Applying DCT combined cepstrum for the assessment of the arteriovenous fistula condition

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Abstract. This paper focuses on a comparison of effectiveness of the artificial intelligence techniques in diagnosis of arteriovenous fistula condition. The use of discrete cosine transform (DTC) combined cepstrum in the feature extraction process made it possible to increase the value of classification quality indicators by about 10% (when compared to the previous approach based on averaged energy values in the third octave bands). This paper presents a methodology of extracting features from the acoustic signal emitted by the fistula. The supervised machine learning technique of k-NN, Multilayer Perceptron, RBF Network and Decision Tree C4.5 classifiers was applied to develop the classification model. For this, signals obtained from 38 patients on chronic hemodialysis were used. The results show that the cepstral analysis and obtained features provide an accuracy of above 90% in proper detection of vascular access stenosis..

Keywords: Cepstrum · Discrete cosine transformation (DCT) · arteriovenous fistula · supervised machine learning · classification models.

1 Introduction

The high quality of data sets used in the classification process has a significant impact on the outcome. This paper focuses on a comparison of effectiveness of the artificial intelligence techniques in diagnosis of arteriovenous fistula (AVF) condition by analyzing the acoustic signal emitted by the flowing blood. The AVF is an artificially formed connection between an artery and a vein, usually located in the wrist. It provides a bypass for the blood flow in one of the two arteries, which supply blood to the hand. A properly functioning AVF is extremely important for people who undergo a hemodialysis. Our diagnosis technique is based on the phono-angiography - a non-invasive method for evaluating the acoustic noise emitted from the vessel and produced by the local blood flow in the vascular system. Based on the characteristic features of signals recorded, the condition of the fistula can be determined.

It has long been known that stenosis in the artery causes a swishing sound, which is heard as a bruit. According to the studies conducted, the character of

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the sound emitted by the blood flowing inside a fistula's vessel vary depending on the state of the fistula. The first mention of the numerical analysis of acoustic signals emitted by the AVF occurred in the mid-1980s [9]. And a detailed overview of various, more precise, methods for detecting vascular access stenosis was presented by Noor [7].

Classification is still one of the biggest challenges in the field of processing acoustic signal for the purpose of medical diagnosis. Researches published to date typically describe the fast Fourier transform (FFT) as a method to transform the acoustic signal into the frequency domain. This transform was also applied by the authors for finding features which are useful for the classification purposes. In the paper [4], an artificial neural network approach has been described for early detection of hemodialysis access problems. In [2], we compared the quality of classifications using SVM and k-NN classifiers and demonstrated the possibility and validity of the multi-class approach. We also compared several methods for feature selection with the developed joined-pairs method, dedicated to fistula problem classification [3]. In paper [6] we propose a similar system of the assessment of AVF condition, where parts of the sound signal corresponding to the cardiac cycle are subjected to the Wavelet transformation. This approach allowed for a bit higher quality of the results and a more reliable diagnosis.

Recently, an innovative idea has been proposed to develop and launch a low-cost diagnostic device that implements classification algorithms to identify patients with renal disease at risk of access stenosis, even before a full loss of access patency [5]. Applied classifiers have been implemented into a supervised learning process and the best ones have achieved 81% accuracy. On the other hand, development of useful data from a recorded acoustic signal for the purposes of classification and medical diagnosis is still difficult, labor-intensive and ambiguous. Therefore, alternative ways of extracting features are still being researched. In the last two decades, a lot of studies have been conducted on the use of digital orthogonal transforms for the analysis of acoustic signals. Therefore, a number of transformations have been introduced with declarations of having a better performance than others.

This paper focused on a comparison of effectiveness of the artificial intelligence techniques in diagnosis of the AVF condition. This diagnosis technique is based on a discrete cosine transform (DCT) [8] processing and data mining tools. To achieve the most realistic estimate of the AVF state we examined various options that are available for the estimation of the spectral envelope of the acoustic signal. A comparison of the various cepstral models showed that the cepstral based real envelope estimator has particularly favorable properties, except that its estimation is quite computationally demanding. In conclusion, we have compared the performance of the DCT with FFT transforms. Instead of FFT approach, DCT process is utilized to represent the time frequency domain approach for efficient signal registered from AVF. This new approach exceeds the performance of a formerly introduced method by almost 10 percent. This valuable result means that patients with kidney disease, who are at risk of losing patency, can be correctly identified with a high probability of 90%.

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2 Materials

The sound emitted by the blood flowing through the AVF, which is the subject of the analysis, was recorded at the Clinical Dialysis Center of the St. Queen Jadwiga Provincial Hospital No. 2 in Rzeszów. Within a few months, recordings from 38 patients were obtained. Each patient was recorded several times, at intervals of 6-8 weeks. Each recording lasted for 30s. The sampling rate was set to 8kS/s, with a resolution of 16 bit.

The recordings were divided into fragments with a length of 8192 samples. Each being in line with the heart rhythm in such a way that the local maximum amplitude corresponding to the moment of heart contraction is located in the middle of the fragment. The fragments partially overlapped (Fig.1). Each fragment was the basis for computation of the feature vector for the classification process.

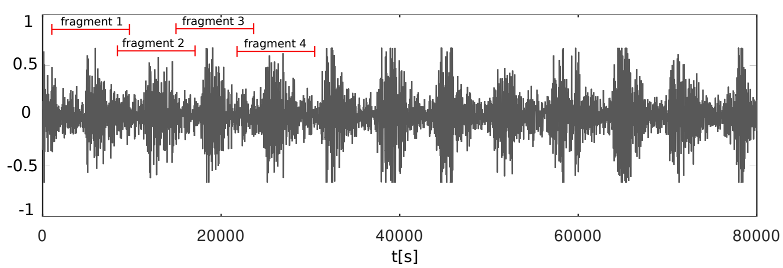

Fig. 1. Dividing the recording into fragments.

On the basis of Doppler ultrasound assessment, the medical staff of the dialysis center assigned each patient to one of the six classes with an increasing degree of AVF pathologisation assessed on the basis of Doppler ultrasound (A - proper AVF function; F - limited flow in the AVF). The numbers of patients, recordings and fragments obtained are presented in Tab.1.

Table 1. Number of patients and vectors in classes

Class	A	B	C	D	E	F
Number of patients	3	5	7	10	9	4
Number of samples	11	23	29	42	37	14
Number of vectors	232	348	516	692	669	251

The study was approved by the local Bioethical Committee of the Regional Medical Chamber in Rzeszow (No. 17/B/2016).

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3 Methods

The studies to date have shown that the condition of the fistula can be assessed by analyzing the frequency spectrum of the sound signal emitted by the blood [4] flowing through the fistula. Measurement of energy content in the third octave bands allowed to build a classification system with over 80% accuracy [5].

When analyzing the frequency spectrum characteristic of fistulas with progressive pathologisation, it can be seen that:

- for a functional fistula, almost all signal energy is concentrated in the 0-200Hz band with a maximum at around 150Hz,
- with the progressive pathologisation, the frequency band in which the signal energy concentrates is extended towards higher frequencies
- with the extension of the frequency band, successive local maxima become visible at frequencies that are multiples of the first maximum.

To conclude, important information about the condition of the fistula can be obtained by analyzing the shape of the envelope of the frequency spectrum of the signal it emits. A tool that enables such analysis is cepstrum. In its original shape, the cepstrum is based on the Fourier transformation. Depending on the adopted strategy, it can operate on a complex frequency spectrum (complex cepstrum) or only on its module (real cepstrum). In case of the real cepstrum, the transform is affected by the loss of some information relating to the phase of the input signal.

For the analysis of the signal from the AVF, a modification of the cepstrum was applied using a discrete cosine transformation (DCT). It transforms a one-dimensional sequence of real numbers (signal) into another one-dimensional sequence of real numbers (spectrum), which is an extension of the input sequence into a series of cosine in the base of orthogonal Chebyshev polynomials.

This transformation can be described as a vector operation by the following formula:

$$\mathbf{C} = \mathbf{x} \cdot \mathbf{W}, \tag{1}$$

where

$$\mathbf{W} = [w_{k,n}]_{N \times N} = c(k) \cos \frac{k\pi(2n+1)}{2N}, \tag{2}$$

is the kernel transform and

$$c(0) = \sqrt{1/N}, \quad c(k) = \sqrt{2/N} \; for \; k > 0. \tag{3}$$

The signal handling operation to extract features for the classification process is shown in the code fragment (Octave[1]) below, and the results of each of the steps for exemplary signal fragments representing cases for classes A, C, and F are shown in Fig.2.

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```
f = dct(x(c-4096 : c+4095));
f = f ./ sum(f);
lf = log(abs(f));
clf = idct(lf);
r = clf(2:10);
```

First, local maximums of the signal amplitude are searched for, corresponding to the moments of contraction of the heart and dividing the recording into fragments (in the example above, the maximum index is stored in the c variable). Next, the fragment 8192 long is extracted and on its basis the DCT is calculated. The result is normalized to compensate for any differences in the volume of the recordings. Then, the logarithm of the absolute DCT value is calculated and the inverse transform is calculatedestimated. Significant information about the shape of the spectral envelope is contained in the first few fringes - in this case, the fringes with indices $k = 1 \div 9$ were used as features in the classification process. Using more features did not improve the quality of the results.

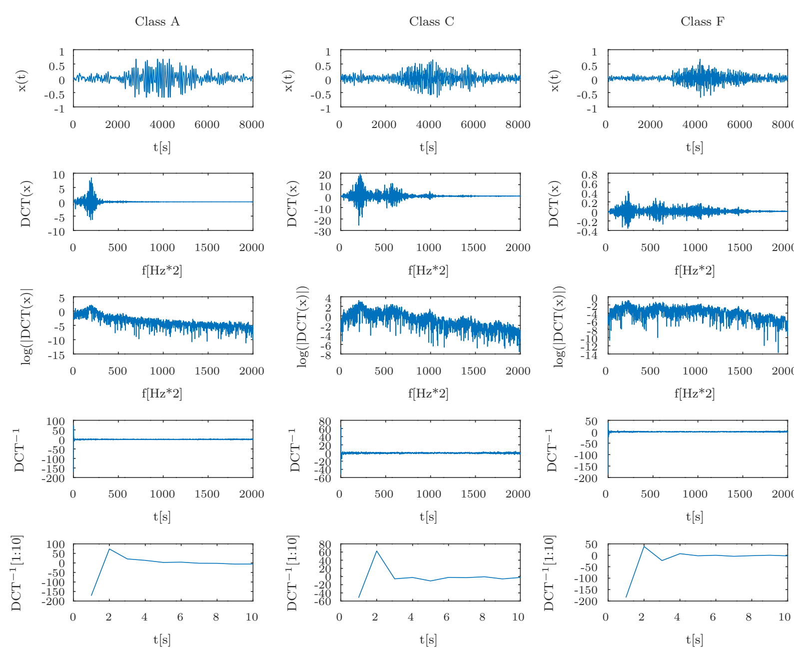

Fig. 2. Subsequent processing steps on the example of recordings for classes A, C, and F.

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4 Results and discussion

Based on the obtained data set, classification systems were built, tested and assessed for the quality. The division of the data set into training and testing subsets was conducted with Leave-one-out method, i.e. in each validation cycle, data derived from one patient was excluded from the set. Excluded data was a test set. This way the effect of 38-fold cross-validation was obtained.

The following classifiers were used in the research: Multilayer Perceptron, Radial Basis Function Network (RBF), k-NN and Decision Tree C4.5.

The settings of each of the algorithms were selected in an iterative tuning process based on the classification quality indicators. The results are presented in Tab.2–5. Each of the table contains a confusion matrix in which the values are presented as a percentage and a list of classification quality indicators calculated on the basis of the confusion matrix. These indicators are presented separately for each class and jointly in the form of an average.

Compared to the results obtained up to date (Tab.6), that is, based on the features calculated as averaged energy value in the third octave bands, a significant increase in the value of classification quality indicators has been observed.

The accuracy of vector assignment increased in each of the classes, allowing the global average F-score to increase from 0.805 to 0.951 for the Multilayer Perceptron. However, an undesirable phenomenon of erroneous classification of individual vectors into many, not only neighboring classes, was also observed. In the previous classification system, inter-class leaks were only observed within immediately adjacent classes. This means that the feature extraction algorithm based on the DCT cepstrum shows a better accuracy with increased sensitivity to noise in the input signal.

Table 2. Confusion matrix and quality indicators for Multilayer Perceptron

A	B	C	D	E	F	classified as
97,9	0,3	1,0	0,3	0,2	0,2	A
4,9	87,3	6,9	0,0	1,0	0,0	B
2,1	1,6	89,9	2,1	3,2	1,1	C
0,0	0,0	1,3	96,1	2,6	0,0	D
0,0	0,0	3,1	0,5	95,3	1,0	E
0,0	0,0	0,0	0,0	3,8	96,2	F

TP Rate	FP Rate	Precision	Recall	F-score	ROC Area	Class
0.979	0.015	0.984	0.979	0.982	0.994	A
0.873	0.005	0.947	0.873	0.908	0.945	B
0.899	0.02	0.894	0.899	0.897	0.964	C
0.961	0.006	0.914	0.961	0.937	0.998	D
0.953	0.012	0.938	0.953	0.946	0.997	E
0.962	0.004	0.911	0.962	0.936	0.999	F
0.940	0.011	0.934	0.940	0.937	0.983	Avg.

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Table 3. Confusion matrix and quality indicators for RBF Network

A	B	C	D	E	F	classified as
96,9	0,7	1,9	0,0	0,5	0,0	A
10,8	80,4	6,9	0,0	2,0	0,0	B
3,7	3,7	84,0	1,1	6,9	0,5	C
0,0	0,0	2,6	90,9	6,5	0,0	D
1,6	0,0	5,7	0,5	92,2	0,0	E
0,0	1,9	0,0	0,0	0,0	98,1	F

TP Rate	FP Rate	Precision	Recall	F-score	ROC Area	Class
0.969	0.034	0.964	0.969	0.966	0.992	A
0.804	0.011	0.872	0.804	0.837	0.977	B
0.84	0.031	0.836	0.84	0.838	0.966	C
0.909	0.003	0.959	0.909	0.933	0.991	D
0.922	0.023	0.885	0.922	0.903	0.982	E
0.981	0.001	0.981	0.981	0.981	0.993	F
0.911	0.017	0.921	0.911	0.916	0.984	Avg.

Table 4. Confusion matrix and quality indicators for k-NN

A	B	C	D	E	F	classified as
97,9	0,2	1,4	0,2	0,3	0,0	A
9,8	84,3	2,9	0,0	2,9	0,0	B
1,6	0,0	89,9	3,7	4,8	0,0	C
1,3	0,0	3,9	92,2	2,6	0,0	D
0,5	0,0	5,7	2,1	91,1	0,5	E
0,0	0,0	1,9	0,0	15,1	83,0	F

TP Rate	FP Rate	Precision	Recall	F-score	ROC Area	Class
0.979	0.025	0.974	0.979	0.977	0.993	A
0.843	0.001	0.989	0.843	0.91	0.959	B
0.899	0.026	0.867	0.899	0.883	0.975	C
0.922	0.011	0.855	0.922	0.888	0.989	D
0.911	0.024	0.879	0.911	0.895	0.984	E
0.83	0.001	0.978	0.83	0.898	0.981	F
0.905	0.014	0.928	0.905	0.915	0.981	Avg.

5 Conclusion

An AVF is an artificially made connection between a vein and an artery. It must be well-functioning to ensure hemodialysis for patients with end-stage renal disease. In this paper, we reported on the process of finding the efficient diagnosis technique based on the artificial intelligence and data mining tools.

The feature extraction method we have described in this article is another in a series of attempts to improve the system for automatic diagnosis of AVF based on an acoustic signal. This activity was performed in a traditional way, as a sequence of following operations: feature extraction, selection and reduction of features,

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Table 5. Confusion matrix and quality indicators for C4.5 Tree

A	B	C	D	E	F	classified as
96,9	1,2	1,2	0,3	0,3	0,0	A
15,7	75,5	6,9	0,0	2,0	0,0	B
2,7	3,2	85,6	2,1	5,3	1,1	C
0,0	0,0	6,5	81,8	11,7	0,0	D
1,0	1,0	7,8	2,1	87,5	0,5	E
1,9	0,0	1,9	0,0	1,9	94,3	F

TP Rate	FP Rate	Precision	Recall	F-score	ROC Area	Class
0.969	0.039	0.959	0.969	0.964	0.968	A
0.755	0.014	0.837	0.755	0.794	0.857	B
0.856	0.035	0.821	0.856	0.839	0.925	C
0.818	0.009	0.863	0.818	0.84	0.957	D
0.875	0.024	0.875	0.875	0.875	0.944	E
0.943	0.003	0.943	0.943	0.943	0.98	F
0.881	0.020	0.893	0.881	0.887	0.945	Avg.

Table 6. Classification quality indicators for averaging energy values in one third octave bands - k-NN [5]

class	A	B	C	D	E	F	Avg.
Precision	0.91	0.68	0.72	0.81	0.78	0.92	0.803
Recall	0.91	0.69	0.67	0.81	0.83	0.92	0.805
F-score	0.91	0.69	0.69	0.81	0.81	0.92	0.805

classification, and interpretation of the classification results. Reported solutions based on the FFT analysis, averaging energy in thirds, wavelet transformation and finally DCT combined cepstrum made it possible to achieve an efficiency of 90%.

We have also compared the quality of classifications using the supervised machine learning technique of k-NN, Multilayer Perceptron, RBF Network and Decision Tree C4.5 classifiers and demonstrated the possibility of the multi-class approach. These operations were performed on the acoustic signal recordings obtained from 38 patients on chronic hemodialysis. The obtained results of F-score indicator are above 0.9 and are higher than the results obtained so far by almost 10% for each of the classification constructed. This means that the modification of the feature extraction method and the use of DCT combined cepstrum allowed for a significant increase in the quality of the classification system. The only disadvantage of this method is that the increase in the level of effectiveness increases the sensitivity of the algorithm to noise, however, it can be solved by extending the recording time to obtain more fragments. More fragments mean more feature vectors in a single study that can be averaged, thus minimizing the effect of noise. The method based on the analysis of the spectral envelope shape has shown promise and further work is planned to optimize and improve it.

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The next step will be to migrate the multiclass classification system to a regression model. Such an approach will enable the assessment of the fistula state in a continuous number of cases, and not only allocating to one of several classes, as before. This is important for tracking changes in the condition of fistula over time to detect potential hazards in advance.

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