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LARDISS—a Tool for Computer Aided Diagnosis of Laryngopathies

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***Abstract*—In the paper, we present a new computer tool supporting a non-invasive diagnosis of selected larynx diseases. The tool is created for the Java platform. The computer-aided diagnosis of laryngopathies, in the presented tool, is based on analysis of a patient's voice signal in time and frequency domains. A number of classification ways proposed for the diagnosis of laryngopathies is listed and described in this paper.**

I. Introduction

IN MEDICINE, there are created specialized expert systems used as decision support for particular areas. However, such tools require a lot of work of doctors as well as computer engineers. Systems based on discovering the knowledge hidden in data are some alternative for systems, where decision rules are determined by the expert. Recently, a lot of various methods and algorithms of intelligent data analysis and mining (among others, medical data) have been designed (cf. [1]). Until now, there have not been designed universal methods which could be applied for each kind of data, giving expected results. Each kind of data requires an individual approach to them, and what follows, designing suitable, specialized methods for them. The approach to undertake such research is natural.

Computer support systems for a medical diagnosis become increasingly more popular worldwide (cf. [2]). One of their advantages is automation of a diagnosis process. Moreover, such systems are based on objective measurements and observations of selected parameters. There is a big demand for creation of flexible, effective and user-friendly platforms for the intelligent support of diagnostic decisions for the medical community. Such platforms ought not to require the technical knowledge of medical personnel. The relevant element is to design modules of entering and processing medical data as well as modules of data visualization (especially, graphical). These two elements of the platform allow using the system without specialized courses for personnel.

Our main goal of research is to deliver to diagnosticians and clinicians an integrated tool supporting a non-invasive diagnosis (based on voice signal examination) of patients with selected larynx diseases. The prototype of such a tool has been created by us using the LabVIEW environment. In this paper, we present a target tool called LARDISS (the acronym comes from LARyngopathy DIagnosis Support System) created for the Java platform. The main features of the application are the following:

- *multiplatforming*—thanks to the Java technology, the application works on various software and hardware platforms (in the future, also, mobile platforms),
- *user-friendly interface*—the interface is designed in order to make it possible to use the application in the medical environment,
- *the module of data visualization*—it allows presenting data in a clear and comprehensible way, for example, in a graphical way for a person who must make a reasonable diagnostic decision,
- *modularity*—the project of the application and its implementation takes into consideration modularity in order to make it possible to extend the application in the future and enlarge its usage on diagnosis of other larynx diseases.

The computer-aided diagnosis of laryngopathies, proposed by us in our previous papers, is based on selected parameters of a patient's voice signal (phonation). There exist various approaches to analysis of bio-medical signals (cf. [3]). In general, we can distinguish three groups of methods according to a domain of the signal analysis: analysis in a time domain, analysis in a frequency domain (spectrum analysis), analysis in a time-frequency domain (e.g., wavelet analysis). We have tested several approaches for the computer tool being developed both based on the voice spectrum analysis (e.g. [4], [5]) and based on the voice signal analysis in a time domain (e.g. [6], [7]). In this paper, we collect and recap a number of methods for classification of voice signals which have been implemented in LARDISS. A multiway approach enables diagnosticians and clinicians to see the examined case from different perspectives. Moreover, a hybrid approach to classify cases gives more certain decisions validated using different methodologies.

The rest of the paper is organized as follows. In Section II, we describe the character of laryngopathy data on the basis of which a diagnosis is made. Section III recalls algorithms proposed by us, in our earlier papers, for a decision support of the classification process of laryngopathies. Section IV delivers a description of the created tool, its functionality and graphical user interface. Finally, Section V provides conclusions.

II. Laryngopathy Data

Data for testing our tool were extracted from sound samples of the subjects. Two groups were taken into consideration [8]. The first group included persons without disturbances of phonation—the control group (CG). They were confirmed by a phoniatrist opinion. The second group included patients of Otolaryngology Clinic of the Medical University of Lublin in Poland. They had clinically confirmed dysphonia as a result of Reinke's edema (RE) or laryngeal polyp (LP). Experiments were carried out by a course of breathing exercises with instruction about the way of articulation. The task of all examined patients was to utter separately different Polish vowels with extended articulation as long as possible, without intonation, and each on separate expiration. Clinical experience shows that harmonics in the voice spectrum of a healthy patient are distributed approximately steadily. However, larynx diseases may disturb this distribution [8]. Therefore, the analysis of a degree of disturbances can support diagnosis of larynx diseases.

III. Classification Algorithms

A. Classification Based on Signal Analysis in Time Domain

Articulation is an individual patient feature. Therefore, we cannot use supervised learning techniques (cf. [1]) to train classifiers on the independent patterns of phonation of individual vowels. For the voice signal analysis in a time domain, we propose to use some unsupervised learning techniques listed and briefly described in this section. For all proposed approaches, a general procedure is as follows. We divide the voice signal of an examined patient into time windows corresponding to phonemes. Next, we select randomly a number of time windows. The main idea is based on examination of time window patterns and their replications in the fragment of a voice signal. It allows detecting all non-natural disturbances in articulation of selected phonemes by patients. Preliminary observations showed that significant replication disturbances in time appear for patients with the clinical diagnosis of disease.

1) Reccurrent Neural Networks: The recurrent neural networks (RNNs) were used by us (cf. [7]) for pattern recognition in time series data due to their ability of memorizing some information from the past. To improve learning ability, we have used the modified Elman-Jordan networks (EJNs) manifesting a faster and more exact achievement of the target pattern. In this approach, for each patient, a recorded voice signal is used for both training and testing a neural network. The coefficient characterizing deformations in the voice signal is constituted by an error obtained during a testing stage of the neural network. We propose to use the approach similar to the cross-validation strategy. One time window is taken for training the neural network and the remaining ones for testing the neural network. The network learns a selected time window. If the remaining windows are similar to the selected one in terms of the time patterns, then, for such windows, an error generated by the network in a testing stage is smaller. If significant replication disturbances in time appear for patients with the larynx disease, then an error generated by the network is greater. In this case, the time pattern is not preserved in the whole signal. Therefore, the error generated by the network reflects non-natural disturbances in the patient's phonation. Below, we recall an algorithm proposed by us in [7] for calculating the error generated by the network (see Algorithm 1). In the algorithm, we use the following functions (procedures):

- $Div2Win(S)$—dividing the voice signal S into time windows corresponding to phonemes,
- $SelWin(W)$—selecting randomly a number of time windows from the whole set W,
- $Train(N, w)$—training a neural network N on a given time window w,
- $Test(N, w)$—testing a neural network N on a given time window w,
- $MSE(E)$—calculating a mean squared error for the absolute error vector E:
$$MSE(E) = \frac{1}{n}\sum_{i=1}^{n}(E_i)^2,$$
where n is a number of elements in the vector E, $E_i = y(x_i) - z(x_i)$ and $y(x_i)$ is the obtained output for x_i whereas $z(x_i)$ is the desired output for x_i.
- $Avg(E)$—calculating an arithmetic average for the vector E of errors.

2) Consistency Factors Based on Rough Set Theory: In this approach, a voice signal is treated as a time series. Consecutive signal samples of selected time windows can be presented in the tabular form as a multistage decision transition system (cf. [9], [10]). In Table I, we give some example of such a multistage decision transition system $MDTS$. Each row of $MDTS$ corresponds to one time window. Each time window consists of k signal samples. Values of signal samples are normalized to the interval $[-1.0, 1.0]$. Each time window can be treated as an episode.

Next, we transform each episode in $MDTS$ into the so-called delta representation, i.e., values of samples are replaced with differences between values of current samples and values of previous samples. After transformation, each episode is a sequence consisting of three values: -1 (denoting decreasing), 0 (denoting a lack of change), 1 (denoting increasing) (cf. [5]). This transformation enables us to obtain a multistage decision transition system with discrete values. For example, after the transformation of $MDTS$ given in Table I, we obtain a new multistage decision transition system $MDTS^*$ shown in Table II.

In the transformed multistage decision transition system $MDTS^*$, we search for unique episodes using Algorithm 2.

Algorithm 1: Algorithm for calculating an average mean squared error corresponding to deformations in a voice signal.

Input : S—a voice signal of a given patient (a vector of samples), N—a neural network.
Output: $\overline{E}_N$—an average mean squared error corresponding to deformations in S.

```
W_all ← Div2Win(S);
W_sel ← SelWin(W_all);
for each window w ∈ W_sel do
    Train(N, w);
    for each window w* ∈ W_sel do
        if w* ≠ w then
            E[w*] ← MSE(Test(N, w*));
        end
    end
    Ē[w] ← Avg(E);
end
Ē_N ← Avg(Ē);
Return Ē_N;
```

TABLE I
A MULTISTAGE DECISION TRANSITION SYSTEM $MDTS$ REPRESENTING SELECTED TIME WINDOWS OF A VOICE SIGNAL

U_T	a_1	a_2	a_3	...	a_k
t_1	1.00	1.00	0.98	...	-0.11
t_2	0.94	0.94	0.95	...	-0.09
...	...	...	...	...	...

Algorithm 2: Algorithm for mining unique episodes in a given multistage decision transition system

Input : A transformed multistage decision transition system $MDTS^*$, a threshold value $\theta \in [0, 1]$ determining uniqueness of episodes in $MDTS$.
Output: A set $\Upsilon_T \subseteq U_T^*$ of unique episodes in $MDTS^*$ with respect to θ.

```
Υ_T ⟵ ∅;
for each t ∈ U_T do
    Create MDTS' by removing t from U_T* in MDTS*;
    Compute ξ_MDTS'(t);
    if ξ_MDTS'(t) ≤ θ then
        Υ_T ⟵ Υ_T ∪ t;
    end
end
```

TABLE II
A TRANSFORMED MULTISTAGE DECISION TRANSITION SYSTEM $MDTS^*$

U_T^*	a_2^*	a_3^*	...	a_k^*
t_1	0	-1	...	-1
t_2	0	1	...	1
...	...	...	...	...

The consistency factor $\xi_{MDTS'}(t)$ of the episode t with the knowledge included in $MDTS'$ is calculated on the basis of rough set theory [11] in the following way. Let

$$X_{a_i}(t) = \{t' \in U_T^* : a_i(t') = a_i(t)\}$$

and

$$Y_{a_i}(t) = \begin{cases} X_{a_i}(t) & \text{if } a_{i+1}(t') \text{ are equal for each } t' \in X_{a_i}(t), \\ \emptyset & \text{otherwise} \end{cases}$$

and

$$Z_{a_i}(t) = \begin{cases} Y_{a_i}(t) & \text{if } a_{i+1}(t) \neq a_{i+1}(t') \text{ for any } t' \in Y_{a_i}(t), \\ \emptyset & \text{otherwise} \end{cases},$$

then

$$\xi_{MDTS'}(t) = \prod_{i=2}^{k-1} \left(1 - \frac{card(Z_{a_i}(t))}{card(U_T)}\right).$$

If time windows, into which a voice signal is divided, are similar (there are no disturbances), then the unique episodes are not present in $MDTS^*$. If significant replication disturbances in time appear for patients with the larynx disease, then time windows differ from each other and unique episodes appear in $MDTS^*$. Hence, the result of searching for unique episodes is an indicator used to classify patient's voice signals according to larynx diseases.

B. Classification Based on Signal Analysis in Frequency Domain

For the voice signal analysis in a frequency domain, we propose to use some family of coefficients reflecting spectrum disturbances around basic tones and their multiples (cf. [5], [4]). Disturbances are expressed by a family of coefficients computed for neighborhoods of a basic tone f_0 and its four multiples (f_1, f_2, f_3, f_4). In a real situation frequencies f_1, f_2, f_3, etc., are not distributed steadily (cf. [8]). It means that we need to find a real distribution of harmonics. In the presented tool, it is done on the basis of the spectrum of a selected N-point time window from the original voice signal. For each original frequency f, a maximum magnitude is searched in the interval $[f - d_1, f + d_1]$. This maximum value is assumed as a real harmonic. The original basic tone f_0 has been obtained for each patient from histogram created in the Multi-Dimensional Voice Program (MDVP). It is a software tool for quantitative acoustic assessment of voice quality, calculating various parameters on a single vocalization (see [12]). On the basis of f_0, its harmonics (for the ideal case) have been calculated.

Each coefficient expresses the distribution of a spectrum around a given frequency f. We can distinguish two types of coefficients:

- the regularity coefficient R determining a degree of slenderness of this distribution (see Algorithm 3),
- the deviation coefficient D determining a relative difference between a real multiple derived from the spectrum and a multiple calculated on the basis of the basic tone f_0 (see Algorithm 4).

Algorithm 3: Algorithm for calculation of regularity coefficients.

Input : Sp—a discrete spectrum of the selected time window in the voice signal of a given patient (a vector of samples), f_0—a patient's basic tone, d_1—deviation for searching maximum, d_2, d_3—deviations for calculating spectrum regularity coefficients ($d_2 < d_3 < d_1$).
Output: R—a family of spectrum regularity coefficients for Sp.

$[f_1, f_2, f_3, f_4] \leftarrow Harmonics(f_0)$;
for *each frequency* f_i *(*$i = 0, 1, 2, 3, 4$*)* **do**
  Calculate the index k_i of the strip in Sp corresponding to f_i;
  Find the index m_i of the maximum value in $Sp[k_i - d_1, \ldots, k_i + d_1]$;
  $I_1 \leftarrow Integral(Sp, m_i - d_2, m_i + d_2)$;
  $I_2 \leftarrow Integral(Sp, m_i - d_3, m_i + d_3)$;
  $R[i] \leftarrow \frac{I_1}{I_2}$;
end
Return R;

Algorithm 4: Algorithm for calculation of deviation coefficients.

Input : Sp—a discrete spectrum of the selected time window in the voice signal of a given patient (a vector of samples), f_0—a patient's basic tone, d_1—deviation for searching maximum.
Output: D—a family of spectrum deviation coefficients for Sp.

$[f_1, f_2, f_3, f_4] \leftarrow Harmonics(f_0)$;
for *each frequency* f_i *(*$i = 1, 2, 3, 4$*)* **do**
  Find the maximum value f_{im} in $Sp[k_i - d_1, \ldots, k_i + d_1]$;
  $D[i] \leftarrow \frac{|f_{im} - f_i|}{f_i}$;
end
Return D;

For calculating a discrete spectrum Sp of a signal W, we use the Discrete-Time Fourier Transform (DTFT), see e.g. [3]. Below, we remind algorithms proposed by us in [4] for calculating both types of coefficients characterizing the spectrum of a patient's voice signal.

In Algorithm 3, we use the following functions (procedures):

- $Harmonics(f_0)$—calculating harmonics (first f_1, second f_2, third f_3, and fourth f_4) of a patient's basic tone f_0, i.e., $f_1 = 2f_0$, $f_2 = 3f_0$, $f_3 = 4f_0$, $f_4 = 5f_0$.
- $Integral(Sp, k_1, k_2)$—calculating a discrete integral I of a fragment (between points k_1 and k_2) of the spectrum Sp, i.e.:

$$I = \sum_{j=k_1}^{k_2} |X[j]|. \tag{1}$$

Coefficients calculated according to Algorithms 3 and 4 describe cases (patients). They are used as training data to build classification algorithms available in the popular data mining and machine learning software tools mentioned in Section IV.

IV. THE LARDISS SYSTEM

The LARDISS system supporting the diagnosis of laryngoapthies is a tool designed for the Java platform. We can distinguish three main parts of the LARDISS system:

- *Knowledge base*. The knowledge base embedded in LARDISS consists of a number of rule sets generated by different data mining and machine learning tools, such as:
  - The Rough Set Exploration System (RSES)—a software tool featuring a library of methods and a graphical user interface supporting a variety of rough set based computations [13]. RSES delivers, among others, rule-based classifiers built on algorithms: exhaustive [14], LEM2 [15], covering [16], genetic [17].
  - WEKA—a collection of machine learning algorithms for data mining tasks [18], [19]. WEKA delivers, among others, decision tree-based classifiers built on algorithms J4.8—an implementation of C4.5 [20] and CART [21].
  - NGTS—a system developed to generate decision rules using the algorithm called GTS (General-To-Specific) [22].
  - RuleSEEKER—a tool for generation and optimization of rule sets [23].
  - BeliefSEEKER—a belief network and rule induction system [24].
- *Multiway classification engine*. One of the main tasks of building expert systems is to search for efficient methods of classification of new cases. Classification in LARDISS is made on the basis of several methodologies. We can group them into two categories: classifiers based on unsupervised learning algorithms described in Subsection III-A and classifiers based on supervised learning algorithms described in Subsection III-B.
- *Visualization engine*. In the LARDISS system, a special attention has been paid to the visualization of analysis of voice signals for making a diagnosis decision easier.

For each classifier, we have obtained classification accuracy greater than 75%. It seems to be a satisfactory result for this kind of data, i.e., voice singal samples.

We can list the following main functionalities of the LARDISS system. LARDISS enables users to:

- load a patient's voice signal sample in the wave format (see Figure 1),
- perform some basic preprocessing operations on a signal in a time domain (cutting/selecting time windows, splitting a signal into consecutive time windows, more

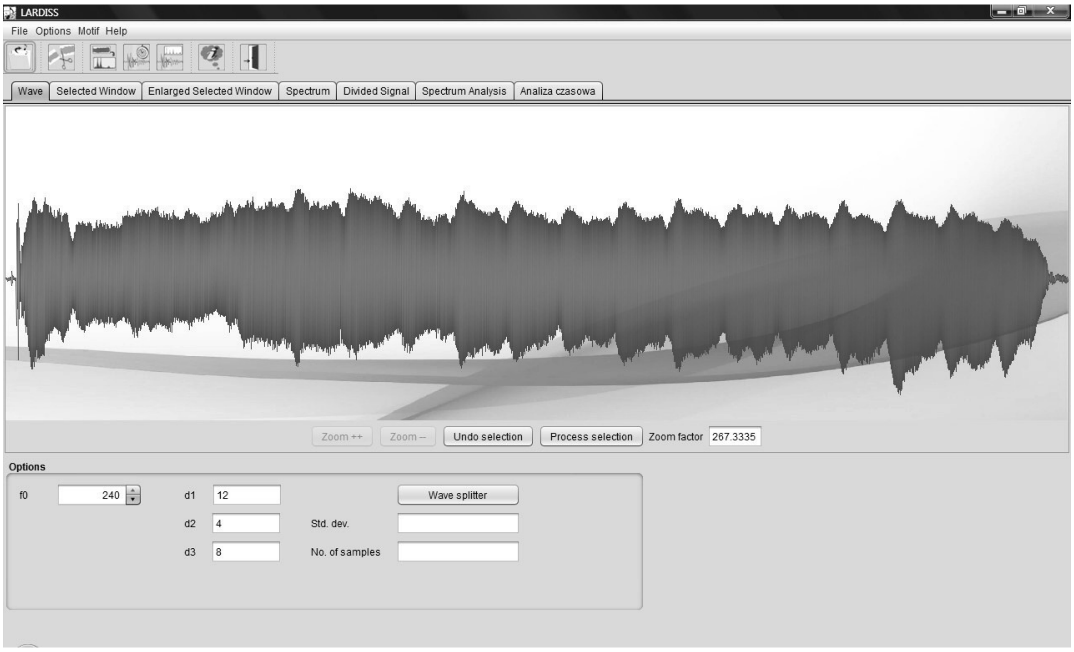

Fig. 1. LARDISS—the main window.

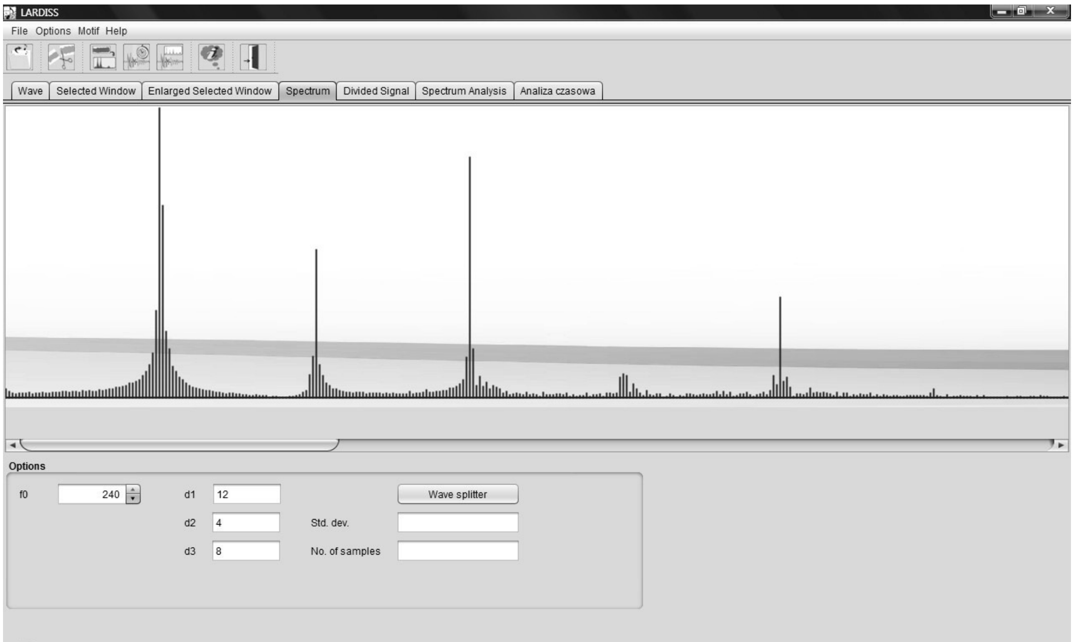

Fig. 2. LARDISS—spectrum visualiation.

detailed visualization of selected time windows, etc.),

- calculate and visualize the Discrete-Time Fourier Transform (DTFT)—spectrum of a voice signal sample (see Figure 2),
- classify a voice signal sample using the signal analysis in a time domain,
- classify a voice signal sample using the signal analysis in a frequency domain with respect to the knowledge base embedded in LARDISS (see Figure 3),
- visualize a decision path for the loaded case—a patient's voice signal—in embedded decision trees (see Figure 3),
- visualize decision rules included in embedded rule sets and used for making diagnosis for the loaded case—a patient's voice signal (see Figure 3).

Figure 3 shows a summary of classification results based on the spectrum analysis. The user can see:

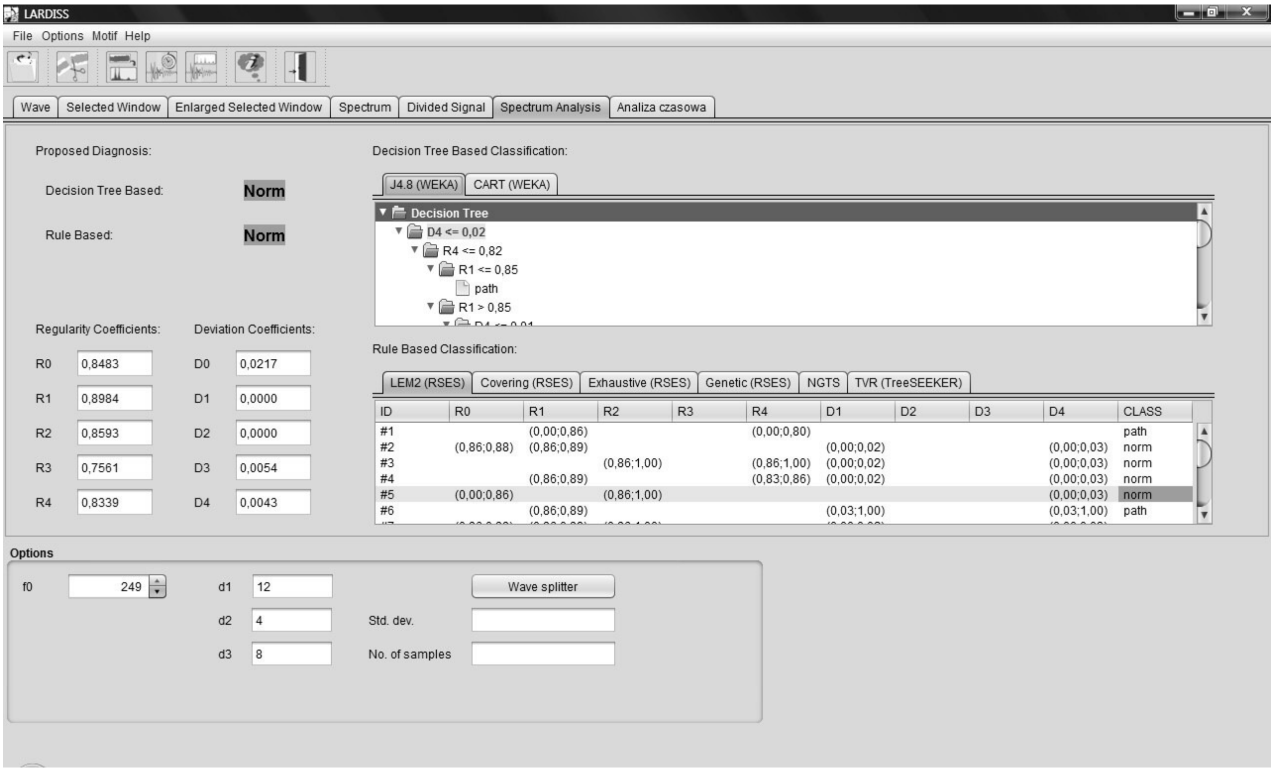

Fig. 3. LARDISS—classification results visualization.

- calculated regularity coefficients,
- calculated deviation coefficients,
- proposed diagnosis made on the basis of decision trees,
- proposed diagnosis made on the basis of decision rules,
- decision trees embedded in the knowledge base,
- decision rule sets embedded in the knowledge base.

Currently, LARDISS is in a testing phase. The approaches implemented in LARDISS have been tested using data collected by J. Warchoł [8] and described in Section II. Selected testing results can be found in [4] and [7].

V. Conclusions

In this paper, we have described a computer tool called LARDISS supporting a non-invasive diagnosis of selected larynx diseases. This tool is evolving continuously. In the future, we plan to add another unsupervised and supervised learning algorithms for building classifiers. Hybridization of classification methods of patients with laryngopathies is the main direction of further research. An important challenge is to design methods enabling distinction between different larynx diseases (for example, laryngeal polyp and Reinke's edema). So far, approaches presented in this paper do not enable us to make this distinction.

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