1] C.G. DeGroff, S.Bhatikar, J Hertzberg, R. Shandas, L. Valdes-Cruz, R.L. Mahajan, "Artificial neural network-based method of screening heart murmurs in children", Circulation, vol103, pp 2711-2716, March 2001.

[2] S.R. Criley, D.G. Criley, J.M. Criley, "Beyond Heart Sound: An Interactive Teaching and Skills Testing Program for Cardiac Examination", Blaufuss Medical Multimedia, San Francisco, CA, USA, Computers in Cardiology, vol 27, pp 591-594, 2000.

J. Clerk Maxwell, *A Treatise on Electricity and Magnetism,* 3 rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68-73.

[3] H. Liang, S. Lukkarinen, I. Hartimo, "A heart sound segmentation algorithm using wavelet decomposition and reconstruction", Engineering in Medicine and Biology Society, Proceedings of the 19th Annual International Conference of the IEEE, vol.4, pp 1630 – 1633, November 1997.

[4] H. Liang, S. Lukkarinen, I. Hartimo, "Heart Sound Segmentation Algorithm Based on Heart Sound Envelogram", Computers in Cardiology, vol. 24, pp 105-108 September 1997.

[5] A. Haghighi-Mood, J.N. Torry, "A Sub-Band Energy Tracking Algorithm for Heart Sound Segmentation", Computers in Cardiology, pp 501-504, September 1995.

[6] J.E. Hebden, J.N.Torry, "Neural network and conventional classifiers to distinguish between first and second heart sounds", IEE Colloquium (Digest), pp 3/1-3/6, 1996.

[7] M. Kamber, L. Winstone, W. Gong, S. Cheng, and J. Han, "Generalisation and Decision Tree Induction: Efficient Classification in Data Mining", In Proc. of 1997 Int'l Workshop on Research Issues on Data Engineering (RIDE'97), Birmingham, England, pp 111-120, April 1997.

[8] G. Koundourakis, "EnVisioner: A Data Mining Framework Based On Decision Trees", Doctoral Thesis, University of Manchester Institute of Science and Technology, October 2001.

[9] J. Han, M. Kamber, 'Data Mining: Concepts and Techniques', Morgan Kaufman Publisher 2001

[10] S.M. Weiss, N. Indurkhya, "Small sample decision tree pruning", Proceedings of the 11th International Conference on Machine Learning, Morgan Kaufmann, pp 335-342, 1994.

Recorded Heart Sound Sources

Educational Material:

[hs1] N. Karatzas, D. Papadogianni, E. Spanidou, F. Klouva, A. Sirigou, S. Papavasiliou, "Twelve Recorded Lessons with heart sound simulator", Merk Sharp & Dohme Hellas, Medical Publications Litsas, Athens 1974.

[hs2] J.M. Criley, D.G. Criley, C. Zalace, "The physiological Origins of Heart Sounds and Murmurs", Harbor UCLA Medical Center, Blaufuss Medical Multimedia, 1995.

[hs3] Littman, 20 Examples of Cardiac & Pulmonary Auscultation.

Internet sites:

[hs4] C. Cable, "The Auscultation Assistant", 1997 http://www.wilkes.med.ucla.edu/intro.html

[hs5] L. Glass, B. Pennycook, "Virtual Stethoscope", McGill University, Molson Medical Informatics Project 1997,
http://www.music.mcgill.ca/auscultation/auscultation.html

[hs6] "VMRCVM Class of 2002", Virginia Maryland regional College of veterinary medicine.
http://students.vetmed.vt.edu/2002/cardio/heartsounds.html

[hs7] YE. Kocabasoglu, RH. Henning, 'Human Heart Sounds',
http://www.lf2.cuni.cz/Projekty/interna/heart_sounds/h12/index.html

[hs8] Frontiers in Bioscience, 'Normal and Abnormal EKGs and Heart Sounds'.
http://www.bioscience.org/atlases/heart/sound/sound.htm

[hs9] Student Internal Medicine Society, 'Class 2000 Cardiology Heart Sounds Wave Files', American College of Physicians, Baylor College of Medicine.
http://www.bcm.tmc.edu/class2000/sims/HeartSounds.html