

# Switching Fuzzy Classifier for Classification of EEG Spectrograms

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*Abstract: The paper introduces the concept of switching fuzzy classifier. The work of the classifier is demonstrated on the classification of EEG spectrograms in different levels of vigilance of car drivers. The switching mechanism is based on the combination of C4.5 classification trees algorithm with a fuzzy classifier. The structure of the classifier arises from the concept of radial fuzzy system with nominal consequents. The system as a whole can be seen as fuzzy classifier with dynamic levels of confidence in the individual fuzzy rules in rule base.*

*Keywords: fuzzy classifier, classification tree, EEG spectrograms*

## 1 Introduction

In the paper we are interested in the idea of a combination of two well-known classification models. Namely, we are interested in a combination of fuzzy classifiers with classification trees. The result of this combination is called switching fuzzy classifier and we demonstrate its capabilities on the task of classification of levels of vigilance of car drivers.

The idea of introduction the switching fuzzy classifier comes from the area of man-machine interactions. In fact, in the context of a major project aimed at development of methods and tools for detection and prevention of decline in the driver's attention, we have an interest in the classification the levels of vigilance of car drivers based on the analysis of EEG (electroencephalographic) signals recorded from the driver's head. Let us here review only information related to data we work with. More information about the project can be found in monograph [1].

The data available to us represent EEG signals recorded from 19 electrodes spread over a driver's head. Our goal is to design a tool for the classification of levels of driver's vigilance on the basis of the analysis of EEG signals. However, suggest a

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tool, using all 19 signals is too complex and inconvenient for the driver. From this reason we focus on the task to select the electrodes which are the most related to the particular levels of vigilance. The importance of this relationship has been studied for single electrodes and their combinations. In the study we have employed the combination of C4.5 classical classification tree algorithm with GUHA data-mining method. The achieved results are presented in the recent paper [1]. In the paper we have identified the most significant combinations of electrodes for each level of vigilance and proposed the combinations of electrodes for composite C4.5 classifier.

This paper presents a follow-up research in this field. Instead we use only C4.5 classification trees we study the combination of a fuzzy classifier with individual C4.5 classifiers. The basic idea is that rules in the rule base of a fuzzy classifier are switched on/off on the basis of the output of relevant C4.5 tree. Thus the rule base of the fuzzy classifier is dynamically changed.

The organization of the paper follows. In the next section we present in more details structure of EEG data we work with. Section 3 describes starting points of our study and the structure of proposed switching fuzzy classifier. Section 4 presents results achieved by application of this concept on EEG data and paper is concluded by final remarks of Section 5.

## 2 EEG Data

### 2.2 EEG Data Acquisition

EEG (electroencephalographic) signals refer to the electrical activity of a brain. The data of our interest were recorded during experiments when volunteer drivers underwent a sessions in a driving simulator.



Figure 1

The driving simulator and screening cap

The simulator is actually a fully equipped car provided by Škoda Auto a.s. The actuators of car are interconnected with computer which controls the projection of driving scenario on projective screens surrounding the car, see Fig. 1. The driver is during driving session equipped with a special screening cap fixing 19+2 (ears) electrodes over her/his head. The electrodes measure EEG signals which are then recorded in a form of time series into a database. The distribution of electrodes is presented in Fig. 2(a).

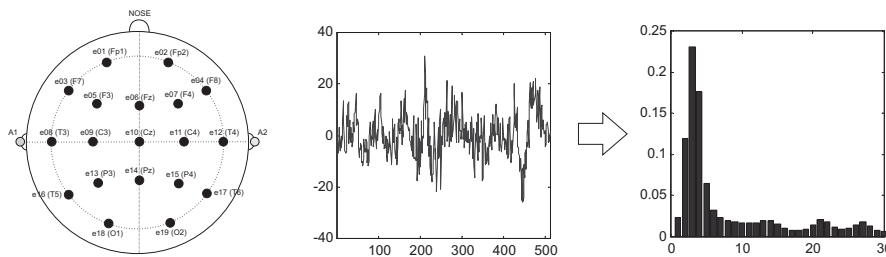


Figure 2

(a) The distribution of electrodes; (b) Transformation from the time to frequency domain

The driver typically attends a session after a long period of vigilance in order to exhibit episodes of vigilance decrease. During a session the driver is “forced” to exhibit three levels of vigilance:

- **mentation** - this level corresponds to a higher mental activity of driver and higher level of vigilance (typically the driver is asked to perform simple counting)
- **wakefulness** - the driver at this level is asked to do no mental activity and try to be maximally relaxed, but still to drive
- **microsleep** - the records classified into this level correspond to situations when driver get off the road or fall asleep

In a typical session several episodes of all three levels of vigilance are indicated and relevant EEG signals are recorded.

Nowadays, we work with the database of 766 classified samples of 19-channel EEG signals. Each sample is classified into one of three levels introduced above. The research task is to design on the basis of this training set a classification tool for correct classification of EEG samples into particular levels.

## 2.2 Data Preprocessing

The preprocessing phase has two steps. In the first one the EEG signals are transformed from the time domain into frequency one. As the result an EEG spectrogram is obtained. In the second step EEG spectrograms are normalized in order to be mutually comparable.

In our case the transformation from the time to frequency domain is performed in terms of Welch's transformation by means of MATLAB Statistics toolbox. Resulting spectrograms then comprise 31 power densities corresponding to individual densities at 0-30 Hz, see Fig. 2(b). Hence, a spectrogram is actually the real vector comprising 31 non-negative numbers.

In the second step spectrograms are normalized so that the sum of power densities is 1 (or any other positive constant) in order to inter-individual discrepancies between drivers were lowered.

### **2.3 Selection of Relevant Electrodes**

The aim of our research is to develop as accurate as possible but not too complex classifier. For this reason, we focused on examining which group of electrodes are most relevant for the detection of different levels of vigilance. This task has been successfully addressed in the recent paper [2], where we used a combination of C4.5 classification tree algorithm and GUHA data-mining method.

Let us briefly introduce the main idea of our approach; details are provided in [2]. First, we gradually used the output of single electrode to create an appropriate classification C4.5 tree. Thus, we received 19 classification trees with different levels of classification accuracy. Further the outputs of individual trees were arranged into the matrix comprising 776 rows and 19 +1 columns, where each row corresponds to single EEG spectrogram and column to the classification tree. Last column, then contains the correct classification. This matrix was then analyzed by GUHA method in order to seek mutual relations among the data.

There is a vast literature on the method for overview see for example [3, 4]. Mention here only that it is the method of exploratory data analysis and is based on logic and statistical backgrounds. It enables mechanically formulate and evaluate polyfactorial hypotheses on relations in data.

In our case we are interested in the question of what small groups of electrodes (not just individual ones) are related to the proper classification of EEG spectrograms into a certain level of vigilance (class). The relation was searched in terms of so-called FEQ (founded equivalence) relation which corresponds to the scalable equivalence of two Boolean propositions, where the evaluation of the antecedent is given by result of classification of C4.5 tree and consequent corresponds to certain level of vigilance.

These relations have been found as the strongest [2]:

- e03 & e06 & e15 ~ mentation
- e07 & e12 ~ wakefulness
- e14 & e16 e17 ~ microsleap

Actually, we have identified three groups of electrodes that are the most relevant for each class (level of vigilance). For each group, we have created corresponding C4.5 tree with binary classification (sample belongs to the class or not). Achieved accuracies of classifications were 95.7%, 95.9 %, and 98.0%, respectively.

We have also tried to create a composite classifier allowing the classification to all three classes. This classifier was based on the combination of the best related electrodes to particular levels of vigilance as these were found by GUHA method analysis. Namely, these are electrodes e07 for mentation, e15 for wakefulness and e14 for microsleep. The accuracy of only 95% has been achieved in this case. To improve this accuracy, we have introduced the concept of switching fuzzy classifier.

### 3 Switching Fuzzy Classifier

In this section, we introduce the proposed model, which extends past research published in [2]. We start with the notion of radial fuzzy system with nominal consequents, which form the basis for fuzzy classifier. Then we link it with C4.5 classification trees for the purpose of switch on/off rules in fuzzy classifier's rule base, which finally gets our model.

#### 3.1 Fuzzy Classifier

We consider fuzzy classifier in the form of a radial fuzzy system with nominal consequents. The rules of this system have standard form of antecedents combined with consequents by a t-norm. Antecedent fuzzy sets  $A_i$  are radial functions which form after combination by employed t-norm a multi-dimensional radial fuzzy set of the same "shape" as the original sets. The most prominent example is the combination of Gaussian fuzzy sets by product. Indeed, by combination of  $n$  one-dimensional Gaussian fuzzy sets  $A_i(x_i) = \exp[-((x_i-a_i)/b_i)^2]$  using product gives the expression of antecedent in form  $A(\mathbf{x}) = \exp[-\|\mathbf{x}-\mathbf{a}\|_{\mathbf{b}}^2]$ , where  $\|\cdot\|_{\mathbf{b}}$  is scaled Euclidean norm  $\|\mathbf{u}\|_{\mathbf{b}} = \sqrt{\sum_i (u_i/b_i)^2}$ ,  $\mathbf{a}=(a_1, \dots, a_n)$  and  $\mathbf{b}=(b_1, \dots, b_n)$ . Hence  $A(\mathbf{x})$  is a multi-dimensional Gaussian fuzzy set. Another example is the Mamdani fuzzy system employing triangular fuzzy sets combined by the minimum t-norm. The theory of radial fuzzy systems is developed in several papers e.g., in [5, 6].

Fuzzy systems with nominal consequents have supports of their consequent fuzzy sets specified on generally unordered finite set of classes. Thus, fuzzy sets in consequents are specified by enumeration. In our case we have three classes of  $c_1 = \text{mentation}$ ,  $c_2 = \text{wakefulness}$ ,  $c_3 = \text{microsleep}$ ; and a consequent fuzzy set then have the form  $B = \{\mu_1/c_1, \mu_2/c_2, \mu_3/c_3\}$ .

An individual rule in the presented system has form  $R_j: A_j * B_j$ , where  $*$  is the employed t-norm.  $A_j$  is a radial antecedent and  $B_j$  is a nominal consequent. Overall computation of the system is based on the standard framework of CRI inference engine with the singleton fuzzifier [8]. As output we obtain nominal fuzzy set  $B' = \max_j R_j = \max_j \{A_j * B_j\}$ . Adopting the winner-takes-it-all strategy gives us the final output  $c'$  of the classification of fuzzy classifier, i.e.,  $c' = \text{argmax}_{\text{classes}} B'$

### **3.2 Fuzzy Classifier for Classification of EEG Spectrograms**

Application of the above concept of fuzzy classifier on EEG data leads us to specification of the following system:

The number of rules in the fuzzy classifier is three. Each rule corresponds to the best related electrode to each class as presented at the end of Section 2.3, i.e., the first rule to electrode e07, the second to electrode e15 and the third to electrode e14. The input space is given by power spectral densities in particular frequencies of EEG spectrograms so it is 31-dimensional. Antecedent fuzzy sets are Gaussian with central points  $a_i$  and spreads  $b_i$ . The parameters were specified as means and standard deviations of individual frequencies over sample set of 776 spectrograms. Specification of membership degrees in consequent fuzzy sets was given by conditional accuracy of each class for corresponding C4.5 classifier.

### **3.3 Switching Fuzzy Classifier**

The idea of switching fuzzy classifier is the following. For a given EEG spectrogram we analyze by associated C4.5 tree if it indicates that the sample falls into the tree's related class or not. Let us remind that C4.5 classifier has only binary output: if the sample is in the class or not (i.e., it is probably in some other but we have no further information). Now, if the C4.5 tree indicates that the sample is not in the associated class then the corresponding fuzzy rule is switched off from the rule base of above introduced fuzzy classifier. The rule is switched on if related C4.5 classifier indicates that the sample is in the class. Schematically the switching fuzzy classifier applied to our problem is illustrated as follows:

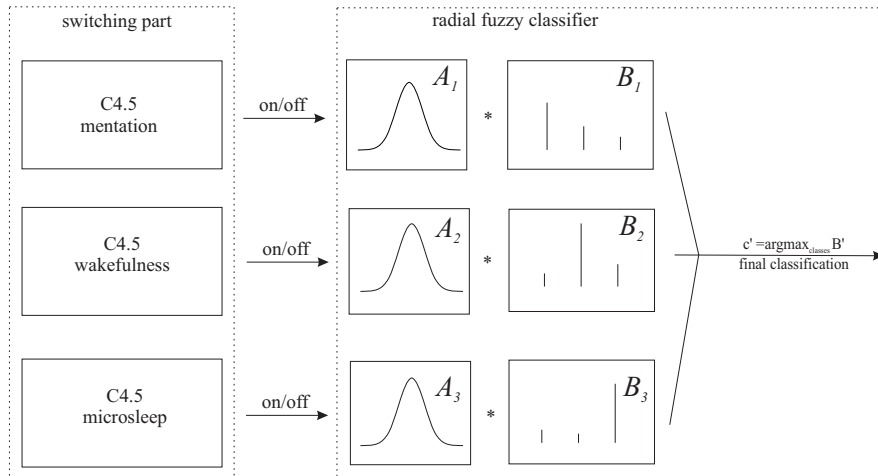


Figure 3  
Switching fuzzy classifier applied on EEG data

## 4 Results

The referred switching fuzzy classifier has been applied to the problem of classification of samples of the above described database of EEG spectrograms. The distribution of the classification for each class is presented in Table 1.

Table 1  
Accuracy of switching fuzzy classifier applied on EEG data

real class ↓	mentation	wakefulness	microsleep
mentation	205	2	1
wakefulness	1	215	2
microsleep	2	2	334

We can see that we have achieved 97,2% accuracy on the database of 776 EEG samples. This result represents 2% improvement over the approach based on the use of composite C4.5 classifier presented in [2] which has reached only 95% accuracy.

### Conclusions

We have introduced the concept of switching fuzzy classifier. The concept is built on the basis of combination of radial fuzzy system with nominal consequents with C4.5 classification trees. The switching mechanism can be seen as dynamic

control of confidence level in the individual rules in the rule base of fuzzy classifier.

The employment of confidence measure enables to simplify input space of rule base as it was shown on classification of EEG spectrograms. In future work with regard to the task of microsleeps detection we focus on comparison of other confidence measures with the switching algorithm. However, it should be noted that the proposed switching algorithm allows to incorporate information that was used for the selection of appropriate groups of electrodes, and therefore its incorporation is natural.

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