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ABSTRACT

Heart auscultation (the interpretation by a physician of heart sounds) is a fundamental component in cardiac diagnosis. It is, however, a difficult skill to acquire. In this work, we present a study for a system intended to aid in heart sound analysis. Based on a wavelet decomposition of the sounds and a neural network-based classifier, heart sounds are associated with likely underlying pathologies. Preliminary results promise a system that is both accurate and robust, while remaining simple enough to be implemented at low cost.

KEYWORDS

Auscultation, phonocardiogram, heart, cardiac, diagnosis.

1 INTRODUCTION

Heart auscultation (the interpretation of sounds produced by the heart) is a fundamental tools in the diagnosis of heart disease. It is the most commonly used technique for screening and diagnosis in primary health care. In some circumstances, particularly in remote areas or developing countries, auscultation may be the only method available.

However, detecting relevant symptoms and forming a diagnosis based on sounds heard through a stethoscope is a skill that can take years to acquire and refine. Because this skill is difficult to teach in a structured way, the majority of internal medicine and cardiology programs offer no such instruction. It would be very advantageous if the benefits of auscultation could be obtained with a reduced learning curve, using equipment that is low-cost, robust, and easy to use.

The complex and highly nonstationary nature of heart sound signals can make them challenging to analyze in an automated way. However, recent technological developments have made extremely powerful digital signal processing techniques both widely accessible and practical. Local frequency analysis and wavelet (local scale analysis) approaches are particularly applicable to problems of this type. Some of these methods have been applied to study the correlation between these sounds and various heart defects (e.g., (Donnerstein and Thomsen 1994), (Barschdorff, Femmer, and Trowitzsch 1995), (El-Asir, Khadra, Al-Abbasi, and Mohammed 1996), (Shino, Yoshida, Yana, Harada, Sudoh, and Harasawa 1996), (Rajan, Doraiswami, Stevenson, and Watrous 1998)). For an excellent survey and discussion of work in this area see (Durand and Pibarot 1995).

In this work we combine local signal analysis methods with classification techniques to detect, characterize and interpret sounds corresponding to symptoms important for cardiac diagnosis. It is hoped that the results of this analysis may prove valuable in themselves as a diagnostic aid, and as input to more sophisticated machine diagnosis systems.

2 A SYSTEM FOR HEART SOUND CLASSIFICATION

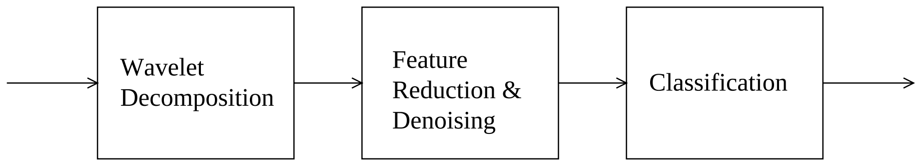

Figure 1. A Simple Heart Sound Classification System

A block diagram of the system used in this study is shown in Figure 1. Heart sounds (sampled at an 8kHz sample rate, 16 bits/sample) are first hand segmented into 4096 sample segments, each consisting of a single heartbeat cycle. Each segment is transformed using a 7 level wavelet decomposition, based on a Coifman 4th order wavelet kernel (chosen due to its relative symmetry and fast execution). The resulting transform vectors, 4096 values in length, are reduced to 256 element feature vectors by discarding the 4 levels with shortest scale. In addition to substantially simplifying the neural network in the classifier which follows, this step also reduces noise. The magnitudes of the remaining coefficients in each vector are calculated, then normalized by the vector's energy. Finally, each feature vector is classified using a three layer neural network (256 input nodes, 50 hidden nodes, and 5 output nodes).

3 RESULTS AND DISCUSSION

The system was evaluated using heart sounds corresponding to five different heart conditions: normal, mitral valve prolapse (MVP), coarctation of the aorta (CA), ventricular septal defect (VSD), and pulmonary stenosis (PS). The classifier was trained using 10 shifted versions (over a range of 100 samples) of a single heartbeat cycle from each type. Shifted training exemplars were used to provide a degree of shift invariance (since, as is well known, wavelet decompositions are generally not shift invariant). In this application, such shifts may occur due to variations in the heartbeat starting time, as found during the segmentation process.

The system was then presented heart sounds with varying degrees of additive noise for classification. Because the sample set available for this study was small, (one patient per heart condition, four heartbeat cycles per patient) the heartbeats used in generating the shifted training exemplars were also used as part of the basis for the evaluation set. Representative examples are shown in Figure 2. The feature vectors produced for these examples are shown in Figure 3. Note that, while the effect of the additive noise can be seen, key features remain relatively stable.

The resulting classification accuracy as a function of the added noise variance is shown in Figure 4. For variances up to and including 3000 (corresponding to the signals and features in the third columns of Figures 2 and 3), classification is 100% accurate for all heart sounds. Above a variance of 3000, the decrease in accuracy varies widely between the different sounds, from a fairly rapid decrease for the normal case to no decrease in the VSD case.

This can be explained in part by noting that, while the peak amplitudes of the normal components of each heart sound (the so-called S1 and S2 components) are comparable in each case, the variance of

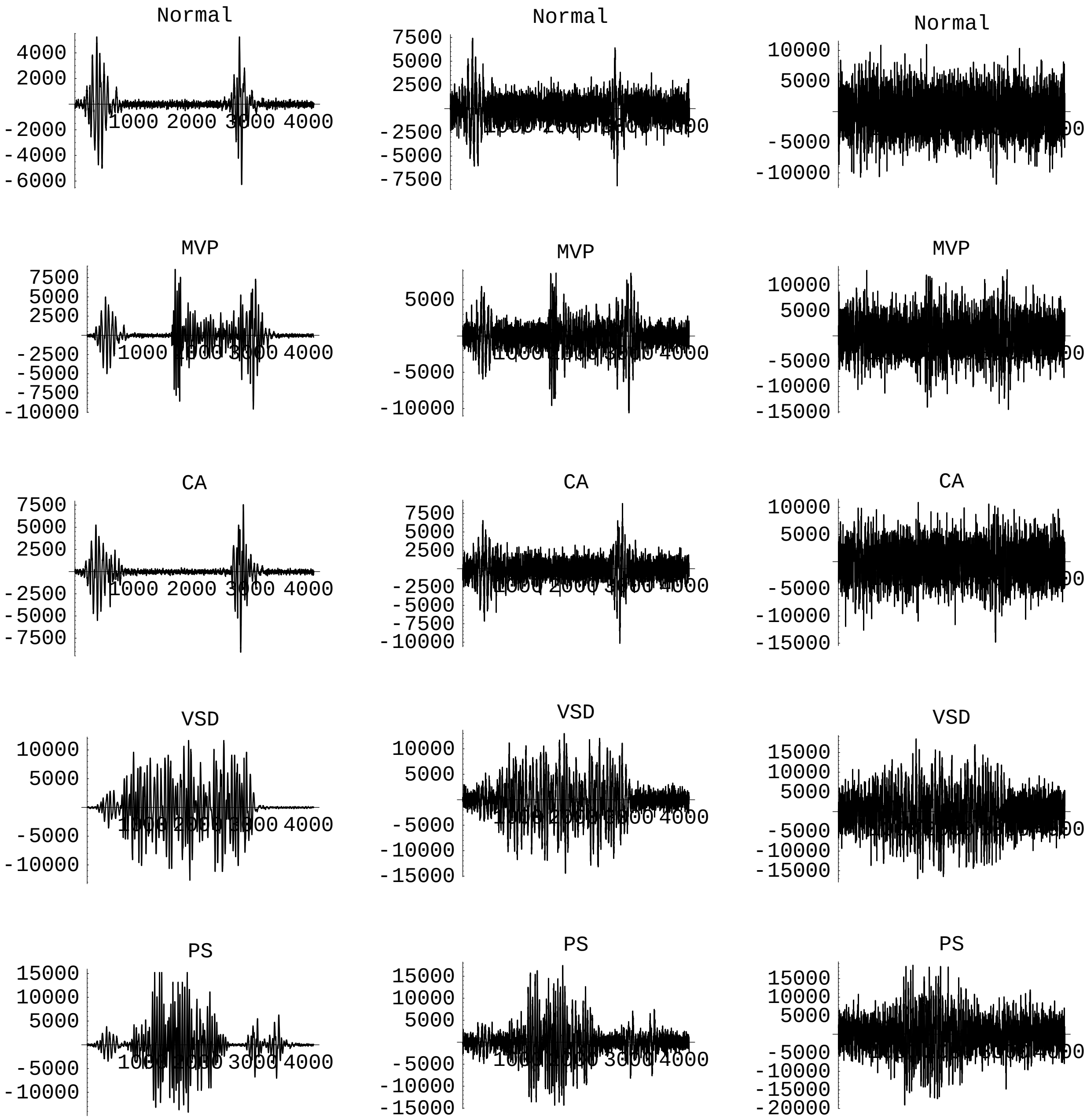

Figure 2. Representative Heart Sounds (left to right) Without Added Noise, with Noise Variance 1000, and with Noise Variance 3000

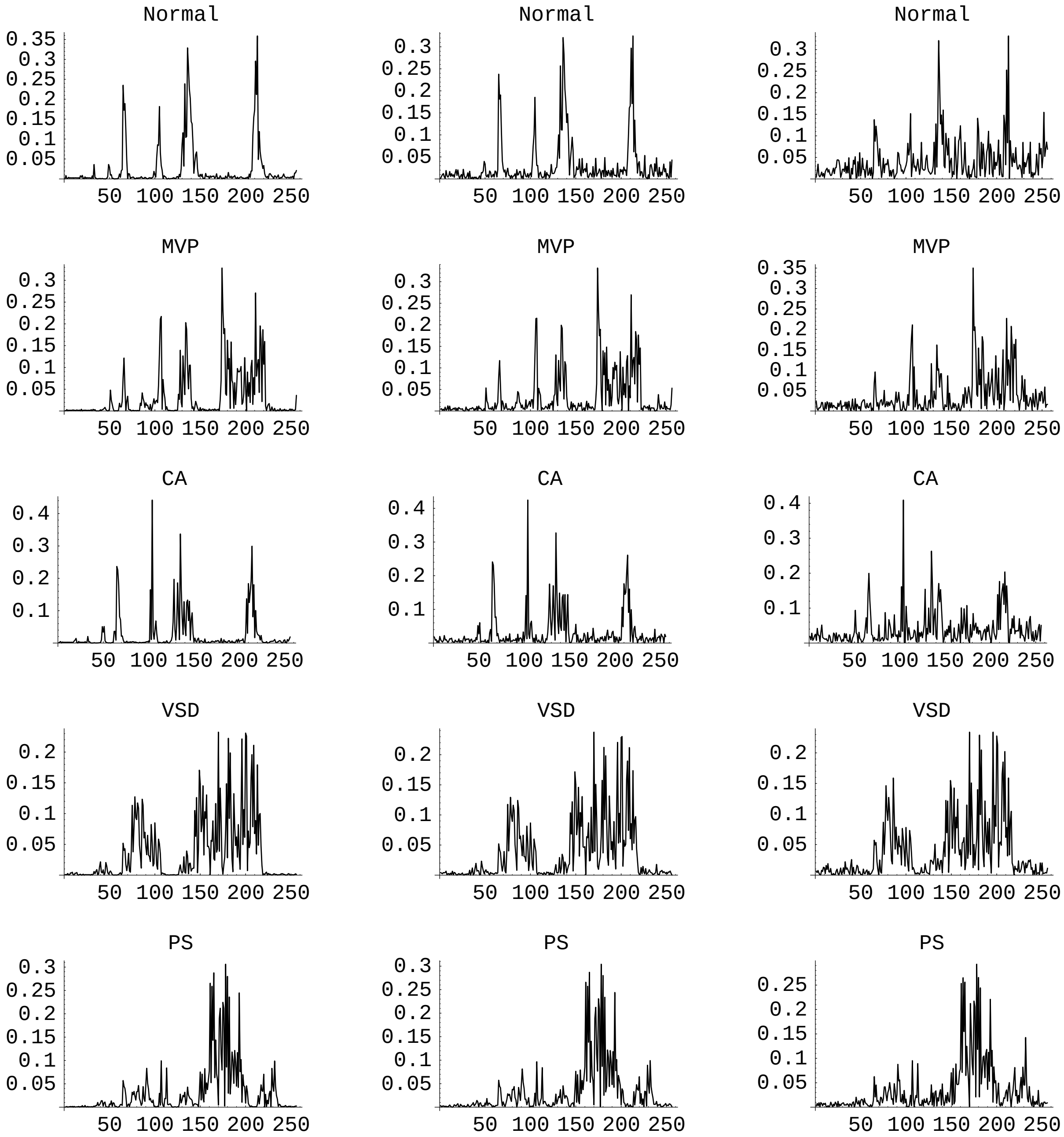

Figure 3. Feature Vectors Corresponding to the Heart Sounds in Figure 2

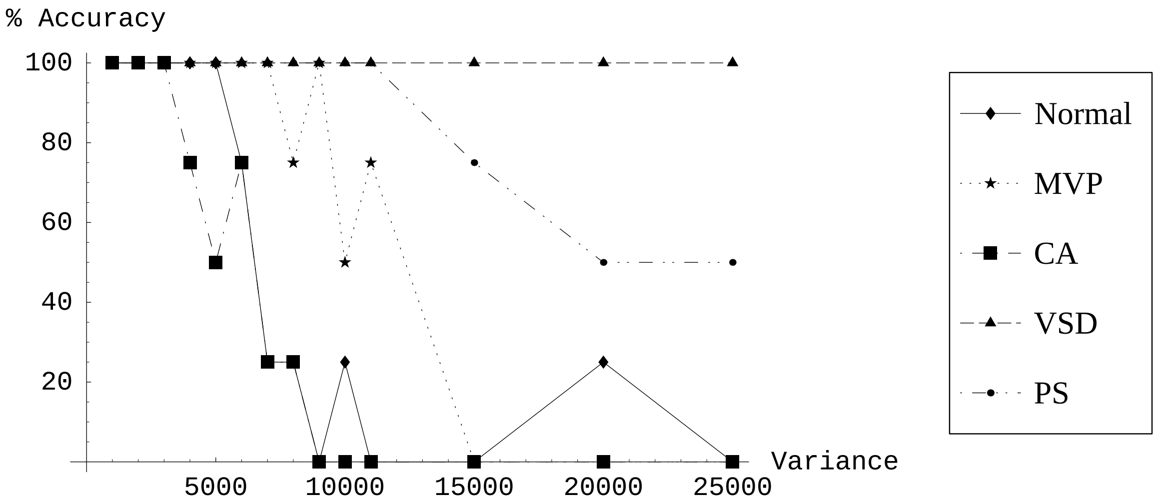

Figure 4. Classification Accuracy (in Percent) as a Function of the Variance of the Added Noise

the sounds differ widely (e.g., by a factor of approximately 16:1 comparing a typical normal heartbeat with one exhibiting VSD). Accounting for this variation, classification accuracy as a function of signal-to-noise ratio (SNR) is shown in Figure 5. For an SNR above 31dB (which is easily obtainable under most practical circumstances) classification accuracy is 100%.

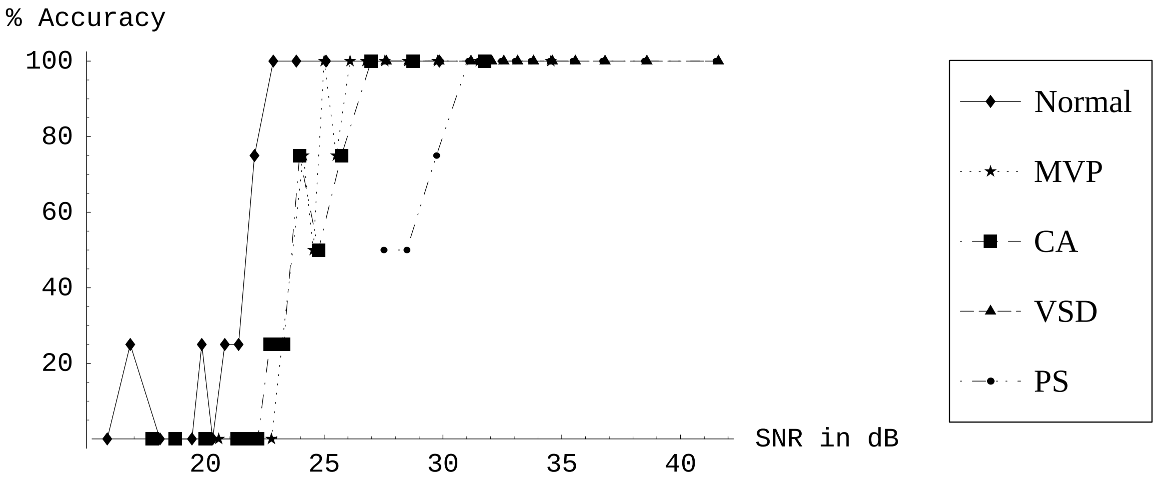

Figure 5. Classification Accuracy as a Function of Signal-to-Noise Ratio (in dB)

4 CONCLUSIONS AND FUTURE WORK

In this work we have presented a study of an approach to machine-aided cardiac diagnosis. The results of this study are promising, suggesting that a system based on this approach will be both accurate and robust, while remaining simple enough to be implemented at low cost.

Areas for future work include the addition of a segmentation component for the automatic extraction of individual heartbeats, the further development of the system to encompass a broader range of symptoms and pathologies, the addition of a knowledge-based component to resolve cases with missing or conflicting symptoms, and an evaluation of the resulting system using a larger and more diverse set of clinical data.

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REFERENCES

Barschdorff, D., U. Femmer, and E. Trowitzsch (1995, Sept. 10-13). Automatic phonocardiogram signal analysis in infants based on wavelet transforms and artificial neural networks. In *Computers in Cardiology 1995*, pp. 753–756. IEEE, Vienna, Austria.

Donnerstein, R. L. and V. S. Thomsen (1994, September). Hemodynamic and anatomic factors affecting the frequency content of Still's innocent murmur. *The American Journal of Cardiology* **74**, 508–510.

Durand, L.-G. and P. Pibarot (1995). Digital signal processing of the phonocardiogram: review of the most recent advancements. *Critical Reviews in Biomedical Engineering 23*(3/4), 163–219.

El-Asir, B., L. Khadra, A.H. Al-Abbasi, and M.M.J. Mohammed (1996, Oct. 13-16). Multiresolution analysis of heart sounds. In *Proc. of the Third IEEE Int'l Conf. on Elec., Circ., and Sys.*, Volume 2, pp. 1084–1087. Rodos, Greece.

Rajan, S., R. Doraiswami, R. Stevenson, and R. Watrous (1998, Oct. 6-9). Wavelet based bank of correlators approach for phonocardiogram signal classification. In *Proc. of the IEEE-SP Int'l Symp. on Time-Frequency and Time-Scale Analysis*, pp. 77–80. Pittsburgh, PA.

Shino, H., H. Yoshida, K. Yana, K. Harada, J. Sudoh, and E. Harasawa (1996, Oct. 31 - Nov. 3). Detection and classification of systolic murmur for phonocardiogram screening. In *Proc. of the 18th Int'l Conf. of the IEEE Eng. in Med. and Biol. Soc.*, Volume 1, pp. 123–124. Amsterdam, The Netherlands.