Automatic Classifiers for Medical Data from Doppler Unit

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Abstract. *Nowadays, hand-held ultrasonic Doppler units are often used for noninvasive screening of atherosclerosis in arteries of the lower limbs. The mean velocity of blood flow in time and blood pressures are measured on several positions on each lower limb. This project presents software that is able to analyze such data and classify it in real time into selected diagnostic classes. It is also capable of giving a notice of some errors encountered during measuring. At the Department of Functional Diagnostics in the Regional Hospital of Liberec a database of several hundreds signals was collected. In cooperation with the specialist, the signals were manually classified into four classes. Consequently selected signal features were extracted and used for training a distance and a Bayesian classifier. Another set of signals was used for evaluating and optimizing the parameters of the classifiers. This paper compares the results of the software with those provided by a human expert. They agreed in 89 % cases.*

Keywords

Medical data recognition, hand-held ultrasonic Doppler unit, peripheral arterial disease.

1. Introduction

Atherosclerosis and illnesses of cardiovascular system are serious threat for modern population. Typical risk factors are smoking, diabetes mellitus, hypertension and lack of movement.

Manifestation of these diseases in human extremities is called Peripheral Arterial Disease [1]. The illness has four stages: 1) Patient feels no subjective troubles. 2) Patient feels pain while moving. 3) Patient experiences pain while in rest. 4) Stage of tissue necrotization and gangrene. Especially the last phase of the disease is very dangerous for patient's extremity and even life. The well timed diagnostic is very important. Lower limb arteries are afflicted more often than those in upper limbs.

There are many methods, how to detect the obstructions within arteries. The first method is a simple physical examination of the limb; a medical doctor inspects the color and the temperature of the extremity. The disadvantage of this is that the pathological changes are often detectable only after the illness enters its final stages.

Angiography or its modern equivalent CT angiography is a very accurate method, but there is some danger connected with the invasiveness of these methods. The best noninvasive method appears to be ultrasonic duplex scan that is able to visualize the profile of the artery along with dynamic representation of blood flow within.

The above mentioned methods require expensive equipment, so these examinations are used in clinical medicine, not in general practice surgery.

For fast noninvasive screening of PAD in diabetological and cardiological ambulances, the ultrasonic Doppler devices have been used for a long time. These measure average blood flow velocity along with distant blood pressures on several typical places on lower limb. From shapes of the waveforms (or the sound emitted by the device into headphones) the expert can detect PAD. These devices are notably cheaper than duplex scanners.

The developed automatic recognition software together with a Doppler unit could help to identify the first phases of the disease and could help to further improve the well-timed diagnostics in general practice surgeries, because the traditional analysis could be partly subjective and depends on experience of the expert.

2. Methods

Before starting the research, we had to collect a large database of real medical data. In our case the data was acquired during the last few years in the Regional Hospital in Liberec. They had to be anonymized before they could be used in the research.

The waveforms were measured by the hand-held ultrasonic unit Multi Dopplex II and sent to a PC for storing via RS232 interface. The device measures the mean velocity of blood in artery within a short time period, a Doppler velocity waveform, along with blood pressures in five standard locations on each leg, e.g. there are 10 waveforms from one patient per one examination. The standard positions examined are following: 1) artery femoralis, 2) a.

poplitea, 3) a. tibialis posterior, 4) a. tibialis anterior, and 5) a. dorsalis pedis. (See Fig.1.)

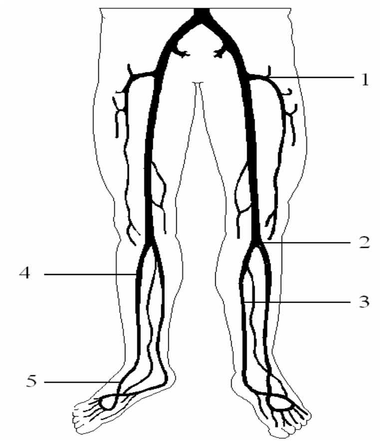

Fig.1. Standard examination positions (picture taken from utility software distributed along with Doppler Unit - Dopplex Reporter).

Multi Dopplex II is a bi-directional device; the waveforms could be displayed as forward and backward flow (See Fig. 2.-4.) or as a difference of these two signals in combined waveforms.

2.1 Classes

For automatic classification, four classes were chosen, into which the signals will be classified. These classes reflect various degrees of artery occlusion but also describe some defects which can be considered by a specialist during examination. [3].

Normal course – Signals acquired by examination of arteries without peripheral arterial disease (PAD) - Fig.2.

Stenotic course – Signals measured in arteries with a stenotic diameter - Fig.3.

Occlusion– Signals measured in arteries with a total arterial obstruction - Fig.4.

Incorrect course – It may happen that during measuring various errors occur. Four kinds of such errors are detected in measured data. 1) The amplification factor was set too high and the course is clipped. 2) The signal is under strong influence of near veins, the dicrotic notch usually present in the normal triphasic waveform is lost in the noise. 3) Measured forward and backward velocities are echoes of each other, after the calculation of the difference the combined signal is almost zero. 4) The signal was not measured at all. This could happen by wrong placing of the probe, but it could also mean the total obstruction of the artery.

The expert of angiology classified a part of the available database manually into designed classes before training of the classifier. This prior knowledge is used in the training process and also in the testing phase, when expert's opinion is compared with results of the classifier.

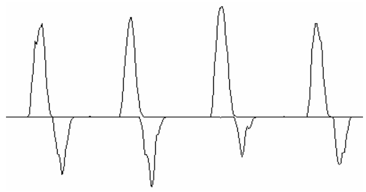

Fig.2. Directional signals acquired by examination of arteries without peripheral arterial disease (PAD)

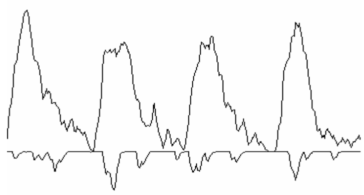

Fig.3. Directional signals measured in arteries with a stenotic diameter.

Fig.4. Directional signals measured in arteries with a total arterial obstruction.

2.2 Features

During the design process, 18 features were considered as potentially useful for the classifier. These features describe the quality of measured signals in time domain, frequency domain or have a special medical meaning.

Obtaining of the absolute values of velocities could be difficult with a simple Doppler unit because the application angle of the probe strongly influences the amplitude of measured data. The standard angle ranges from 45° to 60°.

The further listed features are often used by human experts ([2], [3], [5] and [6]):

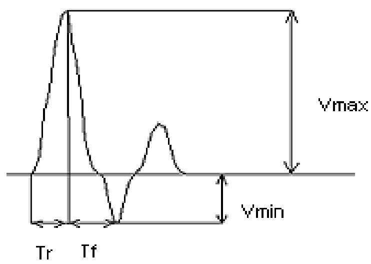

Fig.5. Doppler waveform description.

The list of proposed features is following:

Signal Log Energy

$$E = \ln\left(\sum_{k=1}^{L} n(k)^2\right) \tag{1}$$

where L is the number of samples.

Brachial pressure index (*BPI*) – the ratio of the patient's system blood pressure (measured on a. brachialis) and the distal pressure in the examined position on the lower limb.

Pulsation index (*PI*)

$$PI = \frac{v_{\max} - v_{\min}}{v_{avg}} \tag{2}$$

where $v_{avg.}$ is the average velocity during one pulse duration.

Resistance index, Pourcelot index *(RI)*

$$RI = \frac{v_{\max} - v_{\min}}{v_{\max}}. \tag{3}$$

Maximum velocity(v_{max}) – Max. velocity within a pulse.

Minimum velocity (v_{min}) – Min. velocity within a pulse.

Acceleration (*A*)

$$A = \frac{v_{\max}}{T_r}. \tag{4}$$

Deceleration (*D*)

$$D = \frac{v_{\max} - v_{\min}}{T_f} \tag{5}$$

Velocity-time index (*VTI*) –

$$VTI = \frac{v_{\max} - v_{\min}}{T_r + T_f}. \tag{6}$$

Artery resistance parameter (*RP*)

$$RP = \frac{v_{\max}}{v_{\min}}. \tag{7}$$

A set of 8 frequency features – The standard duration of measuring at one position is 5 seconds using the 100 Hz sampling frequency. The spectrum is calculated from the entire signal via Fast Fourier Transform (FFT). The most of the energy in the spectra is concentrated up to one quarter of sampling frequency. These spectral coefficients are multiplied by eight triangle windows with half overlap in order to get 8 frequency features *F1* to *F8*.

Before computing the features, the signal must be preprocessed. It was done by filtering it by a low pass filter. This filter suppresses high frequency noise, but keeps the shape of the waveform.

The Sequential Forward Search (SFS) algorithm [8] was used to determine the most significant features. Its advantage consists in the fact that it utilizes the target classifier. The algorithm operates as follows:

In the first step, it identifies the feature with the best score. In the *n*-th step, the set of previously selected *n*-1 features is extended by adding that feature from the remaining ones which makes best classification with the *n*-feature set. The algorithm is terminated if the score in the current step is lower than in the previous one or if the number of steps (and already selected features) reaches the limit we set. In this way we get the set of the *K* most informative features.

2.3 Detection of Pulses

All the above mentioned features are calculated automatically in a real time, without human intervention. Most of them require that a single pulse is extracted and its shape and size must be analyzed.

The detection in time domain is quite complicated. With a growing stenosis in the artery the waveforms loose their shape and become non-pulsative. Also the presence of a vein signal (mostly in signals from a. femoralis, a. poplitea) complicates this task.

Autocorrelation function is used for the detection of pulses in the signal. Maxima in the waveform are traced to detect the beginning and end of one pulse. Derivation is used for identifying waveform extremes.

2.4 Classifiers

Two basic types of classifiers were implemented during the design process: The minimal distance classifier and the Bayesian classifier. Other suitable classifier types can be found in [4].

The minimal distance classifier (MDC) represents each class by its best etalon (that sample with the minimum distance to the others). The etalon is described by a *K*-dimensional feature vector. Our classifier uses the Mahalonobis metrics:

$$d(\mathbf{x},\mathbf{y}) = \sqrt{(\mathbf{x}-\mathbf{y})' \cdot \mathbf{\Sigma}^{-1} \cdot (\mathbf{x}-\mathbf{y})} \tag{8}$$

where $\mathbf{\Sigma}$ is covariance matrix of features within each class.

The Bayesian classifier (BC) represents each class C_i by a Gaussian probability density function (pdf) in the *K*-dimensional feature space. Its two parameters are means and variances. Since the classes have different occurrence rates, also the class prior probabilities are taken into account. The pdf is defined as follows:

$$P(\mathbf{x}\,|\,C_i) = \frac{1}{\sqrt{(2\cdot\pi)^K \cdot \det(\mathbf{\Sigma})}} \cdot \exp[-\frac{1}{2} \cdot (\mathbf{x}-\bar{\mathbf{x}})' \cdot \mathbf{\Sigma}^{-1} \cdot (\mathbf{x}-\bar{\mathbf{x}})] \tag{9}$$

2.5 Within-Class Clustering

For better modeling of feature vectors' distributions in the *K*-dimensional space, it is useful to split data in each class into clusters and represent each of them by a separate etalon or a separate pdf.

In our case, the clusters are identified via the well known *K*-Means algorithm in combination with the Linde-Buzo-Gray algorithm (LBG) [7].

During the training phase, each diagnostic class is represented by one or more clusters, where each one is described by its parameters, i.e. mean vectors, covariance matrixes and occurrence counts.

In the testing phase, the minimal distance classifier assigns a measured data represented by the feature vector to the nearest etalon and decides to which class the unknown data belong. The Bayesian classifier assigns the class whose posterior probability is the highest one. The errors of incorrect course are detected before the classification stage. If the signal is identified as incorrectly measured, the classification is denied.

In order to train the classifiers and to make extensive tests a large database of real signals was prepared by an expert. He classified the data from 900 examinations manually. These were measured at 10 standard positions (5 on each leg), i.e. there were 9,000 sample waveforms available. Approximately 15 % of all these signals were found incorrect. (The reason was mostly setting of the amplification too high on a. femoralis, so that the signal was clipped). From the correctly measured ones, 47 % were assigned to the class Normal, 32 % to the class Stenosis, and the rest 6 % into the class Occlusion. In the experiments, data from 720 randomly chosen examinations were used for training the classifier; the remaining data (of 180 subjects) were left for testing. In each individual test, the result of the classifier was compared to the expert's decision. This was done for all test data and then the recognition score was calculated as a ratio of correctly assigned to all available testing samples. The scores were calculated for each measuring position and later averaged over all positions. To make the results more significant, the random database splitting into the training and testing part was repeated 5 times and the final scores were calculated as the means from the 5 tests. In other words, all the scores mentioned in the following section are averaged results from 9000 individual classifications (180 subjects x 10 positions x 5 repetitions).

3. Experimental Part

3.1 SFS Algorithm

The results from the SFS algorithm are illustrated in Fig.6. and Tab.1. It can be observed that the best classification is obtained with 6 features, while adding more ones yields a smaller and then even larger degradation of the performance. The SFS algorithm identified the following best 6 features: *BPI*, deceleration, resistance index (Pourcelot), velocity-time index and second and third frequency feature. As most of the energy of waveform spectra is centered in low frequencies, the higher frequency features did not bring any additional improvement.

If we compare these 6 most informative features with those used by the human experts in vascular labs, we can see that the *PI* feature often used by experts was not selected by the SFS algorithm. This may be caused by the fact that the average velocity in (2) can be influenced by less accurately detected borders of the pulse when compared with a manual measurement.

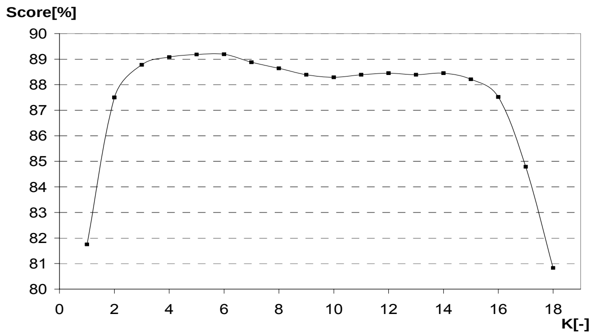

Fig.6. Recognition score as a function of the number of classification features measured by the SFS algorithm.

# of Features	Recognition score[%]	Feature added
1	81.75	VTI
2	87.50	BPI
3	88.78	F2
4	89.08	RI
5	89.18	D
6	89.19	F3
7	88.88	A
8	88.64	F1
9	88.39	Energy

Tab.1. Detailed results from the SFS algorithm's first 9 steps. The scores and added features are shown.

3.2 Testing of the Classifiers

In Tab.2. we show the comparison of the results from the two classifiers and their various settings. The scores are based on correct decisions that include a) classification into a correct diagnostic class and b) correctly detected measurement error. It is evident that the best results were achieved by the Bayesian classifier with multi-modal pdfs and prior probabilities. The best score was 89 %, i.e. the classifier and the expert agreed in 89 % of cases.

In the medicine, the results are often indicated as sensitivity and specificity rates. The sensitivity is defined as

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives}, \quad (10)$$

the specificity is defined as:

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives}. \quad (11)$$

Because the rates are applicable for binary classifiers only, we had to identify as positive such waveforms that contained pathological attributes (classes "Stenosis" and "Occlusion"). The detection of measurement errors is not implicated in these values. Human expert's opinion acts here as the golden standard.

Classifier	Setting	Score [%]
MDC	Mahalonobis – 1 cluster	81.98
MDC	Mahalonobis – More clusters	83.65
BC	1-modal pdf without prior probability	80.17
BC	1-modal pdf with prior probability	84.46
BC	Multi-modal pdf without prior prob.	86.96
BC	Multi-modal pdf with prior probability	89.19

Tab.2. Recognition scores for different classifier types and settings.

Class .	Method	Sensitivity [%]	Specificity [%]
MDC	Mahal. – 1 cluster	87.83	81.93
MDC	Mahal. – More clusters	90.95	85.77
BC	1-modal pdf without p.p.	93.05	75.38
BC	1-modal pdf with p.p	90.23	78.14
BC	Multi-modal pdf without p.p.	90.15	87.90
BC	Multi-modal pdf with p.p.	87.73	90.54

Tab.3. Sensitivity and specificity for different classifier types.

4. Discussion and Conclusions

The strictest view on the performance evaluation is given by the recognition rate of the classifier that has to decide between 4 classes. In our experiments, the best results were achieved by using the multi-modal BC with prior probability. The 89 % agreement can be considered as quite high if we realize that the boundaries between the classes can be questionable in some cases, even for a human expert. Evaluation of the classifier by means of the sensitivity and specificity rates is little bit different. Here, the classifier is forced to accept only two classes. The specificity of the MDC and the one-modal BC is lower, since the classifier often confuses class "Normal" (Negative) to "Stenosis" or "Occlusion" (Positive).

We have found that one of the most critical issues is the peak detection, description and measurement. Skilled experts can do it easily but for a fully automated system it is still a problem. We believe that the influence of vein signal could be partly suppressed by a properly designed high pass filter. This signal has rate of 15 to 20 pulses per minute and appears as a slowly changing trend in the data.

A further extension of the feature set could be also useful, especially by adding features that could be calculated even when the waveform is non-pulsative or distorted in some way. Recently, the frequency attributes fulfill this role. It also seems useful to extend the number of classes for more precise classification of signals. The class Stenosis could be split into two subclasses: mild and severe Stenosis.

At the conclusion we can say that the implemented classifiers are well suited for data provided by Multi Dopplex II. This non-expensive unit is often used in practice and with the developed software even a non-specialist could apply it for early screening of the PAD. The results achieved with the best automatic classifier lead to 89 % agreement with a skilled expert's opinion.

Acknowledgments

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References

[1] TRANSATLANTIC INTER-SOCIETY CONSENSUS (TASC), Management of Peripheral Arterial Disease (PAD). *International Angiology Suppl. 1,* 2000.

[2] ROSE, S. C. Non-invasive vascular laboratory for evaluation of peripheral arterial occlusive disease, *Journal of Vascular and Interventional Radiology*, 2000, p.1107-1114.

[3] ROZMAN, J. et al. Diagnostics of ischemic disease of lower limbs via Doppler measuring of blood flow velocity (in Czech). *Lékař a technika,* NTS ČLS J.E.P, Praha, 1995, pp.76-78, 100-102, 120-123.

[4] ROZMAN, J. Comparison of results of AVG signal classification (in Czech). *Lékař a technika,* NTS ČLS J.E.P, Praha, 1995, pp. 9-11.

[5] LEE, H. G., YUM, M. K. Fourier Transformation of arterial Doppler waveforms of the lower extremity. *Journal of Clinical Ultrasound,* 2004, vol. 32, no. 6, p. 277-285.

[6] MIAO, J. et al. Computer based pattern recognition on Doppler spectral waveform of intra-cranial blood flow. *Comput. Biol. Med.,* 1995, p. 53-63.

[7] LINDE, Y., BUZO, A., GRAY, R. M. An algorithm for vector quantizer design. *IEEE Transactions on Communications*, January 1980, p. 702-710.

[8] DEVIVER, P. A., KITTLER, J. *Pattern Recognition: A Statistical Approach.* Prentice-Hall, 1982.

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