Classification of the Heart Auscultation Signals

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Abstract: Listening to the internal body sounds (auscultation) is one of the oldest techniques in medicine to diagnose heart and lung diseases. The digital heart auscultation signals are obtained with digital electronic stethoscope and can be processed automatically to obtain some coarse indications about the heart or lung condition. There are many ways of how to process the auscultation signals and quite some were published in the last years. In this paper we present one possible set of methods to reach the goal of heart murmur recognition up to the level to distinguish between the pathological murmurs from the physiological ones. The special attention was devoted to signal feature selection and extraction where we used the distribution of signal power over frequencies as the key difference between the normal and the pathological murmurs. The whole procedure including the signal processing, the feature extraction and the comparison of four machine learning classification methods is adequately described. It was tested on a balanced and on an unbalanced dataset with the best achieved classification accuracy of 87.5%.

1 INTRODUCTION

A heart is a muscular organ which pumps blood with oxygen and vital minerals to the various cells of the body. One heart beat consists of the first heart sound (S1) followed by systolic interval when the heart is in the contraction mode, followed by the second heart sound (S2) and the last diastolic interval when the heart fills with blood. The first heart sound and the second heart sound are produced when the atrioventricular and semilunar valves snap shut (Walker et al, 1990).

In this research we focus on a task to separate the pathological heart murmur possibly caused by a heart disease from a physiological murmur caused by other internal organs. This is the first step toward detection of various valvular heart diseases, particularly the aortic stenosis which is the common diagnosis by physicians. Valvular heart diseases can occur throughout the human life because of the stress, eating habits or smoking. In some small amount they can develop even before birth. The physicians can detect these abnormal heart sounds or heart murmurs with a stethoscope but only a trained physician with many years of experience can diagnose more complex heart diseases correctly. There exist much more reliable but also more expensive tests such as echocardiography, x-ray or electrocardiography for diagnosis of the heart disorders which are used as the last resources in the hierarchy of tests. Clinical practice shows that family doctors on the primary level often lacks the necessary training and experience and send patients to further examinations to hospitals even when this is not needed (Haney et al, 1999).

In our country, we have long waiting queues in healthcare caused also by wrong decisions on the primary level. It could be useful for the family doctors to have an intelligent device or a system able to correctly classify the sound signals from a stethoscope and thus assisting the physicians in making the right decisions. Such an instrument could serve also as a domestic appliance for first indication that something is wrong with the heart.

In this paper we present preliminary results achieved by using a previously not used (up to our knowledge) method for feature extraction and four different machine learning classification methods for pathological murmur detection in pre-processed auscultation signals from a digital stethoscope.

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2 PRE-PROCESSING AND FILTERING

The heart auscultation signals should be pre-processed in order to filter out the unwanted noise caused by other internal organs in the body (Ahlström, 2006).

2.1 Normalization

Normalization is a basic statistical operation. It's used to scale heterogeneous sets of data to the same interval, so that they could be compared relevantly. The normalization is necessary for the consistency of data. This is important when we determine the threshold.

In the case of the sound signals from an electronic stethoscope, we normalized the amplitude of each digital signal using the normalization equation (1).

$$y_n[i] = \frac{y[i]}{max(|y[i]|)} \quad (1)$$

Where $y_n[i]$ is a normalized signal amplitude of an i-th sample, $y[i]$ is a digital signal amplitude of a i-th sample and $\max(|y[i]|)$ is the absolute maximal value of the signal y.

2.2 Filtering

In the filtering step, we have used the Butterworth low pass filter, one of the widely used filters in signal processing. The cut-off frequency has been set to 100 Hz because most of the heart murmurs are above 100 Hz. With this process step the murmurs should be removed from the signal, as shown on the two graphs in Figure 1 and Figure 2.

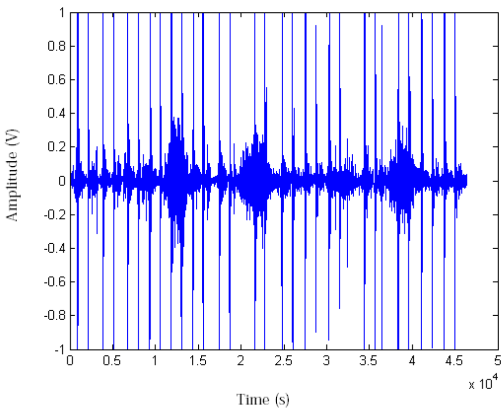

Figure 1: Original heart auscultation signal.

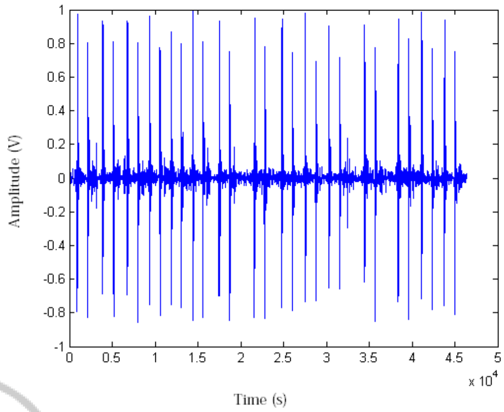

Figure 2: Filtered heart auscultation signal by Butterworth low pass filter.

We have removed the heart murmurs only because the extraction of S1 and S2 heart sounds is much more efficient this way.

3 FEATURE EXTRACTION

Before the classification can take place we must extract the appropriate features from the signal. During the auscultation a physician tries to identify the main constituents of a cardiac cycle, like systolic and diastolic period together with S1 and S2 heart sounds and then he/she tries to analyse related features such as rhythm, timing instants, intensity of heart sound components, splitting of S2, etc. This analysis allows him/her to search for murmurs and sound abnormalities that might correspond to specific cardiac pathologies (Hedayioglu, 2009). Similarly, the automatic feature extraction procedure must do the same. We locate the S1 and the S2 sounds (and consequently the systolic and the diastolic period) in the original signal by first computing the normalized average Shannon energy of the signal (Liang et al, 1997). Then we employ the Burg's power spectral density method to extract power spectral density estimates from the systolic and diastolic periods of the original signal, and to use them in classification algorithms.

3.1 Average Shannon Energy

First we compute the average and the standard deviation of the phonocardiogram with n samples which is needed to standardize the signal [5].

$$\overline{y_i} = \frac{1}{n}\sum_{i=1}^{n} y[i] \quad (2)$$

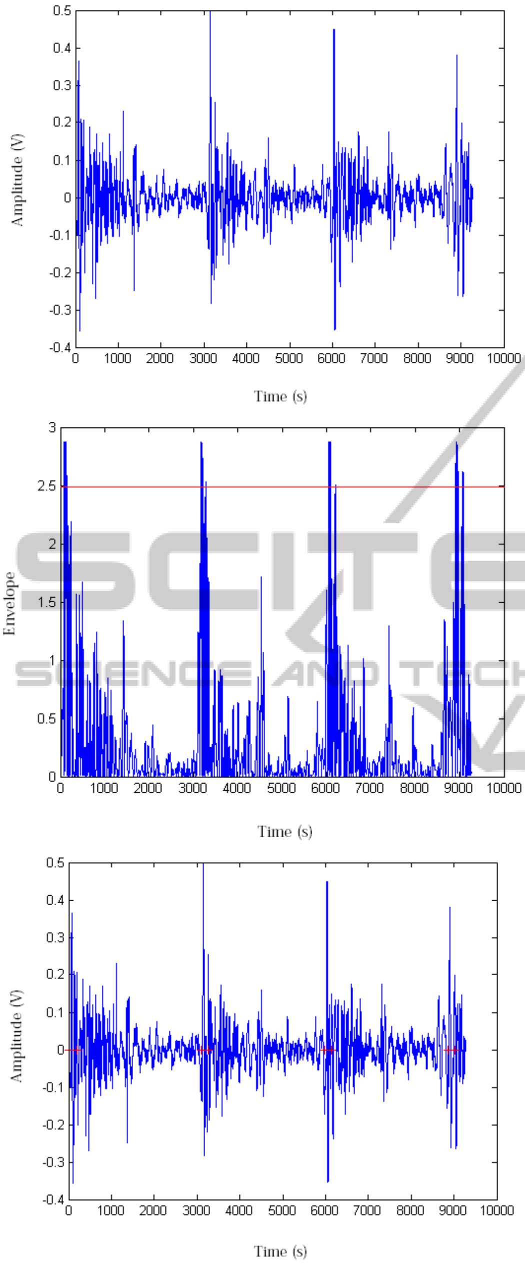

Figure 3: The original heart auscultation signal (top), its average Shannon energy with an appropriate threshold line (middle), and the detected locations of S1 and S2 sounds (red crosses) defining the systolic and diastolic periods in the original signal (bottom).

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y[i]-\overline{y_i}\right)^2} \tag{3}$$

Shannon energy is defined by the equation (4).

$$E[i] = -y[i]^2 \cdot \log\left(y[i]\right)^2 \tag{4}$$

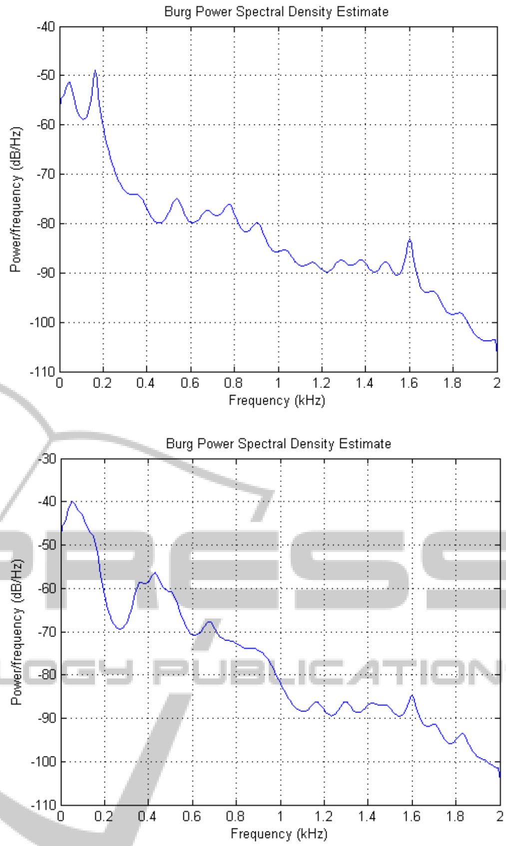

Figure 4: The Burg power spectral density of a heart auscultation signal between S1 and S2 in the case of pathological murmur (top) and in the case of physiologic murmur (bottom).

The last step is to standardize the whole signal using (Atbi and Debbal, 2013).

$$E_n[i] = \frac{E[i]-\overline{y_i}}{\sigma} \tag{5}$$

Now we get an average Shannon energy. If we plot the signal (Figure 3), we can clearly see the S1 and the S2 heart sounds which also correspond to the peaks in the original signal. Setting the threshold is done manually by experimenting for each set of signals. It depends on particular stethoscope involved and its settings.

3.2 Power Spectral Density

The nature is full of non-deterministic (stochastic) processes like the weather, the stock market, speech sound waves etc. Biomedical signals such as ECG, EEG are also of stochastic nature indicating that an appropriate method for analysis should be used. It turns out that the signal power is distributed differently over frequencies in the case of the pathological murmur than in the case of the physiological murmur (Figure 4). We used this fact to define the features used for classification.

For feature extraction we have chosen the Burg's parametric method for power spectral density estimation which is also used in geographical data processing, radio astronomy and biomedicine (Shradhanjali, 2013). It is a generalisation of the Fourier analysis. It returns a vector of different size for even and for odd number of frequency domain parameters (*nfft*): (*nfft/*2)+1 for even and (*nfft*+1)/2 for odd. We have set *nfft* to 512 which is used in speech recognition. Every parameter represents a power per unit frequency. We applied the Burg's method on extracted systolic and diastolic intervals of the original signal *y*. Although it is possible to diagnose different heart diseases within these intervals such as aortic stenosis, mitral stenosis, aortic regurgitation and mitral regurgitation, we limited our research at this stage only to distinct abnormal (pathological) murmur from normal (physiological) murmur. The upper graph in Figure 4 represents an interval between S1 and S2 of a patient with pathologic murmur while the lower one represents an interval with physiologic murmur. The graphs show the slight variation of power distribution over frequencies which must be detected by a classification algorithm.

4 CLASSIFICATION METHODS

The heart auscultation signals were taken from the web accessible database (Bentley et al, 2011). We used the dataset B (normal, murmur) consisting of 266 samples (100 normal, 166 murmur). Pre-processing, filtering and feature extraction was done in Matlab. For testing the classification algorithms we used the Orange open source platform (http://orange.biolab.si).

We tested four machine learning algorithms belonging to supervised learning methods in order to find the most suitable one for classification of the heart auscultation signals. We performed two experiments for each method: with a balanced set (100 – 100) and with an unbalanced set (100 – 166).

In all cases the available data was firstly randomized and then divided into training set (70%) and test set (30%).

4.1 K-NN

K-nearest neighbour algorithm is the simplest machine learning algorithm used for classification and regression. An object represented by selected features is classified by a majority vote of its neighbours in feature space, with the object being assigned to the class most common among its *k* nearest neighbours ($k > 0$). In our case, the euclidian distance was used to measure the distance of an object to its neighbours.

4.2 Support Vector Machine

SVM algorithm searches for a hyper-plane which optimally separates the data classes. Each object is represented by a feature vector in high-dimensional vector space. The location of the hyper-plane is mainly defined by the closest training vectors called support vectors while the faraway vectors are neglected. SVM can be used for classification, regression, or other tasks. It is relatively new ML algorithm invented by Vladimir N. Vapnik in 1993. This method has wide variety of applications in hand writing recognition and also in medical data.

4.3 Artificial Neural Networks

ANN is a black box computational model composed of neurons as in nerve cells, and synapses as the connections between the neurons. There exist a lot of different architectures of artificial neuron networks, but we used one of the simplest topology called multi-layered perceptron which has an input layer, a hidden layer and an output layer. The connections among the neurons are weighted. During the training process these weights are automatically adjusted by a backpropagation algorithm so that the difference between the actual and the desired output is minimal. We say that ANN is a black box since it can be viewed in terms of its input, output and transfer characteristics without any knowledge of its internal workings.

4.4 Logistic Regression

In spite of the misleading name this technique is used for classification and not for regression. It is a probabilistic statistical classification model relying heavily on the logistic (sigmoid) function. Logistic regression is used in various fields including social sciences and medicine.

5 RESULTS

5.1 Parameters Setup

The parameters of the tested classification algorithms were optimized experimentally by trial and error and are thus not strictly optimal but due to experimental results no significant improvement can be expected by computational optimization.

For the K-NN algorithm the parameters were set to:

- number of neighbours: 5,
- metrics: euclidian,
- normalize continuous attributes.

For the SVM the parameters were:

- SVM type: C-SVM,
- kernel : polynomial,
- numerical tolerance: 0,0020.

In the case of the neural network the parameters were:

- hidden layer neurons : 150,
- regularization factor: 0.5,
- max iterations: 5000.

For logistic regression we used:

- regularization: L2 squared weights,
- training error cost: 1.30.

5.2 Classification Results

For each method we calculated standard classification measures: the classification accuracy (CA), sensitivity (Sens), specificity (Spec) and area-under-curve (AUC). Each method was tested two times: on an unbalanced 266 samples dataset (166 positives and 100 negatives), and on a balanced, 200 samples dataset (100 positives and 100 negatives). Each method was run 10 times and the best results are presented in Table 1 and in Table 2.

Table 1: Comparison of the classification methods performance on an unbalanced set of heart auscultation signals (266 samples).

Method	*CA*	*Sens*	*Spec*	*AUC*
K-NN	0.8625	0.9500	**0.60**	**0.8550**
SVM	0.8375	0.9833	0.40	0.4367
Neural network	0.8375	0.9833	0.40	0.6450
Logistic regression	**0.8750**	**1.0000**	0.40	0.4367

Table 2: Comparison of the classification methods performance on a balanced set of the heart auscultation signals (200 samples).

Method	*CA*	*Sens*	*Spec*	*AUC*
K-NN	**0.7679**	0.8947	**0.63**	0.7833
SVM	0.6200	0.8167	0.63	0.5083
Neural network	0.7225	**0.9333**	0.45	**0.8917**
Logistic regression	0.6825	0.9333	0.45	0.6750

In the case of the unbalanced set the results are close together in the sense of CA (within 4%) and sensitivity (within 5%) but differ more in specificity and AUC. The best performance showed LR which detected all signals with murmur (Sens=1.00) and K-NN which outperformed others in Spec and AUC, thus is able to correctly classify an auscultation signal with highest probability. Small AUC values (in the case of SVM even below 0.5) indicate the imbalance in data.

In the case of the balanced set the results are much more dispersed for all measures and worse in accuracy and sensitivity, but better in specificity and AUC. The K-NN showed the best performance regarding the accuracy and specificity while the neural networks performed best regarding sensibility and AUC.

Logistic regression and K-NN can be implemented relatively easily and are suitable to be integrated into digital stethoscope add-on device while artificial neural networks are more demanding and would probably need a server support.

6 CONCLUSIONS

We used digital signal processing, power spectral density functions and machine learning techniques to classify heart murmurs. The initial results are promising and will definitely be improved in the future. For instance, in the related field of speech recognition it took many years of research to reach the accuracy to about 90% (Kim and Stern, 2012).

Biomedical signals are patient dependent, same as human speech, therefore the use of algorithms from speech recognition area, like Hidden Markov Model (HMM), seems to make sense. The recently reported research on the topic (Zhong et al, 2013) shows very promising accuracy (94, 2%).

In the future, we intend to test our approach more extensively on more data recorded from different types of patients (children, adults, elder) leading to more reliable results. We will investigate also the direction towards HMM beginning with simpler Markov models like Markov chain.

Furthermore, we want to investigate automatic classification of various most common valvular heart diseases, like aortic, mitral, tricuspid and pulmonary valve stenosis and insufficiencies. We see the main problem here to obtain the necessary amount of medical data (phonocardiograms) with attributes, like heartbeat rate, blood pressure and sampling locations.

Besides the testing of different classification algorithms, the future goal is also to find a compromise between the classification accuracy and the computational complexity in order to find the most suitable method for implementation within the device with the limited processing power (digital stethoscope itself or mobile phone for example). The current results suggest logistic regression or K-NN method.

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