Fuzzy Logic-Based Automatic Alertness State Classification Using Multi-channel EEG Data

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Abstract. This paper represents an attempt to automatically classify alertness state using information extracted from multi-channel EEG. To reduce the amount of data and improve the performance, a channel selection method based on support vector machine (SVM) classifier has been performed. The features used for the EEG channel selection process and subsequently for alertness classification represent the energy values of the five EEG rhythms; namely δ, θ, α, β and γ. In order to identify the feature/channel combination that leads to the best alertness state classification performance, we used a fuzzy rule-based classification system (FRBCS) that utilizes differential evolution in constructing the rules. The results obtained using the FRBCS were found to be comparable to those of SVM but with the added advantage of revealing the rhythm/channel combination associated with each alertness state.

Keywords: Alertness classification, EEG, fuzzy rule-based system.

1 Introduction

The detection of alertness state has recently attracted much attention due to its link to the human ability to process information. The traditional approach to identification of alertness state through monitoring the subject's face was found to be unreliable due to a number subject-dependent factors such as age and shape of eyes. This situation is further compounded by the the inter-rater disagreement. In addition to this, visual identification is tedious task that requires full attention from the assessor. The existing automatic alertness state detection methods can be broadly divided into signal-based and video-based. Methods that fall into the first category use physiological signals such as the electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), and electrocardiogram (ECG) for alertness identification. Among these signals, EEG and more specifically the five EEG rhythms; namely δ (up to 4 Hz), θ (4 - 8 Hz), α (8

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- 13 Hz), β (13 - 30 Hz), and γ (30 - 100 Hz) has been the most widely used. Some authors attempted to identify patterns characteristic of different alertness states. For example, the authors in [1] associated reduction in vigilance with a decrease in the amplitude, quantity and frequency of the posterior α rhythm and increase in slow wave components. Nakamura et. al. [2] characterized the reduction in vigilance level by (i) decrease in the amplitude, quantity and frequency of the posterior dominant rhythm (or the waves with an approximately constant period usually in the α band) and with the maximum amplitude at the occipital or parieto-occipital region of the head and (ii) increase in slow wave components. Most of the authors, however, adopted the discrete vector feature approach to classification. Features were extracted from one or more of the main four physiological signals, namely EEG, EOG, EMG, and ECG [3,4], using different time-domain, frequency-domain and time-frequency domain based techniques. These features were then fed to different classifiers, such as ANN [3] and SVM [4] to be assigned to either two states (alert/drowsy) [4] or three states of alertness (alert/drowsy/asleep) [3]. A number of video-based methods have been proposed in the literature, such as [5]. However, one needs to deal with a number of issues when using video-based methods, such as occlusions, target displacement and the large variability in eye shapes and facial expressions. In this work we opted for the first option. More specifically we used electrical potentials recorded from the brain following an audio stimulus. These signals are known as cortical auditory evoked potential (CAEP) responses.

In our initial work [6], we showed that high frequency rhythms perform, in general, better than the low frequency ones and that a single channel would not be sufficient for achieving good discrimination between the different alertness states. This paper presents an extension of our initial work, where we propose a two-stage process to 1) identify the cortical regions more suitable for discriminating between alertness states and 2) construct a set of "if-then" rules involving combination of EEG rhythm and channel spatial location instead of the widely used black box classifier. A fuzzy rule-based classification system (FRBCS) is used to assign the classifier input information to one of the four predefined alertness states. A differential evolution (DE) optimization based searching technique is introduced to construct the fuzzy-based rules used by the classifier.

The paper is organized as follows: the fuzzy rule-based classification system is described in section 2. Section 3 presents the the DE-based method for constructing the fuzzy rules. Experimental results and conclusions are given in sections 4 and 5 respectively.

2 Fuzzy Rule Based Classification System for Alertness Detection

The fuzzy rule-based classification system (FRBCS) has been used in many classification problems [7,8,9] due to its transparent model built on linguistic variables. This property makes it more attractive for problems that require transparent mapping from the input variables to the output categories, such

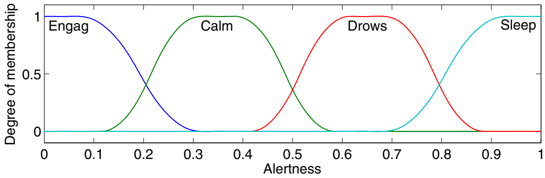


Fig. 1. Alertness membership functions

as medical diagnosis; a property not available in many of the widely used classification algorithms. For the particular problem of alertness state detection, there is another advantage for using FRBCS, namely the reduction of the effect of inconsistency in labeling data by the participating subjects or the human experts. This is achieved by allowing a certain degree of overlap between adjacent states, as shown in Fig. 1.

FRBCS computes the values of an output vector for a given input vector using fuzzy memberships and a pre-defined set of "if-then" rules. The FRBCS design involves 1) defining the membership functions, 2) estimating their parameters and 3) construction of the fuzzy rules. This paper focuses on the construction of rules, as our aim is to identify a limited number of rules that each has a small number of antecedent variables. Some of the widely used methods for constructing the rules are based on artificial neural networks [10] and genetic algorithms [11]. Although these methods have achieved good results in certain applications, we decided to build our own FRBCS for the following reasons. Firstly, we want to control the construction of the rules by starting with a number of rules equal to NC (number of alertness classes), then keep adding another set of NC rules until there is no improvement. The reason behind this approach is to identify the important rule for each of the NC classes, then the second best set of rules that complement the existing ones and so on. Secondly, we want to control the rule complexity, where we aim at constructing "simple" rules that are easy to interpret. Hence, we want no more than K variables in the antecedent part of the rule, where K is a user defined variable. This will help to reveal the relationships between the EEG rhythm/channel combinations and each of the alertness states. Thirdly, differential evolution was shown to possess good exploration capability of the search space [12,13], and hence, we decided to use it here to search for the best variable combination for each rule.

Each feature support is partitioned into three regions, namely "low", "medium" and "high". The Features are first normalized between 0 and 1 before being fuzzified using a pi-shaped membership function. This membership function requires four parameters, which represents the transition points from 0 to 1 and then from 1 to 0. The fuzzification process is performed according to the following steps:

- sort the data samples of each feature and identify the 6%, 47%, 53%, and 94% smaller data samples and assign those values to pp, which is a vector that has four elements
- the parameters of the "low" are: $[-pp(2), -pp(1), pp(1), pp(2)]$

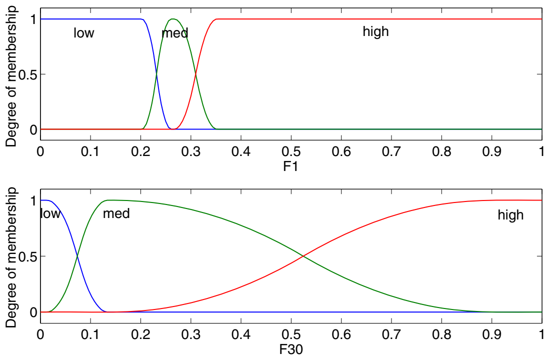


Fig. 2. Membership functions of two different features

- the parameters of the "medium" are: $[pp(1), pp(2), pp(3), pp(4)]$
- the parameters of the "high" are: $[pp(3), pp(4), 2 - pp(4), 2 - pp(3)]$

Although based on this procedure, the generated shape of the membership functions associated with different features may not be similar, each of the three membership regions of a given feature will approximately have the same number of samples with their counterparts of another feature. The reason behind this is that we don't want the "low" region to represent a small portion of samples for feature F_i and large portion of samples for feature F_j. The same is true for the "medium" and "large" regions. Fig. 2 shows the membership functions of two different features.

Rules will have the following format:

Rule n : If F_{n1} is MF_{n1} and . . . and F_{nk} is MF_{nk} then Class is C_n

where MF_{n1} is the membership function associated with feature F_{n1} in rule n, and C_n is one of the alertness state.

We decided not to assign weights to the rules, as we wanted to find the best rule for each class. Rules would then be added to the ones that have already been identified. The next section describes the rule construction process.

3 Construction of Fuzzy Rules Using Differential Evolution

The construction of rules with limited number of antecedent variables (no more than k) is implemented using differential evolution (DE). We modified the code[1] of our previously developed DE-based feature selection algorithm (DEFS) [13] to suit this particular problem. In the DEFS algorithm, the original NF features are distributed among M wheels and one feature is selected from each wheel, i.e, M represents the desired number of features to be selected. The selection of

[1] Available online at: `http://services.eng.uts.edu.au/~ahmed/`

features is optimized using the differential combination and uniform crossover operators of the DE algorithm.

For rule construction, each feature in the antecedent part is represented by one of the four possibilities {low, medium, high, none}, while the consequent part is represented by one of the four possibilities {engaged, calm, drowsy, sleeping}. The number of wheels is set to $NF \times NC$, where NF and NC are the number of features and classes respectively. Each wheel represents one of the features for a given class, and one rule is constructed for each class. The objective is to search for the best membership for each features in the antecedent part of each of the four rules. For each member of the population, the algorithm starts by allowing only k features per rule that are randomly chosen to be assigned a membership function other than "none". Based on the population size, it is unlikely that all members of the population to start with "none" for any of the features. During the optimization process, the DE operators may produce more than k features with a value other than "none". In such case, some of those (randomly chosen) will be reset to "none". The population size is set to 100, all other parameters are kept unchanged.

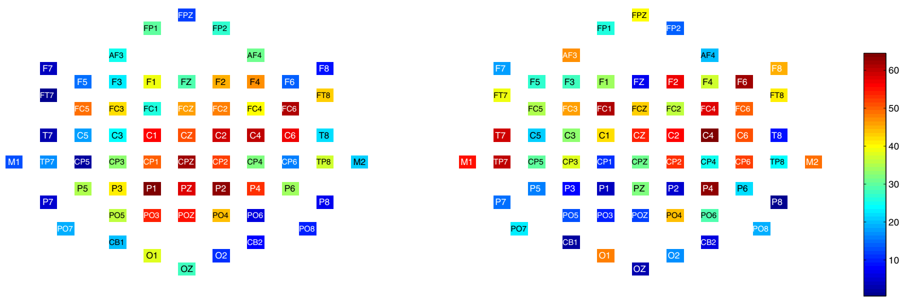
The output values are obtained for each member of the population by evaluating the fuzzy system (defuzzification). The output values are then used to calculate the class-wise classification accuracy of the training set, which in turn used as the "fitness function". It is important to mention that this approach is computationally expensive, and hence, it is not recommended to substitute existing classification methods. However, as mentioned earlier, the main aim of this work is to search for the "best" rhythm/channel combination for each of the alertness states.

4 Experiments and Analysis of Results

Ten normal hearing adult subjects, with an age range of 24 to 53 years, participated in the experiment. A 21 ms /g/ speech sound stimulus was presented every 1175 ms at 55 dB sound pressure level as part of a cortical auditory evoked potential study. Data was recorded using a Neuroscan system that has 64 EEG channels, with the reference channel close to Cz (vertex). Subjects were asked to press one of three buttons every 30 seconds to indicate their level of alertness, i.e, engaged, calm but not drowsy, and drowsy. Each recording session lasted one hour, divided into 6 divisions of 10 minutes each. If the subject did not provide an input in any of the divisions, he/she was considered to have fallen asleep.

The recorded signal was divided into windows of 5 seconds with overlap of 3 seconds. For each window five features corresponding to the energy in the five EEG frequency bands were extracted. Each 10 consecutive windows were grouped to form a segment, and for each subject 75% of the segments were used for training and the remaining 25% for testing. Training windows from all 10 subjects were used to train a multi-class linear support vector machine (SVM) classifier.

For the sake of channel selection, we started by evaluating the performance of each of the 64 channels and its neighbours, where each channel is represented



(a) (b) (c)

Fig. 3. Ranked channel performance based on (a) a single channel and its surroundings, and (b) a single channel and its surroundings with {P1, CP1, P3, PZ, PO3}

using the five EEG rhythms, where based on our initial study we found that a single channel would not be sufficient to discriminate between the four alertness states. The ranked results of the 64 channels shown in Fig. 3(a) indicate that channel P1 and its surroundings {CP1, P3, PZ, PO3} achieved best performance with an average class-wise accuracy of 60.39%. We have then fixed those five channels and added each of the remaining channels, one at a time, along with its neighbours. We found that channel C4 and its surroundings {FC4, C2, C6, CP4} is the best set that complements the existing five channels with an average combined class-wise accuracy of 69.83%, as shown in Fig 3(b).

The obtained performance using 10 channels is lower than that obtained in our initial study [13] because in that study the classifier was trained on the data of each subject individually, while here data from all 10 subjects was used to train the classifier. Note that inconsistency in labeling between the different subjects make the classification task harder.

In order to reveal relationships between the rhythm/channel combination and each alertness state, the construction of fuzzy rules process described in the previous section has been applied to the 10 "best" channels selected by the SVM classifier. The number of elements to be optimized for each rule is 50 (5 rhythms $\times$ 10 channels). We have run the algorithm 5 times, where in each run 4 rules are added to the already identified ones. The sixth run has hardly made any improvement, and hence we decided not to consider it. The obtained rules are:

1. If (γ_{C6} is low) and (θ_{CP1} is high) and (γ_{P3} is med) and (θ_{PO3} is high) then sleeping
2. If (β_{C4} is high) and (β_{P1} is med) and (θ_{PO3} is med) and (β_{PO3} is med) then drowsy
3. If (γ_{FC4} is low) and (α_{CP1} is high) and (α_{PZ} is high) and (γ_{PZ} is med) then calm
4. If (α_{C4} is med) and (δ_{FC4} is high) and (β_{P1} is med) and (δ_{PZ} is med) then engaged
5. If (γ_{FC4} is high) and (θ_{PZ} is high) and (β_{PZ} is high) and (δ_{PO3} is med) then sleeping
6. If (δ_{FC4} is low) and (γ_{C2} is high) and (γ_{P1} is med) and (γ_{PZ} is high) then drowsy
7. If (γ_{C4} is low) and (γ_{C2} is high) and (γ_{P3} is low) and (β_{PZ} is low) then calm
8. If (β_{C4} is low) and (θ_{P3} is low) and (γ_{PO3} is med) then engaged
9. If (γ_{P1} is low) and (γ_{CP1} is high) and (γ_{CP4} is high) then sleeping
10. If (θ_{P3} is low) and (θ_{P1} is high) and (α_{P1} is high) and (γ_{PZ} is high) then drowsy
11. If (δ_{FC4} is low) and (α_{P1} is high) and (θ_{PZ} is low) then calm

12. If (γ_{P3} is high) and (β_{PO3} is low) then engaged
13. If (β_{C2} is low) and (θ_{CP1} is high) and (β_{PZ} is high) and (θ_{PO3} is low) then sleeping
14. If (θ_{C4} is low) and (γ_{FC4} is low) and (β_{P3} is low) and (γ_{PO3} is low) then drowsy
15. If (γ_{C6} is high) and (δ_{CP4} is high) and (β_{PZ} is high) and (δ_{PO3} is med) then calm
16. If (α_{C4} is med) and (α_{C6} is high) and (α_{P1} is med) and (α_{CP1} is low) then engaged
17. If (θ_{C4} is low) and (θ_{C2} is high) and (β_{PZ} is high) and (α_{PO3} is high) then sleeping
18. If (β_{P1} is high) and (γ_{P1} is high) and (δ_{P3} is low) and (γ_{PZ} is high) then drowsy
19. If (γ_{C6} is low) and (θ_{PZ} is high) and (γ_{PZ} is low) and (θ_{PO3} is high) then calm
20. If (θ_{P3} is low) and (γ_{PO3} is high) then engaged

The first four rules produced an accuracy of 58.27%, while using all 20 rules enhanced the accuracy to 67.16%, which is not too different from the results obtained using the SVM classifier. These rules indicate that all five rhythms influence the alertness state classification, especially the higher frequency ones. Note that although the proposed rule construction mechanism does not prevent conflicts between rules, the obtained rules perform well when considered together. These rules indicate that the four alertness states are mainly associated with:

- Sleeping: high β and θ rhythms in the P1 region
- Drowsy: med/high γ, med/high β, med/low θ and low δ
- Calm: med/low γ, high α and med/high θ
- Engaged: med/high γ and low θ in the P1 region. Med/low β and med α

As mentioned in the introduction, existing methods associate drowsiness with a reduction in the α rhythm and increase in slow wave components. The constructed FRBCS rules on the other hand utilized all five EEG rhythms. Hence, in order to verify the importance of the middle three rhythms (θ, α and β), we conducted another experiment using the same set of 10 channels, where we trained the SVM classifier using (i) θ only, (ii) α only, (iii) β only, (iv) θ and β, and (v) θ, α and β. We got the following respective average class-wise accuracies: 45.97%, 36.88%, 39.73%, 56.38%, and 57.80%. These results indicate that utilizing all five rhythms can lead to noticeably better performance than the middle three ones only, which support the constructed antecedent terms of the FRBCS rules.

The confusion matrix obtained using the FRBCS, shown in 1, indicates that the classifier tends to achieve lower misclassification rates with the increase of distance from the true class. For example, when the true class is engaged (column 5), misclassification with sleeping is close to zero, a slightly higher misclassification with the drowsy class, while the highest misclassification was achieved with calm, which is the closest class to engaged. Further improvements are expected to be achieved when optimizing the membership function parameters for each features.

Table 1. Confusion matrix of the FRBCS (T: True, P: Predicted)

P \ T	Sleeping	Drowsy	Calm	Engaged
Sleeping	0.93	0.04	0.07	0.02
Drowsy	0.06	0.65	0.24	0.19
Calm	0.01	0.25	0.55	0.24
Engaged	0.00	0.06	0.14	0.55

5 Conclusion

We presented in this paper a fuzzy rule-based classification system (FRBCS) that utilized differential evolution in constructing the rules. We have shown that the FRBCS is capable of achieving comparable results to that of the well-established SVM classifier. The main advantage of FRBCS is that it transparently maps the input features to the target categories. The obtained rules reveal that importance of combined frequency rhythms of the considered channels in differentiating between the different alertness states.

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