FUZZY RULE-BASED ALERTNESS STATE CLASSIFICATION BASED ON THE OPTIMIZATION OF EEG RHYTHM/CHANNEL COMBINATIONS

Ahmed Al-Ani
Faculty of Engineering and Information Technology
University of Technology, Sydney, Australia
email: Ahmed.Al-Ani@uts.edu.au

Mostefa Mesbah
Department of Electrical and Computer Engineering
Sultan Qaboos University, Muscat, Oman
email: mmesbah@ieee.org

ABSTRACT

This paper presents a method for automatically selecting the optimal EEG rhythm/channel combination capable of classifying the different human alertness states. We considered four alertness states, namely 'engaged', 'calm', 'drowsy', and 'asleep'. Energies associated with the conventional EEG rhythms, δ, θ, α, β and γ, extracted from overlapping segments of the different EEG channels were used as features. The proposed method is a two-stage process. In the first stage, the optimal brain regions, represented by a set of EEG channels, are identified. In the second stage, a fuzzy rule-based alertness classification system (FRBACS) is developed to select the optimal EEG rhythms extracted from the previously selected EEG channels. The IF-THEN rules used in FRBACS are constructed using a novel bi-level differential evolution (DE) based search algorithm. Unlike most of the existing classification methods, the proposed classification approach reveals easy to interpret rules that describe each of the alertness states.

KEY WORDS

Alertness classification; drowsiness; EEG; Fuzzy Rule-Based Classification System; Variable selection; Differential Evolution.

1 Introduction

Alertness plays a major role in the safety, productivity and health of people [1]. The development of automatic alertness state classification has recently attracted an increased attention in a number of scientific disciplines. Most of the currently existing approaches for automatic alertness state classification are based on either physiological signals [2, 4, 5, 6] or image sequences (video) [7, 8]. The first category of methods uses physiological signals such as the electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), and electrocardiogram (ECG),separately or combined, 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 - 13 Hz), β (13 - 30 Hz), and γ (30 - 100 Hz), were found to be reliable indicators of vigilance.

To automatically identify alertness states using EEG, two approaches have been adopted in the literature. In the first approach, known as pattern identification,the aims

was to identify EEG patterns that characterize the different alertness states. Varri et al [2] linked the reduction in vigilance with a decrease in the amplitude and frequency of the posterior alpha rhythm and an increase in the slow wave EEG components. In [3], Nakamura et al. concluded that reduction in vigilance was also accompanied by a maximum of a activity at the occipital or parieto-occipital regions. The second, and most frequently adopted approach,uses discrete features as a basis for state alertness segregation. Used features were extracted from different domains, namely time-domain, frequency-domain and time-frequency domain [4, 5, 6]. These features were then fed to a classifier, such as artificial neural networks (ANN) [4, 5] or support vector machines (SVM) [6] to be assigned to either two states (alert/drowsy) [6] or three states (alert/drowsy/asleep) [4] of alertness. A number of video-based methods have also been proposed in the literature, such as [7, 8]. Video-based methods: Most of the proposed video-based methods follow a three-stage process: 1) Face detection, 2) eyes localizations, and 3) either eyelid movement detection (to compute the percentage of eye closure) or gaze tracking (using either ordinary or infrared cameras). These methods, however, face a number of challenges such as fast movements of eyes, changes in pose, lighting variations, and heavy computational load. Due to the reliability of the EEG in identifying alertness states, we decided to use EEG as a basis for developing a new method for automatically classifying alertness states.

In [9, 10], the authors concluded that all five rhythms along with multi-channel EEG are needed to achieve an efficient discrimination between the different alertness states. They also showed that a basic fuzzy rule-based classification system can achieve a good performance. The authors, however, noticed that the system suffered from its inability to prevent conflict among its fuzzy rules. This paper presents an attempt to overcome this problem. Here we concentrate on the problem of selecting the best spatio-frequency features extracted from multi-channel EEG capable of accurately classifying alertness states. The proposed method is composed of two stages: 1) identify the "optimal" cortical regions and 2) construct a set of IF-THEN rules involving combination of EEG rhythm and channel spatial locations. This new approach contrasts with the widely used black box approach. The IF-THEN rules selection process uses an enhanced version of a differential
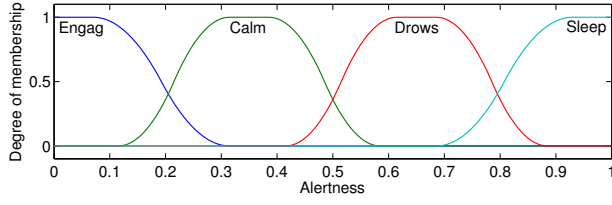
Figure 1. Alertness membership functions

Figure 2. Design of the FRBCS

evolution (DE) based search technique previously proposed by the first author [11]. The enhancements concentrated on the development of a new method for preventing conflicts among the selected fuzzy rules, along with a number of other implemented optimizations deemed necessary to enhance the performance of the overall optimal selection method. The main aim here was to realize a good trade-off between efficiency of the features and their ease of interpretation.

The paper is organized as follows. The fuzzy rule-based classification system (FRBCS) is presented in section 2. Section 3 details the enhanced DE-based method for constructing the fuzzy rules used by the FRBCS. The experimental results and discussions are given in section 4.

2 Fuzzy Rule based Classification System for Alertness detection

Due to its transparent model built on linguistic variables, the fuzzy rule-based classification system (FRBCS) is widely used in classification problems [12, 13]. This property makes it more attractive for problems that require transparent mapping from the input variables to the output classes, such as in the case of medical diagnosis. This property is mostly lacking in many of the widely used classification algorithms. For the particular problem of alertness state detection, there is an extra advantage for using FRBCS. By using fuzzy logic, the effect of inconsistency in labeling data by the participating subjects or the human experts can be accounted for. This is achieved by allowing a certain degree of overlap between adjacent states, as shown in Fig. 1.

FRBCS maps a vector input to a vector output using fuzzy memberships and a predefined set of IF-THEN rules. As shown in Fig. 2 the FRBCS design involves 1) defining the membership functions, 2) estimating their parameters, 3) constructing of the fuzzy rules, and 4) processing the validation data and predicting the output classes. This paper focuses on the construction of rules, as our aim is to identify a limited number of rules with a small number of actions or antecedents to reduce the complexity of the system and obtain easily interpretable rules.

Some of the widely used methods for constructing the rules are based on artificial neural networks [14] and genetic algorithms [15, 16]. Although these methods
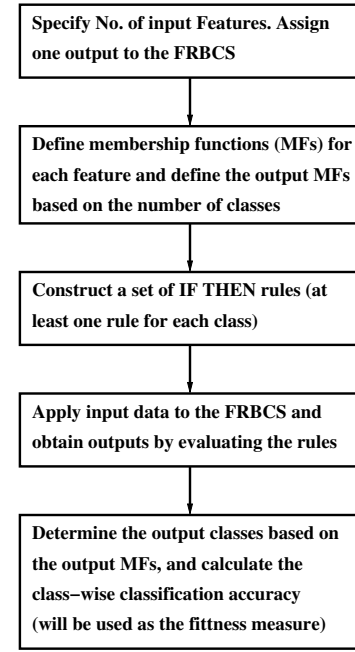
achieved good results in certain applications, we decided to build a new FRBCS for the alertness state classification (referred to as FRBACS) for the following reasons. Firstly, we want to control the construction of the rules by constructing a number of rules equal to NC (number of alertness classes). Secondly, we want to control the rule complexity by constructing simple rules that are easy to interpret. This can be done by favoring rules with fewer antecedent variables through adding a penalty term to the fitness function that is proportional to the antecedent complexity. Thirdly, differential evolution was shown to possess efficient exploration capability in the search space and particularly when applied to feature/variable selection [11, 17].

As shown in Fig. 3, 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. To construct the membership function, four parameters are required. These represent the transition points from 0 to 1 and then from 1 to 0. The fuzzification process is performed according to the following steps:

- Construct a histogram for each of the five features and identify the 6%, 47%, 53%, and 94% quartiles and assign those values to a vector, pp that has four components, $[pp(1), pp(2), pp(3), pp(4)]$

- the components of the "low" membership function are: $[-pp(2), -pp(1), pp(1), pp(2)]$

- the components of the "medium" membership function are: $[pp(1), pp(2), pp(3), pp(4)]$
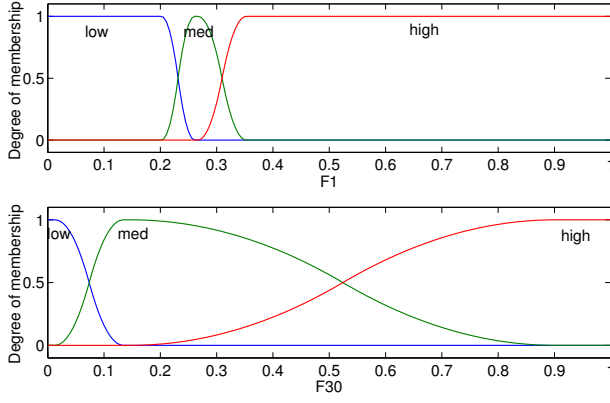
Figure 3. Membership functions of two different features

Figure 4. Wheel representation with the four different feature memberships: None, Low, Med, and High

- the components of the "high" membership function are: $[pp(3), pp(4), 2 - pp(4), 2 - pp(3)]$

Although, based on this procedure, the shape of the membership functions associated with different features may not be similar (see Fig. 3), each of the three membership regions (low, medium and high) will have the same percentage of samples for each of the features. This prevents the three regions, namely low, medium, and high, from being differently represented for the different feature samples.

Using these membership functions, the fuzzy IF-THEN rules take the following format:

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

where MF_{ni} is the membership function associated with the ith feature F_{ni} in rule n, and Cn is one of the four alertness states or classes. In this study, we decided not to assign weights to the rules as we wanted to automatically find the best rules for each class. The next section describes the rule construction process.

3 Construction of Fuzzy Rules using Differential Evolution

3.1 The DE based feature selection algorithm

One of the important components of feature (or variable) selection process is a search strategy to generate candidate feature subsets [18]. Searching for the optimal subset, which can achieve the best performance according to the defined evaluation measure, is a quite challenging task. Among the different existing techniques, stochastic search has attracted a lot of attention. It was found that including some randomness in the search process helps these methods in avoiding local minima [18]. Some of the widely used stochastic methods in feature selection are: simulated annealing genetic algorithm (GA), ant colony optimization (ACO), particle swarm optimization (PSO) and differential
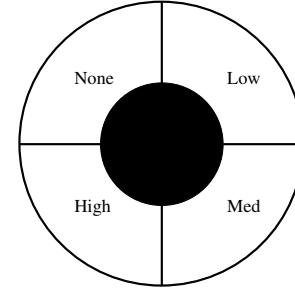
evolution (DE) [11]. We decided to adopt the DEFS (Differential Evolution based Feature Selection) method presented in [11][1] due to its superior performance.

DE is a simple population-based optimizer that encodes all the parameters as floating-point numbers and manipulate them with arithmetic operators. Considering that we have N_P members in the population, the first step in the DE optimization technique is to generate a D-dimensional real-valued parameter vector for each member, where D is the number of parameters that need to be optimized. The objective of the feature selection algorithms is to search for the best M features from the original NF ones, where $M < NF$. To achieve this in DEFS, the NF features are randomly distributed among M wheels, where one feature is selected from each wheel at any given time to form a candidate subset. The obtained subset of each of each population member is evaluated and sorted based on its performance. The differential combination and uniform crossover operators of the DE algorithm are used to produce members of the next generation. After a certain number of iterations, the best K subsets are saved and the features that form them are fixed in their corresponding wheels, while the rest of features are re-shuffled among the wheels and the algorithm starts another round of optimization. This process is repeated until a pre-defined stopping criterion is met. More details can be found in [11].

3.2 The FRBACS algorithm

The DEFS algorithm has to be modified for the purpose of rule construction. As we are dealing with N-channel signals ($N = 10$ in the present case) that are each represented with F features ($F = 5$), then for this particular problem $D = 50$. Unlike DEFS, here each feature has its own wheel, as shown in Fig. 4, where, in the optimization phase, each feature can take any value in the range $[0.5, 4.5)$, thus when rounded, it will take the following values: 1 (low), 2 (medium), 3 (high), or 4 (none).

The fuzzy rule-based alertness classification system (FRBACS), in its first run, constructs four rules (one for each alertness state). Unlike in DEFS, wheels do not need

---

[1]code is available online at: http://services.eng.uts.edu.au/āhmed/

to be re-shuffled here. If, for example, the ith feature of the nth rule, F_{ni}, represents the α rhythm of channel p and the algorithm selects 'medium' to represent it, the antecedent part of that rule will contain the following:

$$if \ldots \text{ and } \alpha_p \textbf{ is med and } \ldots$$

In order to reduce the rule complexity (represented by the number of antecedents), the algorithm favors the selection of the last variable ('none') by assigning it a higher probability than the other three variables.

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 is used as the "fitness function", as in wrapper-based feature selection methods. There is, however, an important issue that needs to be considered when dealing with multi-channel EEG. Due to the nature of the EEG generation mechanism [19], one would expect that the fuzzy rules should be free from conflicts for the case of closely located EEG channels. In other words, any rule consisting of the same feature from neighboring channels should not contain conflicting antecedents. As the original FRBACS is not guaranteed to be free from such conflicts, either within the same rule or between different rules, we proposed to modify the algorithm to overcome this limitation. The modified algorithm is presented in the next section.

3.3 The modified FRBACS algorithm

The modified FRBACS is a bi-level process with a penalty term that is added to the fitness measure. The five EEG rhythms (δ, θ, α, β and γ) extracted from each brain region constitute the first level. The second level contains the EEG rhythms of the individual channels, as shown in Fig. 5 (here a region is formed from five channels). Each of the five rhythms in the first level can take only two values, namely 0 or 1. Selecting 0 for a given rhythm in the first level implies that this rhythm will be absent from all the channels of the region. This will help reduce the number of antecedent variables of the fuzzy rules. However, if value 1 is selected for the given rhythm, the rule will be allowed to be have this rhythm presented in the individual channels of the region. This rhythm can take one of four values: 'low', 'medium', 'high', or 'none'. Based on this process, for a given rhythm, the selection of 1 in the first level does not guarantee that this rhythm will be present in all five channels and, therefore, as precedents in the fuzzy rule. This can happen, for example, when some or all channels are represented by 0 in the second level. In order to avoid conflicts within the same rule, a penalty term is added to the fitness function to prevent neighboring channels having two extreme values, such as 'low' and 'high', for the same rhythm from appearing in the same antecedent.

Due to the randomness component of the DE algorithm, the constructed rules are not guaranteed to be the same each time the algorithm is run, which is the main limitation of this implementation of Fuzzy rule-based classi-

Region A	Delta		Theta		Alpha		Beta		Gamma	
	0	1	0	1	0	1	0	1	0	1

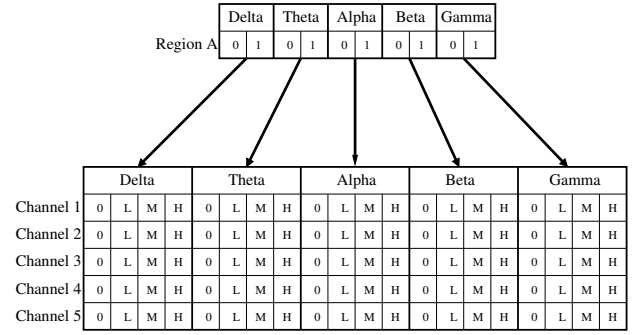|	Delta				Theta				Alpha				Beta				Gamma			
Channel 1	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H
Channel 2	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H
Channel 3	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H
Channel 4	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H
Channel 5	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H	0	L	M	H

Figure 5. Rhythm/channel representation for a given region of five channels

fication. One possible way to resolve this issue is through "re-optimization". We decided to use the existing L set of rules, obtained by running the algorithm L times, as the starting points for L members of the population for the final or "re-optimization" run. For the remaining members of the population, the rules are randomly initialized. The main idea behind re-optimizing the rules is to produce new rules that are obtained by fusing/modifying the already constructed ones.

4 Experimental Analysis and Discussion

4.1 Description of data

Ten adult subjects, with an age range of 24 to 53 years, participated in the experiment. The EEG data was recorded using a 64 channel Neuroscansystem (Compumedics, Abbotsford, Australia) as shown in Fig. 6, with the reference electrode chosen close to Cz (vertex).

Subjects were asked to press one of three buttons every 30 seconds to indicate their perceived level of alertness, i.e, 'engaged', 'calm but not drowsy', and 'drowsy'. Each recording session lasted one hour. The one-hour recording was divided into 6 divisions of 10 minutes each. If the subject did not provide an input for more than 3 minutes, 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 (δ, θ, α, β and γ) were extracted. Each 10 consecutive windows were grouped to form an epoch. For each subject, 75% of the epochs were used for training and the remaining 25% for testing. This procedure was chosen to reduce unrealistically biasing the classifier toward high testing accuracy. Training windows from all 10 subjects were used to train both the linear support vector machine (SVM) classifier, used in channel selection, and our proposed FRBACS in all conducted expreiments.
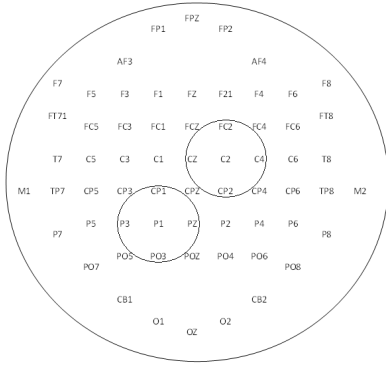
Figure 6. EEG channels used for recording data with two neighborhood examples

4.2 Channel Selection

For the sake of channel selection, we started by evaluating the performance of each of the 64 channels and its neighbors where, as mentioned earlier, each channel is represented using the energy values of the five conventional EEG rhythms. The brain regions are defined by an EEG channel (or electrode) and its circular neighbors. An example of a region represented by the central channel C2 is {C2, FC2, CZ, CP2, C4}. Note that channels located at the edges may have less than four neighbors. The performance of each region was evaluated by feeding their spatio-frequency features (energy of the different rhythm/channel combination) to an SVM classifier. The SVM classifier was chosen due its good performance shown in many classification problems, including EEG. It was also used as benchmark in this study.

The classification result suggests that the best region is {P1, CP1, P3, PO3, PZ}, which produced an average class-wise testing accuracy 60.39%. We have fixed this optimal region, added another region, repeated the classification, and registered the new performance. The best additional channels obtained was C2: FC2, CZ, CP2, C4 which when, combined with the first optimal region, produced an average class-wise classification accuracy of 69.83

The obtained performance using 10 channels is acceptable given the fact that the classifier was trained using data from 10 subjects where, a degree of inconsistency in the labeling has been noticed across subjects, and to some extend within subjects. This inconsistency was reflected in the overlap between classes, such as 'engaged'/'calm' and 'calm'/'drowsy' during classification. We tried adding a third set of channels to the already two selected regions, and found that the best third set is {PO6, P4, PO4, CB2, P08} that, when combined with the previously two optimal regions, produced an accuracy 72.69% (an increase of less than 3%). Because of the increased interpretation complexity of fuzzy rules when using more than 2 sets of channels and limited improvment in performance, we decided to only consider the first two optimal regions.

4.3 Optimization of fuzzy rules

In order to reveal relationships between the spatio-frequency features, represented by the rhythm/channel combination, and each of the alertness states, the process of constructing fuzzy rules (described in the previous section) was applied to the 10 best channels (2 spatial regions) identified in the previous section. We started by constructing four fuzzy rules, one for each alertness state. We run the modified FRBACS algorithm multiple times and recorded the obtained rules. This was performed since there is a certain degree of randomness in the search procedure of the algorithm that causes it to produce different results for different runs. The rules obtained after 15 runs are shown in Table 1. These rules produced a testing set accuracy that ranged from 57.23% to 59.24%. In each of the 15 runs, four rules were constructed (one for each alertness state). The table shows the EEG rhythms for the two brain regions we selected. For example, the third row of the table shows the constructed antecedent part of the rule of the first run, and the consequent of this rule is the 'asleep' state. This particular row indicates that the antecedent of the rule is interpreted as following: For the five channels {P1, CP1, P3, PZ, PO3}, the membership of the θ rhythm for three of them (Channels CP1, P3 and PO3) is high, the membership of the α rhythm for three of them (Channels CP1 and P3) is medium, and the membership of the β rhythm for two of those channels (Channels CP1 and PO3) is medium.

Even though the 15 runs produced rules that are not fully consistent, one can notice some degree of similarity between them in terms of dominant rhythms and their memberships for each alertness state. Based on that we can summarize the table as follows:

Sleep: In the P1 region: θ is high, α is medium and β is medium

Drow: In the C4 region: β is high. In the P1 region: δ is medium, α is medium and β is medium

Calm: No dominant antecedent

Eng: In the C4 region: δ is high and α is medium. In the P1 region: θ is medium and α is med/low

As the rules are not fully consistent and no suitable rule that describes the 'calm' state could be found, we decided to re-optimize the rules by utilizing the already constructed ones from the 15 runs.

4.4 Re-optimization of IF-THEN rules

The re-optimization process is implemented at the second level only. The first level is assigned a constant value that is either 0 (the rhythm has no entries in the corresponding column in Tab 1), or 1. The population size is set to 500, where the first 15 represent the rules of the 15 runs obtained earlier (shown in Table 1). The remaining 485 members of the population were randomly initialized. As before,

Table 1. Constructed rules of the FRBACS over 15 runs

Asleep									
C4 and surrounding channels					P1 and surrounding channels				
δ	θ	α	β	γ	δ	θ	α	β	γ
						hhh	mmm	mm	
							mm	mm	mm
							mm	m	
		l			m		mmm	m	
								mm	
						hhh	mmm		
					m	h	mmm		
						hhh			
					m	hhh	mmm	mm	
			l			hhh		mm	
						hhh	mmm		
						hhh		m	m
								mm	
	m				m	hhh			
	m					hhh			
Drowsy									
m			h				mmm	mm	
					m		mm	mm	
		hh					mmm	mm	
					m		mmmm		m
			h		mm				
m			h				mmm		
							mmmm	mm	
			h		m		mmm	mm	
			h		m		mmm		
			h		m		mmm		
			h				mmmm		
			h				mm		
		hh			mmm				
			h		m		mmm		
			h		m	mm			
Calm									
mmm	mm				hm			mmm	
					hmh	mmm			
		mh					mm		
							ll	lll	
			mhm		m				
hhmm					mh		llml	lll	
							mll	l	
					lm		mh	mm	
hmm					mll				
mmml		hhm	h						
	mmmm						hm		
							mm	hh	hm
			mm				lll		
mmh									hmh
								mhmm	mmh
Engaged									
	m		m			m	lmm		
			m			m	m		mm
						mm	mm		m
			m				l		
			m			m			
h			m			mm	mm		
			m			m	l		
	m					mlmm	m		
	mm					m	lmm		
h			m			m	m		
						m	mlm		
h								mm	
						mm		mm	
h			m			m			
			m			ml			

Table 2. Best rule for each class after re-optimization

Asleep									
C4 and surrounding channels					P1 and surrounding channels				
δ	θ	α	β	γ	δ	θ	α	β	γ
						hhh	mm		
Drowsy									
			h				mmm	mm	
Calm									
			lm				mhh		
Engaged									
h		m				m		mm	

Table 3. Confusion matrix of the FRBACS (T: True, P: Predicted)

P \ T	Asleep	Drowsy	Calm	Engaged
Asleep	0.91	0.10	0.09	0.03
Drowsy	0.02	0.49	0.19	0.12
Calm	0.07	0.37	0.60	0.42
Engaged	0.00	0.04	0.12	0.43

'engaged' states. In addition, the algorithm identified a rule for the 'calm' state that did not have a dominant antecedent in the previously constructed 15 rules. One can also notice from the obtained rules that all five EEG rhythms are utilized in identifying the different alertness states.

The confusion matrix obtained using the optimized modified-FRBACS, shown in Table 3, indicates that the classifier tends to achieve better discrimination rates when the true states are farther away from each other. For example, when the true state is 'engaged' (column 5), the misclassification rate between this state and the 'asleep' state is almost zero. A slightly higher misclassification rate can be seen in the case of the 'drowsy' state. The lowest discrimination rate was achieved for the case of the 'calm' state; which is the closest to the 'engaged' state. The table also indicates that the highest misclassification rates were achieved between 'engaged' and 'calm', and between 'calm' and 'drowsy'. Since the 'calm' state appeared to be confused with the 'engaged' and 'drowsy' states, we decided to investigate the effects of eliminating this state on the performance of the classification. This three-state classification problem is similar to a number of methods proposed in the literature such as [4].

4.5 Classification of three alertness states

We removed all samples that were labelled 'calm' and started the optimization of the remaining three states from the rules that were obtained in section 4.4. Those three initial rules (one rule per state) were found to produce an average class-wise classification accuracy of 73.27%. After optimization, the average class-wise classification accuracy of the testing set jumped to 78.16%, which is approximately 5% more than the initial accuracy and about 17% more than the four classes accuracy. Despite the fact that the SVM

a penalty term is used to prevent rules from having conflicting antecedents and to favor the construction of simple rules. The new optimized rules, shown in Table 2, resulted in an average class-wise testing accuracy of 60.87%. These results show that the rules are not too different from the ones concluded from Table 1 for the 'asleep', 'drowsy' and

Table 4. Best set of three rules without the 'calm' state

Asleep									
C4 and surrounding channels					P1 and surrounding channels				
δ	θ	α	β	γ	δ	θ	α	β	γ
						hm			m
Drowsy									
			h				mm	mm	
Engaged									
					m	m		m	m

Table 5. Confusion matrix of the FRBACS when considering three alertness states (T: True, P: Predicted)

P \ T	Asleep	Drowsy	Engaged
Asleep	0.92	0.05	0.01
Drowsy	0.07	0.75	0.31
Engaged	0.01	0.20	0.68

classifier achieved a higher accuracy (83.86%), the proposed FRBACS has a clear advantage over it, as it classified the data based on the three simple rules shown in Table 4. When compared with Table 2, one can notice a change in the rule associated with the 'asleep' sate, a minimal change to the 'drowsy' rule, while the 'engaged' rule was clearly affected by the deletion of the 'calm' state. The confusion matrix obtained using the new set of three rules, shown in Table 5, indicate there is less overlap between states when compared to the confusion matrix of four states.

Table 4 also indicates that the P1 region played a more important role than the C4 region. This is supported by the higher accuracy achieved by P1 region using the SVM classifier (section 4.2). The obtained results are expected to be further improved with the addition of a new set of rules and optimizing the membership parameters.

5   Conclusion

We presented in this paper a fuzzy rule-based alertness classification system (FRBACS) that utilized differential evolution in constructing the rules. We have shown that the FRBACS is capable of achieving good results. Due to inconsistency in labelling among the 10 subjects, that we collected the data from, we decided to investigate the effect of removing the 'calm' state, that seemed to confuse both the subjects and the classifier due to its closeness to the the 'engaged' and 'drowsy' states. This led to a noticeable improvement in classification performance. Future efforts will be geared toward enhancing the performance of the proposed method, by optimizing the different steps of the classification process, while maintaining the ease of interpret ability of the different fuzzy rules.

References

[1] D.L. Fisher, M. Rizzo, J.K. Caird, and J.D. Lee, Editors, *Driving Simulation for Engineering, Medicine, and Psychology*, CRC Press, Boca Raton, FL, 2011.

[2] A. Varri, K. Hirvonen, J. Hasan, P. Loula, and V. Haikkinen. A computerized analysis system for vigilance studies. *Computer Methods and Programs in Biomedicine*, 39, 1992, 113-124.

[3] M. Nakamura, T. Sugi, A. Ikeda, R. Kakigi, and H. Shibasaki. Clinical application of automatic integrative interpretation of awake background. EEG: quantitative interpretation, report making, and detection of artifacts and reduced vigilance level. *Electroencephalography and clinical Neurophysiology*, 98, 1996, 103-112.

[4] M.K. Kiymik, M. Akin, and A. Subasi. Automatic recognition of alertness level by using wavelet transform and artificial neural network. *Journal of Neuroscience Methods*, 139, 2004, 231-240.

[5] M.B. Kurt, N. Sezgin, M. Akin, G. Kirbas, and M. Bayram.The ANN-based computing of drowsy level. *Expert Systems with Applications*, 36, 2009, 2534-2542.

[6] M.V.M. Yeo, X. Li, K. Shen, and E.P.V. Wilder-Smith. Can SVM be used for automatic EEG detection of drowsiness during car driving? *Safety Science*, 47, 2009, 115-124.

[7] E. Vural, M. etin, A. Eril, G. Littlewort, M. Bartlett and J. Movellan, Drowsy driver detection through facial movement analysis. *Proceedings of the 2007 IEEE International Workshop on Human-computer Interaction*, Rio de Janeiro, Brazil, 2007.

[8] K.-A. Hwang and C.-H.Yang, Attentiveness assessment in learning based on fuzzy logic analysis.*Expert Systems with Applications*, 36, 2009, 6261-6265.

[9] A. Al-Ani, B. Van Dun, H. Dillon, A, Rabie, Analysis of Alertness Status of Subjects Undergoing The Cortical Auditory Evoked Potential Hearing Test, *International Conference on Neural Information Processing, ICONIP 2012*, 2012, 92-99.

[10] A. Al-Ani, M. Mesbah, B. Van Dun, and H. Dillon, Fuzzy Logic-Based Automatic Alertness State Classification Using Multi-channel EEG Data, *International Conference on Neural Information Processing, ICONIP 2013* 2013, 176-183.

[11] A. Al-Ani, A. Alsukker and R.N. Khushaba, Feature subset selection using differential evolution and a wheel based search strategy, *Swarm and Evolutionary Computation*, 9, 2013, 15-26.

[12] E. Avci, D. Avci, The speaker identification by using genetic wavelet adaptive network based fuzzy inference system. *Expert Systems with Applications*, 36(6), 2009, 9928-9940.

[13] H. Yan, Z. Zou, and H. Wang, Adaptive neuro fuzzy inference system for classification of water quality status, *Journal of Environmental Sciences*, 22(12), 2010, 1891-1896.

[14] H. Iyatomi and M. Hagiwara, Adaptive fuzzy inference neural network, *Pattern Recognition*, 37, 2004, 2049-2057.

[15] A. Gonzlez and R. Prez, SLAVE: a genetic learning system based on an iterative approach, *IEEE Transactions on Fuzzy Systems*, 7, 1999, 176-191.

[16] H. Ishibuchi, T. Yamamoto and T. Nakashima, *IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics*, 35(2), 2005, 359-365.

[17] K.V. Price, R.M. Storn, J.A. Lampinen, *Differential Evolution: A Practical Approach to Global Optimization*, Springer, 2005.

[18] I. Guyon, S. Gunn, M. Nikravesh and L.A. Zadeh *Feature Extraction: Foundations and Applications*, Springer-Verlag New York, 2006.

[19] F.H.L. Da Silva and A. Van Rotterdam, Biophysical Aspects of EEG and Magnetoencephalogram Generation, in D.L. Schomer and F.H.L. Da Silva, Eds., *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, 6th Edition, Lippincott Williams & Wilkins 2011