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Arteriovenous Fistula Stenosis Detection using Wavelets and Support Vector Machines

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Abstract— **The objective of this exploratory study was to develop signal processing methods for assisting in the diagnosis of arteriovenous fistula stenosis on patients suffering from end-stage renal disease and undergoing haemodialysis treatments. The proposed method is based on the classification of vessels sounds utilizing parameter extraction from wavelets transform coefficients. The coefficients energy of selected scales (frequency bands) were fed to a support vector machine based system for classification. Results suggested that this technique can be useful for diagnosis purposes to physicians during the auscultation procedure.**

I. INTRODUCTION

Hemodialysis is a common treatment for patients suffering from end-stage renal disease. During this treatment the blood is purified from waste products and excess fluid is removed by using a dialyzer. To reach the blood, a vascular access, usually placed on one of the patients forearms is used to insert the needles coming from the dialyzer. A very common type of vascular access is the so-called *arteriovenous (AV) fistula*. The fistula is made through a surgical operation during which an artery and a vein in the arm are connected together. The connection point is referred to as an *anastomosis* and is often located near the patients wrist or elbow. The state of the fistula may deteriorate in course of time. The most common form of fistula failure is venous stenosis [1] ,[2], [3].

A stenosis is an abnormal narrowing of a bodily canal which can be caused by calcification or when the vessel's wall is exposed to abnormal physical stress like turbulence or high blood pressure. When exposed to physical stress the wall gets thicker as a response and new wall material is built up on the inside of the vessel, narrowing the lumen. When the dialysis becomes inadequate as a result of too low blood flow the fistula must be revised and remedied. An early detection of stenosis is desirable since it permits their correction prior to total occlusion and thereby prolongs the life of the fistula. It has been reported that turbulence related to stenosis of vessels create audible sounds due to the vibrations on the surrounding structures, that can be analyzed to provide information about the severity of the blockage [4].

Though Doppler ultrasound and angiography (X-ray) examination are widely used in AV fistula diagnosis, auscultation is first performed by physicians to evaluate its functionality. To help clinics, the National Kidney Foundation (US) has published guidelines for the vascular access . They state that physical examination of the fistula (monitoring) should be performed weekly and should include inspection and palpation for pulse and thrill at different sites of the fistula [1], [2]. The clinician can also use a stethoscope to listen for sounds originating from the fistula, called bruits. Utilizing the advances in signal processing, diagnostic tools can be developed to help physicians in diagnosing fistula state so that frequent referrals to alternate expensive tests such as Doppler Ultrasound may be reduced.

Phonoangiography (recording of sound from vessels) is a non invasive, low cost technique that can be used with success for monitoring the vessels functioning. A considerable amount of research work have been done in this area for diagnosis purposes, as in coronary artery and carotid artery disease to mention some [4], [5].

The research results have shown that stenosis has two basic acoustical effects: a general increase in the sound level and an introduction of new high frequency components in the power spectra. The changes in frequency are dependent on the distance from the stenosis and its severity.

Literature reports the use of the Wavelets Transform for processing of phonocardiography signals due to the highly non stationary nature of these signals [4]. The introduced method of classifying arteriovenous fistula stenosis is based on parameter extraction from the coefficients of the Wavelets Transform of the recorded sounds. After calculating a reduced set of features obtained from those coefficients, a support vector machine is used for classification. In may applications the support vector machines have shown a good performance, better than other traditional learning machines such as neural networks and have been used as powerful tools to solve classification problems as they provide a good generalization capacity.

II. METHODOLOGY

A. Data and patients

The data set used in this work, consisted of recordings from 8 patients (labelled K_1 to K_8 here) undergoing haemodialysis treatment that were collected at the Department of Clinical Physiology, Lund University Hospital [6]. As a measuring device, a microphone attached to a stethoscope head was used during the recording sessions. Signal acquisition was performed using the BIOPAC ™, BP100 system.

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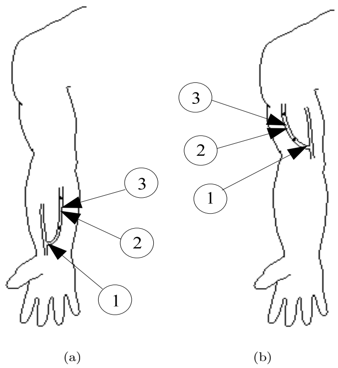

Fig. 1. Main recording sites. (a) forearm (b) upper arm.

The recorded signals vary in amplitude; gains of 50 and 200 were set depending on signal strength, the time duration of the signals is about 10 seconds. A sampling frequency of 10050 Hz was selected during all recording sessions.

The recordings were made at several sites around the fistula. In patients with stenosis in some region, additional recordings were made on the areas where it was present. The main sites are located at the anastomosis (site 1) and some centimeters downstream (sites 2 and 3) as shown in Fig 1.

B. Signal Processing

The signals were firstly normalized in amplitude to make fair comparison since gains are different and the signals at some locations are stronger and also present different strength from patient to patient. A high pass filter with a cut off frequency of 40 Hz was used to remove base line wander and other artifacts. To obtain zero phase distortion, after filtering in the forward direction, the filtered sequence was then reversed and run back through the filter. Down sampling was applied to the signals to reduce sampling rate to a value of 2000 Hz, which is convenient for the scale selection used during wavelet analysis.

1) Segmentation: Portions of period durations around the peaks are to be used in the analysis (see Fig. 2). Previous works have shown that the turbulent sounds are closely related in the time domain to the peak of the blood flow waveform as in [7] where the partially occluded femoral artery of a dog was used.

Peak detection was performed as follows: Homomorphic filtering, was first applied to obtain the input signals envelope. A low pass filter with a cut off frequency of 5 Hz was then applied to smooth the noisy envelope, this smoothed envelope is then used to find signal peaks. To avoid false peak detection a minimum inter peak distance of 0.4s was set as lower limit. Interquartile distance is used here as a selection criterion: Accepted period lengths are period lengths with durations T_i inside the interval $Q_1 - 1.5 * IQR \leq T_i \leq Q_3 + 1.5 * IQR$, where Q_1, Q_3, IQR are the first quartile, third quartile and the interquartile range respectively. The peak indexes belonging to the accepted periods, are used finally to perform the segmentation of the input signals. The selected periods are denoted $x_i(n)$

TABLE I

WAVELET DECOMPOSITION

Detail	Frequency range[Hz]	Time Resol.[ms], F_s= 2000
1	500 - 1000	1
2	250 - 500	2
3	125 - 250	4
4	62.5- 125	8

2) Wavelet decomposition: Several results have reported frequency peaks in the region of 300 to 500 Hz [5], 200 to 800 Hz [7] , and between 250 to 1000 Hz [8] in the sound recording from stenotic vessels.

Although most of the experiment carried out in previous works were mainly devoted to the study of stenosis in the carotid and coronary arteries, we have used these results as a starting point. The approach used here is to select appropriated scales in such a way that these frequency peaks fall into some of the selected frequency bands. In order to accomplish this, 4 levels of decomposition were selected. As we are using a sampling frequency of 2000 Hz, the frequency ranges for the different scales are as shown in table 1.

Several types of wavelets were tested (Daubachies 4, Daubachies 6, Coifflet 1) yielding no significant differences on the results. Daubachies type 4 wavelets were utilized for the results shown here. It was expected that turbulent sounds caused by stenosis wolud produce more energy content in some of the frequency bands of the recorded signals spectra which then could be used for discriminating purposes.

3) Parameter Extraction: Every selected period $x_i(n)$ coming from the segmentation step was then normalized to have unit energy, that is,

$$x_i^n(n) = \frac{x(n)}{(\sum_n x_i(n)^2)^{\frac{1}{2}}} \tag{1}$$

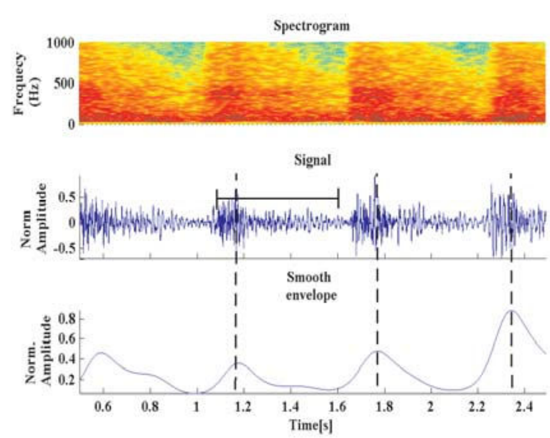

Fig. 2. Example of the segmentation process. The selected region is marked by the black line on top of the signal. A spectrogram is included to visualize the time-frequency signal properties.

TABLE II

SIGNALS FROM PATIENT K_2

Signal	Site	Avg.Cyc. duration [s]	cycles	Patient
1	4	0.58169	16	K_2
2	5	0.58285	15	K_2
3	4	0.57646	16	K_2
4	5	0.59502	15	K_2

Four wavelets coefficients were then calculated for each selected period of the recorded sample. The features to be extracted from the wavelets coefficients $d_i(n)$ were the scale energies SE_i defined as,

$$SE_i = \sum d_i(n)^2 \tag{2}$$

The magnitude of the coefficient energies presented a high dynamic range; a (base 2) logarithmic transformation was applied before the classifying step to improve the performance of the classifier.

4) Feature selection and Classification: Principal Component Analysis (PCA) and the sequential forward selection (SFS) algorithm were helpful in selecting the best features from the initial set of four energy coefficients. For the sake of simplicity we restricted ourselves to retain only the 2 most information carrying features; $SE_1(n)$ and $SE_2(n)$ were found to be the best selection. This seems to be reasonable since these coefficients contain high frequency information and that region is where the turbulence energy is expected to be located.

The Support Vector Machine (SVM) is a useful technique for data classification. A classification task usually involves training and testing data which consist of some data instances. Each instance in the training set contains one target value (class labels) and several attributes (features). The goal of SVM is to produce a model which predicts target value of data instances in the testing set which are given only the attributes.

A SVM classifier implemented using a MATLAB ™, toolbox [10] was used here to classify the logarithmic transformed normalized scale energy vectors of the wavelets coefficients into two groups: Stenotic ('s') or Non stenotic ('n').

III. RESULTS AND DISCUSSION

One interesting case among the patients that participated in the recording sessions is that of patient K_2, who developed stenosis in the fistula, this condition was remedied by balloon dilatation afterwards. The recording sessions for this patient provide a valuable before-and-after case. The segmentation of these four signals is summarized in table 2. Signals 1 and 3 corresponds to the case after angioplasty and 2 and 4, to the before angioplasty case.

In Fig. 3 logarithmic regression plots of the coefficient energy per scale for both before and after angioplasty recordings from that patient are shown. It can be seen from the graph that the behavior of the coefficient energies varies from

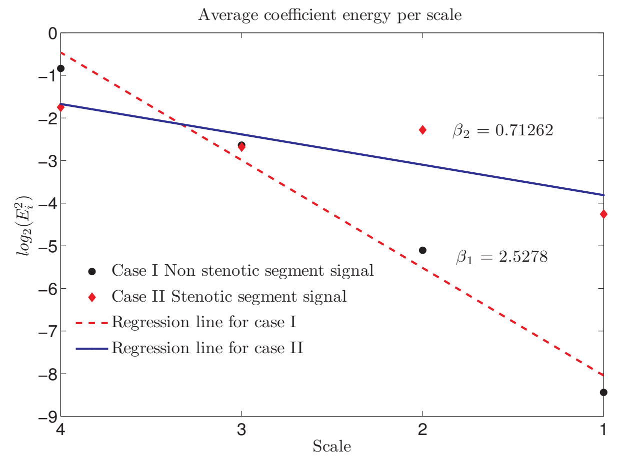

Fig. 3. Plot of the base 2 logarithm of the average energy per scale and line regressions for a stenotic and non stenotic case. As it can be seen from the graph the energy content is higher at lower scales (higher frequencies) for case II.

the stenotic and non stenotic case. In the former the energy content in the high frequency region (lower scale) is high compared to the non stenotic case. This is similar to the finding in [9] where the coefficients variance is considered in the context of fractal analysis of turbulent flow.

Using the four signals of table 2 we obtained a total of 62 periods and their corresponding scale energy vectors. Cross validation was applied to this set for measuring the performance; a number of periods randomly chosen is used for training the SVM and the remaining periods are used for testing. Ten-fold, six-fold and leave-one-out cross validation were applied. The correct classifications rates of stenotic cases were 98.7 %, 98.6% and 98.5% respectively.

As can be seen from Fig. 4 data appear to be linearly separable so a linear kernel with a regularization parameter C = 0.1, was finally selected.

These rates were rather optimistic, and could reveal overtraining. A validation was performed on the signals from the remaining patients K_1, K_3, K_4, K_5, K_7, K_8 (sounds signals

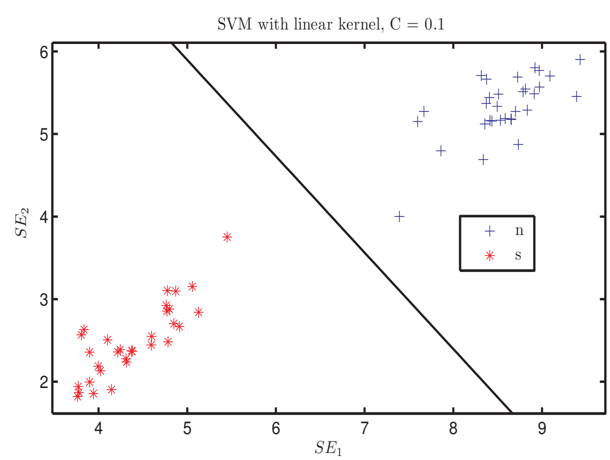

Fig. 4. SVM classification.

from K_6 were rejected due to poor quality). Every signal was segmented into periods, then the classifier was applied to every single period of the signals under examination. To label a signal as coming from a stenotic segment recording, its amount of periods classified as 'stenotic' should be larger than 80%. The same apply to the 'non stenotic' case. Using this rather arbitrary approach a result of 83% of correct detection was obtained, this is probably due to the small set for training and also that the signals used for training the classifier came from only one patient. It was also noticed that some recordings coming from patients classified as 'non stenotic' had spectra with significant power levels above 400 Hz which led to classify them as stenotic. This probably suggest that frequency bands should be analyzed is shorter steps (more scales). Additional attention should be pay to the recording sites in order to decide which are the best locations.

IV. CONCLUSIONS AND FUTURE WORKS

In this report we used wavelets transforms to study the recordings from stenotic and healthy vessels. The energy levels found at different frequencies or scales can be used to discriminate between these two cases. The energy of the detail coefficients at two selected scales were used as the features to be used for a linear classifier. The percentage of correct selection, in the sample test was about 83%. However, a definitive conclusion cannot be drawn until more data are available for training and testing.

A future measuring campaign is foreseen where more data will be available and when these results are going to be reviewed.

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