EEG Signal Classification Based On Fuzzy Classifiers

Jan Rabcan, *Member, IEEE*, Vitaly Levashenko, *Member, IEEE*, Elena Zaitseva, *Member, IEEE*, and Miroslav Kvassay, *Member, IEEE*

***Abstract*—Electroencephalogram (EEG) signal classification is used in many applications. Typically, this classification is implemented based on methods which consist of two steps. These steps are known as the step of signal preprocessing and the step of the classification. The signal preprocessing step transforms initial signal into classification attributes. According to several studies, this transformation can result in the loss of some useful information and, consequently, the formed classification attributes are uncertain. This information loss can be taken into account if the classification attributes are fuzzy and the fuzzy classifiers are used at the step of classification itself. The transformation of initial EEG signal into fuzzy attributes needs one more procedure at the step of signal preprocessing. This procedure is fuzzification. An approach based on fuzzy classifiers for EEG signal classification is considered in this article. The approach is evaluated based on two classifiers: fuzzy decision tree and fuzzy random Forest. The classification accuracy is 99.5% for fuzzy decision tree and 99.3% for fuzzy random forest. The comparison with similar studies based on non-fuzzy classifiers indicates that fuzzy classifiers are effective tool for EEG signal classification and have best classification accuracy.**

***Index Terms*—Electroencephalogram (EEG) signal, fuzzy decision tree, fuzzy random forest, signal classification.**

I. Introduction

THE signal classification is often used in many industrial applications which functioning is based on result of automatic classification of signals. It causes the strict requirements for classification accuracy and development of new methods and algorithms of highly accurate signal classification. One of areas with higher requirements on signal classification accuracy is based on electroencephalogram (EEG) analysis. This signal is commonly used in development of human-computer interaction [1] and medicine [2]–[5]. Medical applications of automatic EEG classification are known for diagnosis of epilepsy [2], Alzheimer disease [3], depression [4] and other diseases [5]. Every of these application in medical diagnosis has some specifics related to different properties of EEG signals. Most investigated EEG diagnosis application is diagnosis of epilepsy, which belongs to most common chronic neurological disorders [6].

Epilepsy appears as recurrent, unprovoked seizures. The seizure is a short change in normal brain activity, which can be defined as an unexpected electrical disturbance of the brain and overdischarge of neurons. This electrical disturbance can be recorded using EEG [6]. The analysis of EEG signal allows indication of seizures. The automatic implementation of this analysis is based on methods for automatic signal classification. This classification should select EEG signals that agree with seizures. Therefore, the EEG signal classification methods are developed as methods for classification of a specific signal that is EEG signal [7].

The methods for classification of EEG signal are typically composed of two steps [8]. The first step is known as signal preprocessing. As a rule, two procedures of feature extraction and dimensionality reduction are used in this step. The EEG signal preprocessing is needed to form the classification attributes. This is achieved by removing noise, extracting useful information for the classification itself and transforming initial signal into a set of numeric samples. The numerical samples can be classified at the second step that is classification itself. The classification can be implemented based on classification methods of machine leaning [7]. Most often used classifiers are K-nearest neighbors (KNNs) [8], neural networks (NNs) [9], support vector machine (SVM) [10]–[12], and decision trees [13]. The classification accuracy for all of these classifiers is determined mostly by the initial data (numerical samples) formed at the step of the preliminary transformation [14]. Therefore, the output of the signal preprocessing is very important for signal classification [15]. This can be illustrated by the studies of EEG signal classification based on SVM. In this case, it has been shown that different procedures of feature extraction [11], dimensionality reduction [10], and specific procedures of signal preprocessing based on fuzzy approximate entropy [12] influence classification accuracy.

Potapov [15] have shown that in addition to suppressing noise and extracting useful features, the signal preprocessing causes also loss of some information that is useful in the classification. Since the initial data for classification (in this case data after the signal preprocessing) affects classification accuracy, this lost

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The authors are with Zilinska Univerzitav Ziline, 01026 Zilina, Slovakia (e-mail: jan.rabcan@fri.uniza.sk; vitaly.levashenko@fri.uniza.sk; elena.zaitseva@fri.uniza.sk; miroslav.kvassay@fri.uniza.sk).

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information should be taken into account in signal classification methods and, especially, in classification of EEG signal. This means that data for classification should be considered as uncertain data and special methods and algorithms for uncertain data classification should be used. One of possible approaches to uncertain data classification is application of fuzzy classifiers, which are often used in data mining [14]. The study in [16] shows the efficiency of fuzzy classifier based on fuzzy decision tree (FDT) for signal classification. The investigation of the hybrid classifiers for EEG signal analysis is in [17].

In this article, an approach of classification of EEG signal based on fuzzy classifiers is presented. Application of the approach in epilepsy seizure detection is considered, but it can also be adopted for other problems related to classification of EEG signal. The proposed approach represents further development of the investigation of signal classification using FDT considered in [16]. The study of application of fuzzy classifiers for signal classification in [16] showed that data after the signal preprocessing should be presented as fuzzy data. However, the typical procedures of the step of signal preprocessing allow forming crisp data [15]. We have proposed to introduce new procedure at step of signal preprocessing, which permits to form fuzzy data at this step. This new procedure is fuzzification. This implies that the proposed approach has two modifications: new type of classifiers (fuzzy classifiers) is used instead of crisp data classifiers at the step of the signal classification, and the procedure of fuzzification is added at the signal preprocessing step. In this article, two classifiers are considered: FDT [16] and fuzzy random forest (FRF) [18]. These tree classifiers are inducted using the cumulative mutual information (CMI) considered in [16].

The rest of this article is organized as follows. The proposed approach for EEG signal classification based on fuzzy classifiers is presented Section II-A. The dataset for evaluation of the proposed approach is introduced in Section II-B. The detailed discussion of the signal preprocessing (the first step) of the proposed approach is in Section III. This section presents two typical procedures of the signal preprocessing (the feature extraction and the dimensionality reduction) and introduces the procedure of the attributes fuzzification. The fuzzy classifiers are considered in Section IV. The induction of FDT and FRF are presented based on CMI method in Section IV. Section V deals with the evaluation of the proposed approach in prediction of epileptic's seizures. In this section, the approach based on FDT and FRF is compared with approaches using nonfuzzy classifiers. Finally, Section VI concludes this article.

II. Fuzzy Classifier Application in EEG Signal Classification

The goal of the use of fuzzy classifier in EEG signal classification is increasing of the classification accuracy by the taking into account the information lost at the step of the signal preprocessing. The modification of the method for the signal classification by the use of fuzzy classifier is considered, because the development of methods for analysis of EEG signal is based on signal classification methods [7].

A. Design of Approach

Typical signal classification method is composed of two steps [17]: signal preprocessing and classification itself. The preprocessing step is necessary to remove noise in the original signal by extracting significant features of signal and to reduce the dimension by feature selection. The signal preprocessing allows transforming EEG signal into a set of numeric attributes that can be used for classification as input data. The transformations at the preprocessing step are implemented by two procedures [14]: feature extraction and dimensionality reduction (feature selection).

The feature extraction is implemented by spectral transformations, such as Fourier [13], Wavelet [12], and Welch's [19] transform. The result of this procedure is a vector of attributes, which has dimension of original EEG signal. These attributes are specific properties of investigated signal, but, their vector has to be reduced to be acceptable for the classification. This reduction is provided by the procedures of feature selection as linear discriminant analysis (LDA), principal component analysis (PCA) and independent component analysis (ICA) [10]. The result of EEG signal preprocessing agrees with a set of numerical data that is interpreted as classification attributes. This set represents input data for the classification. At the step of classification, classifiers such as KNN [8], NN [9], SVM [11], and decision trees [13] are typically used.

Surveys of studies on EEG classification, for example in works [5] and [13], have shown that efficiency and accuracy of signal classification are determined not only by the classification step but depend also on its input data, that means, data obtained as the result of the preprocessing step. Therefore, there are many studies of influence of methods of feature extraction [12], [13], [17], [19] and feature selection [5], [7], [10], [15] on the accuracy of classification of EEG signal. The details of these studies are considered in Section III. This influence results from a loss of some information at the signal preprocessing step. This loss can be attributed to the spectral transformation of original EEG signal (the feature extraction) and to removal of less informative attributes in the procedure of feature selection [15]. The information loss caused by the feature extraction and feature selection can be interpreted as the uncertainty of data obtained after the signal preprocessing, and different methods used in these two procedures can result in different accuracy of the same classifier. Because of that, we propose an approach for EEG signal classification that allows considering the uncertainty of data obtained after the step of the signal preprocessing.

The data uncertainty in classification methods can be considered using fuzzy classifiers [14]. This in turn requires that input data for fuzzy classifier is fuzzy. However, the data formed after the signal preprocessing is crisp notwithstanding the use of fuzzy based procedures in feature extraction (spectral transformation) [20] and feature selection (dimensionality reduction) [21]. The transformation of crisp data into fuzzy can be implemented by fuzzification procedure [22]. All these imply that the use of a fuzzy classifier in the classification of EEG signal and addition of a procedure of fuzzification at the EEG signal

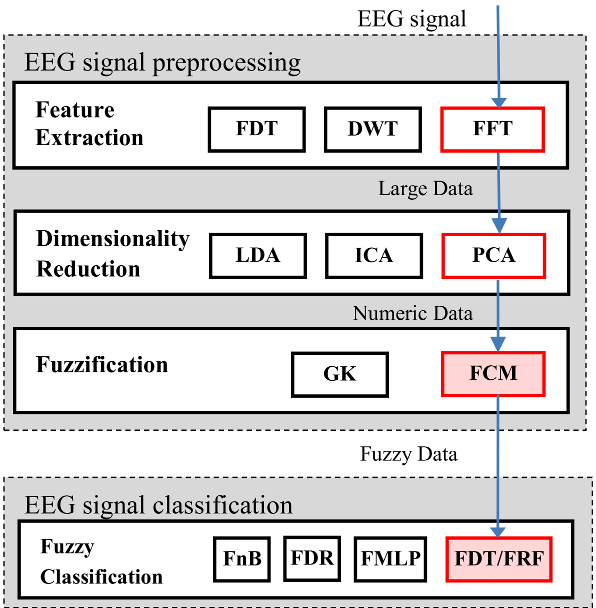

Fig. 1. Principal steps of the algorithm for classification of EEG signal.

preprocessing step can give better results than methods based on non-fuzzy classifiers.

The structure of the proposed approach is shown in Fig. 1. This approach has two steps. The first of them is the signal preprocessing. This step includes three procedures that are procedures of feature extraction, dimensionality reduction and fuzzification. The feature extraction can be implemented, for example, by discrete Fourier transform (DFT), fast Fourier transform (FFT) or discrete wavelet transform (DWT). The procedures of LDA, PCA, and ICA belong to the most often used for the dimensionality reduction. The procedure of fuzzification at the step of the signal preprocessing can be implemented based on fuzzy c-mean (FCM) algorithm or Gustafson–Kessel algorithm. The second step of the EEG signal classification is the classification itself. This can be implemented by fuzzy classifiers as fuzzy Naïve Bayes (FnB), fuzzy decision rules (FDRs), fuzzy multilayer perceptron (FMLP), FDT, or FRF. In this article, we propose to use FDT and FRF for EEG signal classification and procedures of FFT, PCA, and FCM at the step of the EEG signal preprocessing.

B. Dataset Used in the Article

According to the review of EEG signal applications [1], the most often used public dataset for development of methods for automatic recognition of epilepsy is a set introduced by researchers from Bonn University in [6] (sometimes named as "Bonn university database"). This dataset is also used in investigation presented in this article for evaluation of the proposed approach. It consists of 500 records of EEG signal (samples). Every record or sample has duration of 23.6 s. The samples in the dataset are divided into 5 classes (denoted as classes A, B, C, D, and E), and each of them includes 100 records.

Samples of classes A and B were obtained from persons not suffering from epilepsy, therefore, they contain no epilepsy seizures. The difference between samples in these two classes lies in a fact that samples from class A were obtained from patients with open eyes during recording, while the samples from class B were obtained from persons with closed eyes during the recording. Samples from these two classes are included in the dataset because open eyes influence the electrical activity of the brain according to [6].

Samples from the remaining three classes were obtained from persons suffering from epilepsy. In case of classes C and D, the samples were recorded during seizure free intervals. The former were recorded from the hippocampal formation of the opposite hemisphere of the brain, while the latter from within the epileptogenic zone. Finally, samples belonging to class E were measured only during epileptic seizure.

The goal of our approach is to distinguish samples from classes A. B, C, and D ("seizure free" samples) from those in class E ("seizure" samples). For this purpose, the samples from the first 4 classes are merged into one class, while those in class E represent another class. This merging implies that the used classifier has to be a binary classifier that is able to recognize signals recoded during epileptic seizure.

III. Signal Preprocessing

The signal preprocessing step includes two typical procedures. These procedures are feature extraction and dimensionality reduction (known as feature selection). One more procedure added in our approach (see Fig. 1) is a procedure of fuzzification.

In this article, the influence of different fuzzy classifiers on the quality and efficiency of EEG signal classification is investigated primarily. Nevertheless, the transformation of EEG signal into classification attributes at the step of signal preprocessing has a big impact on the result of classification.

There are many studies of influence of different procedures of feature extraction and feature selection on the result of EEG signal classification. Therefore, we provide a short review of these procedures below to choose some of them for the realization of study of impact of fuzzy classifier on efficiency of EEG signal classification.

A. Feature Extraction

The feature extraction is used to remove noise, artifacts and other defects, which are results of eyes blinking and muscular activity [5]. Another reason of using feature extraction methods is a need of transformation of the signal from a form of time-dependent function to a form acceptable for the classification. These methods increase the differences between classes of EEG signals using power spectral density for selective representation of EEG signal instances [19]. Most often used methods are based on spectral transformations.

The review of methods for feature extraction shows that DFT [13], FFT [17], and DWT [23] are often used in EEG signal classification. Implementation of the feature extraction using Welch's method has been considered in [9] and [17]. Most often used transformation in EEG signal analysis with good result according to [23] is DWT. Nevertheless, the study in [13] has shown that the result obtained for various methods of feature extraction may be impacted by the classifier used at the step of classification. The interesting result for EEG signal classification based on decision tree inducted according to method C4.5 has been presented in [13]. This article has shown that FFT allows achieving the best result of EEG signal classification in comparison with DWT for this classifier. The decision tree-based classifier is also used in our investigation in this article. Therefore, the feature extraction procedure is implemented based on FFT in this article for the evaluation of the proposed approach based on FDT and FRF classifiers. The study in [24] shown that the efficiency of the procedure of feature extraction depends on the initial signal and FFT for different sets of EEG signal has different efficiency. The similar investigation for other procedures of feature extraction in frequency and time-frequency domains has been in [25]. Because the influence of fuzzy classifiers is investigated in this article, the feature extraction can be implemented based on one of the considered procedures.

In the investigation of efficiency of FDT and FRF for dataset of EEG signal from [6], the matrix with 128 columns and 500 rows is formed after feature extraction implemented based on FFT.

B. Dimensionality Reduction

Procedures of PCA, LDA, and ICA are used for dimensionality reduction or feature selection in many studies dealing with signal classification including EEG signal classification. The study in [26] has shown benefits of PCA in comparison with other methods for signal classification. Subasi and Gursoy [10] have compared these methods and proposed LDA for EEG signal classification because it acquires the best performance. Survey of methods for feature selection in [27] has pointed out the dependency of the signal classification efficiency on the specifics of classification problems, procedures used for feature extraction, and the used classifiers. This is confirmed by works [5] and [7]. There are also some modified methods for the feature selection. These can be found, for example, in [28].

PCA is used in our investigation to analyze fuzzy classifiers at the step of classification of EEG signal. The PCA allows transforming data with a small number of training samples per class. The PCA converts the feature matrix into a new matrix of the same size. The columns in this matrix represent the features of the signal and are named as "principal components" [10]. The most important principal components are selected to reduce data dimensionality. Here is important to indicate the criterion used to define the number of principal components. One of the most commonly used is Kaiser criterion [10], which selects those principal components whose variance is bigger than 1.00.

The PCA with Kaiser criterion allows reducing the matrix of 128 features of initial EEG signals from [6] to 8 principal components. This way, each EEG signal is represented by eight principal components denoted as X_i ($i = 1,\ldots,8$). These components are considered as attributes for the fuzzification and are used in the classification.

C. Fuzzification

The principal component X_i agrees with a vector of real numbers $(x_1, x_2, \ldots, x_k, \ldots, x_K)$, where K agrees with the count of initial samples (signals). Fuzzification transforms each principal component X_i into fuzzy attribute $A_i (i = 1, \ldots, n)$. Each fuzzy attribute A_i consists of m_i ($m_i \geq 2$) linguistic terms. A jth linguistic term of fuzzy attribute A_i, for $j = 1,\ldots, m_i$, is represented by fuzzy set $A_{i,j}$. Fuzzy set $A_{i,j}$ with respect to principal component X_i is determined by membership function $\mu_{A_{i,j}}(x)$:$X_i \to \langle 0, 1\rangle$, which defines membership degree $\mu_{A_{i,j}}(x)$ for each $x (x \in X_i)$. This degree determines how element$x$ belongs to the fuzzy set $A_{i,j}$. In more formal way, fuzzy set $A_{i,j}$ is an ordered set of pairs of elements of vector X_i and their membership degree defined as $A_{i,j} = \{(x, \mu_{A_{i,j}}(x)), x \in X_i\}$.

In this article, we use fuzzy C-means (FCM) algorithm for obtaining fuzzy membership function. The goal of the FCM is to assign each elements x_k, for $k = 1,\ldots, K$, of vector X_i to m_i clusters defined by center c_j, for $j = 1,\ldots, m_i$, with partition degree $u_{k,j}$. For this purpose, the FCM tries to minimize the following objective function:

$$\text{minimize} \sum_{j=1}^{m_i} \sum_{k=1}^{K} (u_{k,j})^r d(x_k, c_j)^2 \tag{1}$$

where $d(x_k, c_j)$ denotes a distance between scalar value x_k and center c_j of cluster j, and r represents the fuzziness parameter. The partition degree $u_{k,j}$ used in the formula corresponds to the membership degree of kth instance (scalar value x_k) into cluster j and is calculated using the next formula

$$u_{k,j} = \frac{1/d(x_k, c_j)^2}{\sum_{t=1}^{m_i} 1/d(x_k, c_t)^2}, \text{where } c_j = \frac{\sum_{k=1}^{K} (u_{k,j})^2 x_k}{\sum_{k=1}^{K} (u_{k,j})^2}. \tag{2}$$

The output of the FCM algorithm are partition degrees $u_{k,j}$ defining the membership degree of scalar value x_k to fuzzy set $A_{i,j}$. In the article, eight principal components obtained after the PCA are transformed using the FCM into eight fuzzy attributes A_i, for $i = 1,\ldots,8$. Values of these attributes are used as inputs for the second step of the EEG signal classification, which is the classification itself. In this second step, the classifier has to be trained firstly. Since the classifier is FDT or FRF, not only inputs but also the output has to be fuzzy. Therefore, using the FCM algorithm we fuzzify output attribute B defining occurrence of epileptic seizure.

IV. Fuzzy Classification

There are different fuzzy classifiers. Most often used are NN [7], recurrent NN [9], SVM [10], SVM with permutation entropy [11], and decision trees [13]. In this article, we consider two fuzzy classifiers based on decision trees. These classifiers are FDT and FRF.

A. Fuzzy Decision Tree

Decision trees are composed of two types of nodes that are internal nodes and leaves. The internal nodes are associated with input attributes A_i. Outgoing edges of each internal node represent all possible values that the input attribute associated with the node can take. The leaves of a decision tree agree with classes, i.e., values of output attribute *B*. If a new instance (sample) should be classified, then we start in the root of the tree and travel down the tree. During each visit of an internal node (including the root), we continue to a next node via an edge corresponding to a specific value of the attribute associated with the internal node and defined by the new instance. This process is repeated until we reach a leaf of the tree. The reached leaf defines value of the output attribute for the new instance.

Our approach for classification of EEG signal uses FDT inducted based on the CMI [16]. This specific measure of output attribute *B* is defined as follows:

$$\mathrm{I}\left(B; U_{q-1}, A_{i_q}\right) = \sum_{j_q=1}^{m_{i_q}} \sum_{j=1}^{m_b} \left(\begin{array}{r} M\left(B_j \times U_{q-1} \times A_{i_q,j_q}\right) \\ \times \left(\begin{array}{r} \log_2 M(B_j \times U_{q-1} \times A_{i_q,j_q}) + \\ +\log_2 M(U_{q-1}) - \log_2 M(B_j \times U_{q-1}) \\ -\log_2 M(U_{q-1} \times A_{i_q,j_q}) \end{array} \right) \end{array} \right) \quad (3)$$

where $U_{q-1} = \{A_{i_1,j_1} \times \ldots \times A_{i_{q-1},j_{q-1}}\}$ is the fuzzy set defined by the sequence of fuzzy terms $A_{i_1,j_1}, \ldots, A_{i_{q-1},j_{q-1}}$ of selected attributes $A_{i_1}, \ldots, A_{i_{q-1}}$ from the root of the tree to the *q*th node, and $M(B_j \times U_{q-1} \times A_{i_q,j_q})$ represents cardinality of fuzzy set $B_j \times U_{q-1} \times A_{i_q,j_q}$. The information measure used for induction of individual decision trees has value defined by

$$i_q = argmax\left(\mathrm{I}\left(B; U_{q-1}, A_{i_q}\right) / \mathrm{H}\left(A_{i_q} | U_{q-1}\right)\right) \quad (4)$$

where argmax denotes a function returning index i_q of input attribute with maximal value of CMI from random selected set of unused attributes, and $\mathrm{H}(A_{i_q}|U_{q-1})$ is the cumulative conditional entropy. This entropy is calculated as

$$\begin{aligned} &\mathrm{H}\left(A_{i_q}|U_{q-1}\right) = \sum_{j=1}^{m_{iq}} M\left(A_{i_q,j}, U_{q-1}\right) \\ &\times \left(\log_2\left(M\left(U_{q-1}\right)\right) - \log_2 M\left(A_{i_q,j} \times U_{q-1}\right)\right). \end{aligned} \quad (5)$$

The CMI divided by this entropy eliminates the tendency of preferring an attribute with many linguistic values.

During FDT induction, two prepruning parameters are used to avoid overfitting of the classifier. These parameters are denoted as α and β and are used in the following manner.

1) If confidence degree b_j of the analyzed internal node is greater than the value of parameter β, then the induction from the analyzed node is stopped. This fact corresponds to a situation when the confidence of the decision that the output attribute belongs to the class *j* is enough. The confidence degree used in this case has the next form

$$b_j = \frac{M\left(B_j \times A_{i_1,j_1} \times \ldots \times A_{i_{q-1},j_{q-1}} \times A_{i_q,j_q}\right)}{M\left(A_{i_1,j_1} \times \ldots \times A_{i_{q-1},j_{q-1}} \times A_{i_q,j_q}\right)}. \quad (6)$$

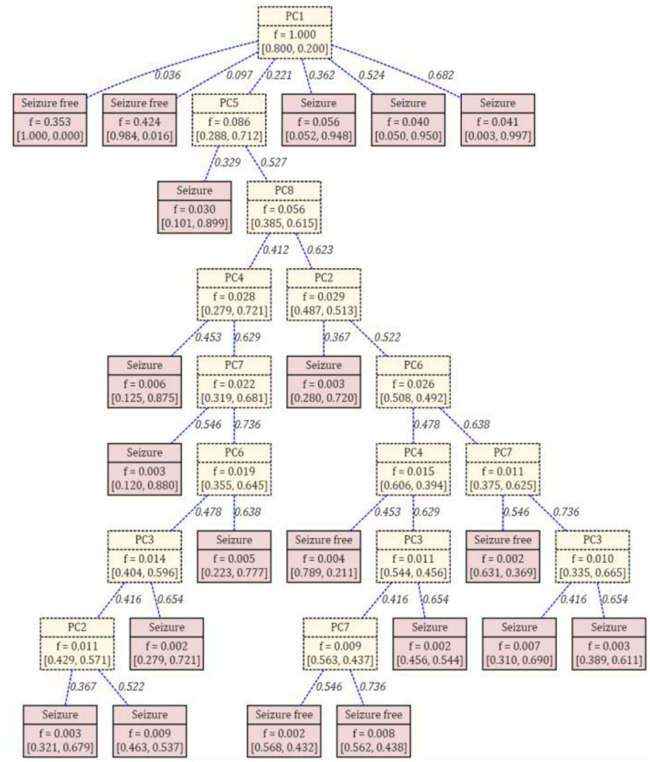

Fig. 2. Illustrative example of FDT for EEG signal classification ($\alpha = 0.009$ and $\beta = 0.850$).

2) If frequency $f(U_q)$ of branch is less or equal to the value of parameter α, then the induction in the branch is also stopped. The frequency used in this criterion is defined as follows:

$$f\left(U_q\right) = M\left(A_{i_1,j_1} \times \ldots \times A_{i_{q-1},j_{q-1}} \times A_{i_q,j_q}\right) / K. \quad (7)$$

Based on the values of parameters α and β, the FDT induction is gradually stopped in individual branches. These values have to be selected experimentally from 1 to 0. In this article, we set parameters α and β empirically as 0.05 and 0.95, respectively. It was found that a confidence degree with a value greater than 0.95 would allow reaching a decision with the sufficient confidence and value 0.05 of parameter α would eliminate various no-principal decisions. Decreasing value of parameter α or increasing value of parameter β allow us to would result in induction of larger FDTs. Such FDTs describe the considered dataset more precisely, but they are very sensitive to noise data used for FDT induction. As a result, such FDTs are not suitable for classification of new instances. The experiments have been iterated about 1000 times for training dataset. The values of α and β of the best decision for tested dataset are proposed for application, which will be used for classification of new samples.

For example, one of simplest (but not efficient) FDT for eight attributes for classification of EEG signal is shown in Fig. 2. The attributes of in this FDT are numerate from PC1 (attribute A_1) to PC8 (attribute A_8). Each node in this FDT has three rows. In case of internal nodes, the text in the first row denotes input attribute associated with the node. In case of leaves, the first row

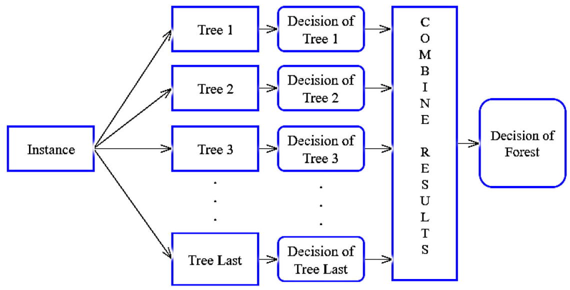

Fig. 3. Strategy of classification by FRF.

carries information about the dominant output class. The second row in both types of nodes tells us the frequency of a branch that comes to the node. Finally, the third row contains information about membership degrees to the output classes (first number – "seizure" class, second number – "seizure free" class). The FDT contains also some numbers on edges. These numbers agree with the values of centroids obtained after fuzzification using FCM.

B. Fuzzy Random Forest

A random forest belongs to ensemble methods. These methods combine multiple classifiers into one classifier system to obtain better classification accuracy than can be acquired by any of the constituent classifiers alone [18].

The FRF combines a set of individual FDTs. One of the advantages of random forests over individual decision trees is their stability. Decision trees are sensitive to variations in data. Small change of input data can result in a change of the tree's structure. Generally, random forests does not suffer from overfitting while decision trees tend to overfit input data [18]. The overfitting occurs when leaves have a small number of instances in proportion to the number of input data. This problem can be solved using pruning techniques. Furthermore, decision trees are well interpretable classifier. On the other hand, in case of random forests, it can be very difficult to explain the meaning of hundreds of trees.

The FRF implemented in this article is based on bagging [18]. The bagging creates a new dataset for each classifier by sampling (with replacement) instances from the training dataset. Replacement causes that one instance from a training dataset can occur in the sampled dataset multiple times. In [18], the bagging is extended by random attribute selection. In this case, the splitting attribute is chosen from a randomly selected subset of unused attributes (in a tree branch) for each nonleaf node of the inducted tree. The selection of spliting attributes from the subset for FRF trees induction is done in this article by information measure based on the CMI [16].

The FRF consists of a specified count of FDTs. Each of these FDT provides some decision (classification result). To obtain decision of the forest, the results from individual trees have to be combined together (see Fig. 3). In this article, we achieve this by summation of the membership degrees of belonging to each class divided by the count of trees.

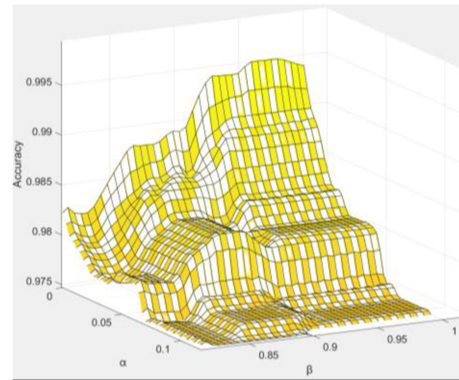

Fig. 4. Dependency between values of pruning parameters α and β and accuracy of the classification.

V. Accuracy Evaluation

The comparative analysis is made on dataset presented in [6]. This dataset contains 500 records of EEG signals divided into 5 classes. Identification of patients during epileptic' seizure is a goal of our analysis. The data in the original dataset are merged into two classes ("seizure" and "seizure free"). Each EEG record with duration of 23.6 seconds is cut into smaller records with 2.95 second duration. As a result, a larger dataset with 4000 EEG records is obtained. In the step of the signal preprocessing (see Section III), these records are transformed using FFT, PCA, and FCM into a set of 4000 samples with 8 fuzzy attributes. After this, the dataset of fuzzy samples is split into two subsets. One set (the training subset) is used to induct FDT or FRF based on the methods described in Section IV and another one (the testing subset) to evaluate the inducted FDT or FRF by measures of accuracy, specificity, and sensitivity. Splitting data into training and testing subsets is preformed randomly in a ratio 70:30 [17], [34]. The process of splitting and evaluation is repeated 100 times to minimize influence of the random split of the analyzed dataset.

As the first, the FDT is considered. We experimentally estimate values of parameters α and β. This experimental analysis is based on results of multiple FDTs induction. More precisely, we analyze values of parameter α from range 0.0 to 0.3 and values of parameter β from range 0.75 to 1.0. In estimation of the best values of both parameters, the values in the ranges are changed using a step with value 0.001. For each combination of values of these two parameters, an FDT is inducted according to the process described in the previous paragraph, and the accuracy of its classification capability is estimated. The influence of values of both parameters on the classification accuracy can be seen in Fig. 4. It can be noticed that the best accuracy is reached for $\alpha \approx 0.230$ and $\beta = 0.864$. The FDT inducted using these values of parameters α and β is the most suitable one for classification of EEG signals. Therefore, the FDT with these parameters is also used in the comparative analysis.

The FRF is another fuzzy classifier used in this article. The number of decision trees is specified as an input parameter of this classifier. It is important to find a good value of this parameter since a small number of decision trees can lead to

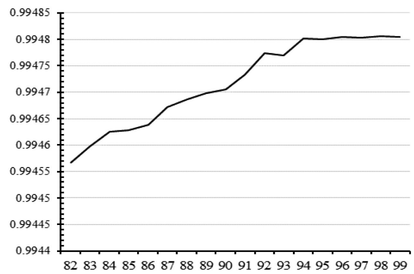

Fig. 5. Accuracy (y-axis) of FRF depending on the number of inducted FDTs (x-axis) for epileptics' seizure prediction.

poor classification performance while a big number can cause suffering of the algorithm from slow computing power. For this purpose, we implement a simple iterative procedure to find smaller value of this parameter in combination with the greatest accuracy of the classification. The building of FRF starts from 3 FDTs. One tree is added to FRF and accuracy is evaluated in each iteration. This procedure finishes when classification accuracy stops growing (see Fig. 5).

We show efficiency of the proposed approach based on FDT and FRF by 6 metrics of binary classification evaluation. These metrics are: accuracy; specificity; sensitivity; precision; F1 score; and Matthews correlation coefficient (MCC). The accuracy is defined as a proportion of instances classified correctly to the number of all instances. However, this metric can be misleading in case of imbalanced datasets, i.e., datasets containing much more samples of one class than another. To solve this problem, other metrics are often used. The most common ones are sensitivity and specificity, which are also widely used in medicine. The sensitivity represents the ratio of correctly classified positive samples to all positive samples (in our case samples belonging to class "seizure"). Similarly, the specificity agrees with the proportion of the correctly classified negative samples to all negative samples (in this article samples belonging to class "seizure free").

Another metric that we used is precision known also as positive predicated value. This metric is defined as the ratio of correctly classified positive samples to all samples that are classified as positive. In our case, this metric is computed as the ratio of samples correctly classified by classifier as "seizure" to all samples classified as "seizure."

The next metric is F1 score. This metric is calculated as the harmonic mean of sensitivity and precision and takes value from 0 to 1. Values near to 0 imply that sensitivity or precision of classifier is poor while values near to 1 indicate that the classifier has perfect sensitivity and precision, i.e., it is able to classify almost all positive samples as positive and almost no negative sample is recognized as positive.

The F1 score does not take into account negative samples that are correctly classified as negative, which can be a weakness of this metric in case of highly imbalanced datasets. Metric that consider also correctly classified negative samples is MCC. Unlike the F1 score, the MCC does not depend on a choice of which class is considered to be positive and which to be negative. Thanks to this, the MCC is useful not only for balanced but also for highly imbalanced datasets. In essence, this metric is a correlation coefficient between real classes of samples and classes obtained using classifier. As a correlation coefficient, it gives a value from -1 to 1, where value -1 implies total disagreement between the real class and the class predicated by classifier, while value 1 means perfect match. Values near to 0 indicate that classifier has random behavior and its prediction has no practical value.

TABLE I
COMPARISON OF PROPOSED APPROACH WITH OTHERS

Classification algorithm	Fuzzy	F1 Score	Precision	MCC	Sensitivity	Specificity	Accuracy
FDT	Fuzzy	0.989	0.981	0.985	0.996	0.993	0.995
FRF	Fuzzy	0.963	0.988	0.828	0.994	0.995	0.994
Fuzzy Naive Bayes classifiers	Fuzzy	0.924	0.862	0.887	0.999	0.917	0.952
Fuzzy Decision Rules	Fuzzy	0.942	0.976	0.722	0.912	0.889	0.910
Fuzzy Multi-Layer Perceptron	Fuzzy	0.956	0.919	0.900	0.997	0.889	0.948
KNN	Non-fuzzy	0.934	0.923	0.843	0.946	0.892	0.925
Naive Bayes	Non-fuzzy	0.968	0.949	0.923	0.987	0.928	0.962
C4.5	Non-fuzzy	0.984	0.978	0.963	0.992	0.969	0.981
Multi-Layer Perceptron	Non-fuzzy	0.950	0.913	0.886	0.991	0.881	0.942

Using the previously introduced metrics, we compare our approach for classification of EEG signals, which is based on FDT and FRF, with other approaches that use non-fuzzy or other fuzzy classifiers. The comparison includes four nonfuzzy and three other fuzzy classifiers. The tested nonfuzzy classifiers are KNN, Naive Bayes, decision tree inducted based on C4.5 algorithm, and multi-layer perceptron NN. The three more fuzzy classifiers used in comparison fuzzy Naive Bayes, FDRs, FMLP NN neural network. To obtain relevant results, we try to find the best values of parameters of these classifiers during experiments. Because of that, training of all these classifiers is based on multiple runs and selection of best configuration of parameters of each classifier. After this we obtain results given in Table I. This table contains values of all previously mentioned metrics for the best values of parameters of the classifiers obtained during the experiments implemented in MATLAB. The summarization analysis of all metrics for classification efficiency in Table I gives that the best of these classifiers is FDT. Two classifiers which are decision tree based classifier inducted by C4.5 and FRF are a little worse. According to this result the decision tree based classifiers are efficiency for the EEG signal classification and two of three best classifiers are fuzzy classifiers.

In the next step, we also compare results obtained by our approach with results of other studies performed on the same dataset and focusing on prediction of epileptic seizures. These results are given in Table II. As we can see, the studies differ in methods used at the step of EEG signal preprocessing (the methods used for feature extraction and dimensionality reduction) or in classifier used at the second step. The classification accuracy present in the last column is taken from the considered studies.

The comparison of our approach with others based on fuzzy and nonfuzzy classifiers given in Table I gives that the classification accuracy of the FDT and FRF is the best. Furthermore,

TABLE II
COMPARISON OF PROPOSED APPROACH WITH OTHER STUDIES DEALING WITH PREDICTION OF EPILEPTIC SEIZURES

Study	Preprocessing methods	Classifier	Accuracy
K. Polat and S. Güneş [13]	DWT	Decision Tree (C4.5)	0.987
M. A. Naderi, et al [9]	FFT, PCA	Multilayer Perceptron Neural Network	1.000
K.Polat and S.Güneş[17]	FFT, PCA	Artificial Immune Recognition System based classifier	0.998
J. B. Jian, B. Goparaju et al. [29]	Complete Ensemble Empirical Mode Decomposition	Random Forest	0.980
This study	**FFT, PCA, Fuzzification**	**FDT**	**0.995**
		FRF	**0.994**

if we look in detail at other metrics, then we can recognize that the FDT reaches the best results also for the F1 score and MCC and the second-best results in case of the precision and specificity. No other classifier achieves such great results. In case of the FRF, the best values are obtained for precision and specificity (metrics for which the FDT reaches the second-best values). However, regarding other metrics, this classifier is inferior to FDT. Especially, the MCC of the FRF belongs to the worst ones, therefore, the FDT seems to be the best classifier in the analysis of EEG signals for the purposes of epileptic seizures.

Results given in Table II indicate that our approach can also outperform some of the existing studies. Actually, there are only two studies that have better classification accuracy than our approach. However, the perfect accuracy from [9] has been obtained by a fact that the classifier is trained using the whole dataset and all samples used in the training are also used in the testing. The classifier from [17] is based on artificial immune recognition system with fuzzy resource allocation mechanism. Since this classifier uses fuzzy-based mechanism, it is also able to take into account uncertainty of data obtained after the feature extraction and feature selection (dimensionality reduction), which supports our statement that fuzzy-based classifiers give better results in analysis of EEG signals.

To analyze effectiveness of our approach, we also compare the runtime of training (inducting) fuzzy classifiers with training of other classifiers. In this experiment, the runtime of preprocessing step is excluded from the training time and is calculated separately. We find that the three procedures of the signal preprocessing take 2.705 seconds for FFT, 7.530 seconds for PCA, and 1.347 s for fuzzification on a computer with Intel Core I7 330 CPU, 16GB of RAM, and Windows 10 operating system. Please note that fuzzification is necessary only for fuzzy classifiers. The runtime of training the classifiers is given in Table III. This experiment is realized with using of MATLAB library. Training of each algorithm is repeated for 100 times and then it is averaged. Before the training time is estimated, the best configuration of algorithms parameters is found (according to the classification accuracy). Finally, we also estimate the time needed for classification of new instances when the classifier is inducted.

TABLE III
COMPUTATIONAL COMPLEXITY EVALUATION OF CLASSIFIERS

Classification algorithm	Training Time [s]	Classification Time [s]
FRF	182.177	2.661
FDT	2.981	0.385
Fuzzy Naïve Bayes classifiers	1.371	0.111
Fuzzy Decision Rules	2.886	0.385
Fuzzy Multi-Layer Perceptron	7587.12	0.722
KNN	0.358	3.518
Naive Bayes	1.001	0.108
C4.5	2.085	0.204
Multi-Layer Perceptron	4987.12	0.422

The comparison made in Table III shows that perceptron-based algorithms need longer time to training. In our configuration, both perceptron (for fuzzy data and for nonfuzzy data) have three hidden layers. The shortest time for training is necessary in case of KNN algorithm (based on use of space-partitioning data structure k-d tree). Fuzzy based approaches require longer time for training. This is caused by processing of uncertainty present in data. Regarding classification, all algorithms are very effective. The fastest is C4.5 and the slowest is KNN. The fuzzy classifiers are also slower in classification speed, but the differences are not significant in comparison to nonfuzzy classifiers. Except FRF, all fuzzy classifiers need less than 1 s for classification of new samples.

From a theoretical point of view, the best time complexity of the training phase has KNN algorithm equal to O(1). But, the time complexity of its classification is equal to K (number of instances) which negatively affects the classification time, especially for large datasets. The time complexity of training of Naïve Bayes is equal to $O(n \times m_B)$ where n is the number of input attributes and m_B defines a number of output classes. The time complexity of C4.5 algorithm is equal to $O(K \times n^2)$. The time complexity of the multilayer perceptron is determined by many factors. For evaluation of a single instance, it is necessary to process all weights and all neurons. If MLP has full connectivity between layers then a number of weights w are equal to the multiplication of a number of hidden layers and the number of nodes. If the training set has K instances than the training complexity is given as $O(w \times K \times e)$ where e denotes the number of epochs. Unfortunately, we cannot determine the number of epochs e which is needed to train MLP. In the case of fuzzy algorithms, the complexity of FDT in comparison with C4.5 is similar $O(K \times n^2)$. But, the preliminary data processing is increased by the fuzzification process $O(n)$. A Fuzzy Random Forest must build multiple FDT. Therefore, the complexity of this algorithm is extended by multiple FDT induction. Used algorithm of FMLP adds a special layer which transforms input values to memberships of fuzzy sets. This layer is responsible for complexity increase because it multiplies inputs by a number of used fuzzy sets.

According to Table I, the best results in classification of EEG signals are obtained with fuzzy classifiers. This is caused by considering the uncertainty of the formed classification attributes of

EEG signal by their representation as fuzzy attributes. Among considered classifiers, the FDT and FRF are the best ones. This is achieved by the controlled process of induction of these classifiers. At the same time, we suppose that the convolution NNs would obtain good accuracy too. As one of the results of this article, we can state that fuzzy-based classification in analysis of EEG signals has great efficiency since it allows taking into account the uncertainty resulted from feature extraction and dimensionality reduction of initial EEG signal.

VI. Conclusion

EEG signals belong to biosignals playing an important role in study of human brain activity. Their automatic processing and analysis represent key tasks in the development of interfaces for human-computer interaction or in the development of medical support systems for diagnosis of various neurological disorders. One of these disorders was epilepsy characterized by recurrent, unprovoked seizures. These seizures was recognized in EEG signal of a person suffering from epilepsy.

Several studies dealing with analysis of EEG signals to detect epileptic seizures exist. Most of these studies process EEG signal in two steps. In the first step, the preprocessing of the signal was performed. The goal of this step was to extract features from the signal and select those that were most relevant for classification. In the second step, the selected features are classified using some of the common classifiers. A possible drawback of this approach was a fact that the selected features have usually a character of numeric crisp attributes. According to investigation in [15], such attributes obtained as the output of the preprocessing step do not contain all information carried by the original signal. Because of that, they should be evaluated not as crisp data, but as data with uncertainty. This implies that the classifier used at the second step should be a classifier able to process uncertain data. Such classifiers are typically based on fuzzy logic.

Application of fuzzy-based classifiers calls for modification of the signal preprocessing step. This modification was considered in [16] by adding procedure of fuzzification into this step. After adding this procedure, a fuzzy classifier was used in the step of classification (see Fig.1). In [16], the key classifier used in the classification has been FDT. In this article, we further developed manipulation with this classifier in the analysis of EEG signals for the purposes of epilepsy detection, but we also tried to use its composite form known as FRF. According to results given in Tables I and II, the classification accuracy of these two classifier was very similar, but the FDT was slight better. Furthermore, if we compare accuracy of these two classifiers with others, then we see that they were the best. Also, if we look at other metrics given in Table I, we recognize that FDT reached the best or the second-best value in 5 out of 6 used metrics (the only metric where other classifiers were better is sensitivity). The FRF reached the similar result in case of three metrics (precision, sensitivity, and accuracy), but completely failed in case of MCC, which was sometimes considered to be the most informative single metric in analysis of classifiers with two classes. Therefore, the FDT can be regarded as better classifier than the FRF.

The investigation in this article was primarily focused on the classifiers and influence of application of fuzzy classifiers instead of classifiers for crisp data. Because of that, the procedures of EEG signal preprocessing were not considered in detail and, in all the experiments, procedures of FFT, PCA and FCM were used to obtain fuzzy data from EEG signals. The best classification accuracy was obtained based on fuzzy classifiers (see Table I) for these signal preprocessing procedures, so it was logical to assume that improvement of the quality of the preprocessing improve the classification result. Therefore, it was interesting to study impact of alternative procedures in the signal preprocessing step on the results of fuzzy-based classification. In future investigation the other fuzzy classifiers will be considered and procedures of the step of signal preprocessing will be investigated in more details. The modification and use of the different procedures of signal preprocessing have influence to classification result. The analysis and evaluation of accuracy of the classification result for different classifiers and different procedures of signal preprocessing will allow obtaining the optimal algorithm for EEG signal classification based on fuzzy classifier.

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Jan Rabcan (Member, IEEE) received the M.S. degree in information systems and the Ph.D. degree in applied informatics from the University of Žilina, Žilina, Slovakia, in 2016 and 2019, respectively.

Since 2019, he has been with the Department of Informatics, University of Žilina. He is an Author of more than 20 papers in data analysis and system reliability evaluation.

Vitaly Levashenko (Member, IEEE) received the M.S. and Ph.D. degrees in computer science from the Belarus State University of Informatics and Radioelectronics, Minsk, Belarus, in 1989 and 1994, respectively.

From 1998 to 2004, he was with the Belarus State Economic University, Minsk. Since 2004, he has been with University of Žilina, Žilina, Slovakia. He is currently a Full Professor with the Department of Informatics, University of Žilina. He is an Author of three books and about 100 articles. His research interests include data analysis, classification problems, and system reliability evaluation.

Elena Zaitseva (Member, IEEE) received the M.S. and Ph.D. degrees in computer science from the Belarus State University of Informatics and Radioelectronics, Minsk, Belarus, in 1989 and 1994, respectively.

From 1996 to 2004, she was with the Belarus State Economic University, Minsk. Since 2004, she has been with the University of Žilina, Žilina, Slovakia. She is currently a Full Professor with the Department of Informatics, University of Žilina. She is an Author of more than 100 articles. Her research interests include mathematical methods in reliability and safety analysis, classification problem and algebra logic-based methods application in reliability evaluation of complex systems.

Dr. Zaitseva is a Member of technical committee of European Safety and Reliability Association and chair of Reliability Association chapter of Czechoslovakia section of IEEE.

Miroslav Kvassay (Member, IEEE) received the M.S. degree in information systems and the Ph.D. degree in applied informatics from the University of Žilina, Žilina, Slovakia, in 2012 and 2015, respectively.

Since 2015, he has been with the Department of Informatics, University of Žilina. From 2019, he was an Associate Professor with the University of Žilina. He is an Author of more than 50 articles. His research interests include mathematical methods in reliability and safety analysis and algebra logic-based methods application in reliability evaluation of complex systems.