# Analysis of Alertness Status of Subjects Undergoing the Cortical Auditory Evoked Potential Hearing Test

Ahmed Al-Ani[1], Bram Van Dun[2], Harvey Dillon[2], and Alaleh Rabie[1]

[1] Faculty of Engineering and Information Technology, University of Technology, Sydney, Ultimo NSW 2007 Australia
[2] National Acoustic Laboratories, Chatswood, Sydney NSW 2067 Australia
{ahmed,Alaleh.Rabie}@eng.uts.edu.au,
{Bram.VanDun,Harvey.Dillon}@nal.gov.au

**Abstract.** In this paper, we analyze the EEG rhythms of subjects undergoing the cortical auditory evoked potential (CAEP) hearing test. Investigation of the importance of the different EEG rhythms in terms of their capability in differentiating between the different alertness states when considering 64 channel EEG montage is conducted. This is followed by considering subsets that contain 2, 3, 4 as well as all 5 EEG rhythms. Finally, a feature subset selection method based on differential evolution (DE) that has particularly been proposed to deal with multi-channel signals is used to search for the best subset of EEG rhythms for the various channels.

**Keywords:** Alertness state,CAEP hearing test,Feature selection.

## 1 Introduction

Cortical auditory evoked potentials (CAEPs) are brain responses that are evoked by sound and processed in or near the auditory cortex. Brain responses are time locked to some specified event, which can be an auditory tone, a change in a train of stimuli (such as a series of 1000 Hz tones changing to 2000 Hz tones), a missing stimulus (such as a tone omitted from a sequence of tones), or a stimulus that has been designated as a ”target” stimulus [1]. Auditory evoked potentials reflect activation of the auditory pathways from the cochlea to the cortex, and hence can provide objective information on the functioning of the auditory pathways. Accordingly, the CAEP responses have become an important measurement in the estimation of hearing sensitivity in both children and adults [1]. In order to record the electrical activities that occur as a result of auditory evoked potentials, a number of electrodes that are placed on the scalp are used. Because of the high level of background noise in comparison to the amplitude of evoked potentials, many sweeps are usually recorded (between 60 and 100), which would then be averaged to better visualize the evoked potential patterns, as desired positive and negative peaks are expected to be replicable

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[1]. However, subject drowsiness affects CAEP responses [2]. Hence, in order to interpret CAEPs properly, one needs to have a good idea about the alertness state a subject is in.

The traditional way for the detection of alertness state is by monitoring the subject's face. However, this approach is not very reliable as it is affected by a number of factors, which include differences between subjects, such as age and shape of eyes. Assessors' understandings of the different alertness states, which can be different from one assessor to another, also have an impact, and hence the process may require training and standardization. In addition, this can be a tedious task that would require full attention from the assessor.

The automatic detection approach seems more practical. The different alertness detection methods that have been proposed in the literature vary in their robustness and accuracy. Most of these methods either utilize video recording or biomedical signals, such as EEG, EMG and EOG. The latter approach has attracted more attention from researchers with special focus on the five EEG rhythms; namely $\delta$ (up to 4 Hz), $\theta$ (4 - 8 Hz), $\alpha$ (8 - 13 Hz), $\beta$ (13 - 30 Hz), and $\gamma$ (30 - 100 Hz).

In [3], a combination of EEG, EMG and EOG channels was used. $\alpha$ and $\theta$ activities were extracted from the EEG channels, level of muscle activities was extracted from the EMG channel, while the EOG channel was used to extract eye movement and blinking. A rule-based analysis was then utilized to detect the alertness state. Reduced vigilance level was defined in [4] to be characterized 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 $\alpha$ band) and with the maximum amplitude at the occipital or parieto-occipital region of the head; (ii) increase in slow wave components. A number of equations based on EEG rhythms were proposed to address these points. In [5] an artificial neural network (ANN) with two discrete outputs: drowsy and alert, was constructed. Time series of interhemispheric and intrahemispheric cross spectral densities of full spectrum EEG were used as input to the ANN. Similarly, the method proposed in [6] is also based on ANN. However, power spectral density (PSD) of discrete wavelet transform (DWT) of the full spectrum EEG was used as input to the network input, which has three discrete outputs: alert, drowsy and sleep. A similar approach was proposed in [7], but instead of only using EEG channels, they also used EMG and EOG channels. The drowsiness detection method proposed in [8] is based on the analysis of EEG to detect bursts of $\alpha$ activity (using linear coherence measure and cross approximate entropy between EEG channel pairs) and analysis of EOG to detect eye blinks. In [9], a support vector machine (SVM) was utilized to classify EEG data into two distinct states; alert and drowsy. It was stated that $\beta$ activity dominates the alert state, while the drowsy state is evidenced by $\alpha$ dropouts. Hence, power spectral density (and a number of related features) of the the first four EEG rhythms were used as input features to the classifier. An SVM classifier was also used in [10] to detect drowsiness level. The Karolinska drowsiness score (KDS) was used as a reference. The SVM was trained with the 11 eyelid related features extracted from EOG with three different drowsiness levels. Apart from

EEG and EOG data, [11] have used heart rate variability to detect the drowsiness level using artificial neural networks.

Despite the useful findings of the above methods, the importance not only of individual rhythms and channels but also their combination is still to be investigated. In this paper, we will evaluate the potential of rhythm/channel combinations in predicting alertness states using a linear support vector machine (SVM) classifier. The subject's indication of his/her current state is used to train the SVM classifier and validate the predicted results. Moreover, we present a novel feature selection algorithm that enables the search for optimal rhythm/channel combination based on a differential evolution (DE) optimization algorithm. In addition, because there is a largely unknown effect of CAEPs on EEG rhythms (for example [12,13]), we cannot assume there is no difference between the classification of EEG with and without CAEPs. Due to the importance of analyzing CAEP responses during different alertness states, we decided to use EEG data containing CAEPs.

The paper is organized as follows: the feature selection algorithm is described in section 2. Section 3 presents the proposed study, while the conclusion is given in section 4.

## 2 Multi-channel Feature Subset Selection

The objective of multi-channel EEG feature selection is to search for the optimal feature representation for each channel, such that the classification accuracy of the identified feature subset (formed by concatenating the selected features of all channels) is maximized. We propose to encode all possible feature subset combinations using gray code. Hence, for the 5 rhythms, 5 binary bits are used in the following order: $00000, 00001, 00011, 00010, 00110, \ldots, 10001, 10000$, where for each of the five rhythms '1'('0') represents the inclusion (exclusion) of the feature. For instance, if for channel $j$ the binary code chosen by the algorithm is 10101, this means that channel $j$ is represented by a subset of 3 features ($\delta, \alpha$ and $\gamma$). The particular code 00000 indicates that channel $j$ is not used. A circular representation of the code is adopted, i.e., 00000 comes after 10000.

Differential evolution (DE) has started to attract increased attention and has been applied to a wide range of optimization problems due to its simplicity and convergence capabilities [14]. The differential evolution based feature selection algorithm is implemented using a population-based approach, where current members of the population are used to generate the next generation using the two DE operators of differential combination and uniform crossover. The algorithm is implemented as follows:

1. for each of the $P$ members of the population, randomly generate a real value vector, $\mathbf{x}_i$, of length $N_{Ch}$, where $N_{Ch}$ is the number of channels. The values of the vector have to be in the range $[0.5, N_{Fc} + 0.5)$, where $N_{Fc}$ represents the number of feature combinations in each channel ($32 = 2^5$ for the 5 EEG rhythms). Thus, when the numbers are rounded they are bounded by the list boundaries, i.e., 1 and 32.

2. produce the corresponding subset for each member of the population from the rounded numbers then evaluate the subset.
3. find the $k$ best subsets.
4. for each member of the population $i$
   – for each channel, $j$, determine whether to perform uniform crossover or differential combination by evaluating the following formula: $rand(0,1) \leq CO$, where $CO$ is crossover probability
   – to implement differential combination, choose two members of the population, other than $i$. The first member is randomly chosen from the $k$ best members, while the other is randomly chosen from the rest of the population. Let's refer to those two members as $m$ and $n$. Calculate a new value for this vector element according to the equation

$$x_{j,i}^{new} = x_{j,i} + F \times (x_{j,m} - x_{j,n}) \tag{1}$$

   where $F \in (0,1)$ is a scale factor that controls the rate at which the population evolves.
   – otherwise, to perform uniform crossover, assign $x_{j,i}^{new} = x_{j,l}$, where $l$ is a randomly chosen member of the best $k$ subsets identified in step 3 (selected using a roulette wheel approach).
   – check the boundaries as follows:

$$x_{j,i}^{new} = \begin{cases} x_{j,i}^{new} - N_{Fc} & \text{if} \quad x_{j,i}^{new} > N_{Fc} + 0.5 \\ x_{j,i}^{new} + N_{Fc} & \text{if} \quad x_{j,i}^{new} < 0.5 \end{cases} \tag{2}$$

   – identify the features of the newly generated subset, then evaluate the subset.
   – if the newly generated subset achieved a lower fitness than the old one, then assign $\mathbf{x}_i = \mathbf{x}_i^{new}$, otherwise keep $\mathbf{x}_i$ unchanged.
5. goto step 3 until the stopping criterion is met.

The use of both uniform crossover and differential combination operators enhances the search through proper exploration and exploitation of the search space. The rationale behind using a gray-scale binary representation is to only allow the inclusion or removal of one rhythm between any two successive binary values, and hence makes the transition smoother than that when using the normal binary representation.

## 3 Experiments and Analysis of Results

Ten normal hearing adult subjects participated with an age range between 24 to 53 years. A pure-tone audiometric test was performed to verify the normality of their auditory system ($\leq$ 20 dB hearing loss). A 21 ms /g/ speech sound stimulus was presented every 1175 ms at 55 dB sound pressure level. Data was then 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. If no button was pressed for more than two minutes, the subject was considered to be fallen asleep. In addition, a video camera was used to provide evidence of sleep onset. Each recording session lasted one hour, divided into 6 sessions of 10 minutes each.

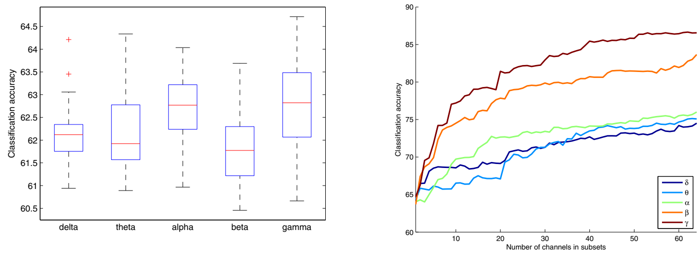
The recorded signal has been divided into windows of 5 seconds with overlap of 3 seconds. Each window is represented by the energy value of each of the five EEG rhythms, i.e., five features/window. A linear support vector machine (SVM) classifier has been used to evaluate the performance of these features in each subject, where windows have been split into two groups, namely training and validation given that each alertness state is well represented in each group.

We have started by evaluating the performance of the five EEG rhythms for each of the channels. Classification accuracies of the validation set averaged across the 10 subjects indicate that none of the five rhythms was able to produce convincing results when relying on one rhythm only. All classifications accuracies lie between 61 and 64 %, as shown in Fig. 1(a).

The performance of combined channels were then evaluated for each rhythm, where subsets of channels were formed by concatenating channels starting from the best one and ending with the channel that achieved the lowest accuracy to form subsets of sizes that range between 1 and 64. The obtained results are shown in Fig. 1(b). The figure indicates that there is a noticeable difference in the performance of the five rhythms, with $\gamma$ achieving the best results followed by $\beta$, $\alpha$, $\theta$ and finally $\delta$. This pattern is nicely sorted according to frequency content, with the best classification accuracy for the highest frequency band. The three slowest brain oscillations, on the other hand, do not really diversify between awake and drowsy states. $\delta$ is generally only present in deep sleep. $\theta$ is not prominently present in adults. $\alpha$ reduces with open eyes, when drowsy or asleep. On the other hand, $\beta$ and $\gamma$ both involve active concentration and consciousness, hence there is a significant discrimination possible between awake ($\beta$ and $\gamma$ present) and drowsy ($\beta$ and $\gamma$ generally not present) [15].

These results also might suggest that CAEP presence does not have much effect on classification. CAEPs are composed of lower frequencies (3 to 15 Hz), corresponding to $\alpha$ and $\theta$ regions, which are oscillations not contributing much to classification accuracy (Fig. 1(b)). However, as CAEPs also can evoke $\gamma$-bursts [12,13], it is possible their presence still have an effect, all be it at higher frequencies.

It is well-known that ranking of features (or channels) does not guarantee that the best $k$ individual features would form the best subset of size $k$. Accordingly, we implemented a sequential forward search (SFS) strategy that starts with the best channel then adds another channel to form a subset of two channels by examining all remaining 63 channels with the already selected one. This process is repeated until all 64 channels are selected. When comparing both strategies (ranking of features versus SFS), the latter is found to form subsets of more scattered channels. This indicates that complementary channels are not usually located next to each other.

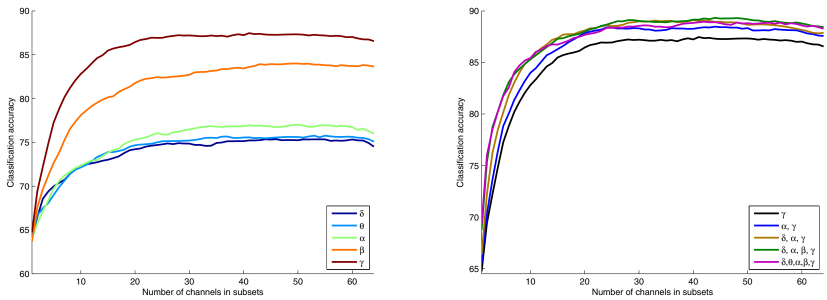



(a) (b)

**Fig. 1.** Classification accuracy of the five EEG rhythms (a) across all channels, and (b) considering incremental subsets formed by ranking the 64 channels for each rhythm

The performance of channel subsets formed using a sequential forward search for the five rhythms, shown in Fig. 2(a), indicates noticeably faster convergence than the ranking approach. In fact, for all rhythms near best solution was found using approximately half of the total number of channels.

Combined rhythms have then been examined, where each channel is represented by two rhythms. All possible ten combinations have been evaluated, and the two combinations that produced the best performance were: $\{\theta, \gamma\}$ and $\{\alpha, \gamma\}$. The same procedure was followed to evaluate combinations of three rhythms and four rhythms. For the case of three rhythms, the best two combinations were: $\{\delta, \alpha, \gamma\}$ and $\{\delta, \beta, \gamma\}$, while $\{\delta, \alpha, \beta, \gamma\}$ produced the best results when considering four rhythms. Fig. 2(b) shows the performance when considering best subsets formed using 1, 2, 3, 4 and all 5 rhythms. Results indicate that differences in performance between combinations of 3, 4 and 5 rhythms are minimal with combination of 4 rhythms achieving slightly better performance than the rest of combinations.




(a) (b)

**Fig. 2.** Classification accuracy of the five EEG rhythms considering incremental subsets formed using (a) SFS of one rhythm, and (b) SFS of combined rhythms

The proposed feature selection algorithm described in section 2 has then been applied to search for best feature subsets in each channel. The population size $P$

was set to 30 and reaching a pre-defined maximum number of iterations, which was set to 350, was used as the stopping criterion. A crossover probability was fixed to $CO = 0.5$. A value of $k = \text{round}(P/10) = 3$ was used here.

**Table 1.** Best achieved accuracy of the three selection approaches

| Method | 1F | 2F | 3F | 4F | 5F |
|---|---|---|---|---|---|
| Ranking | 86.65 | 88.02 | 88.31 | 88.59 | 88.28 |
| SFS | 87.47 | 88.60 | 89.11 | 89.33 | 88.95 |
| DEFS | 89.42 | 90.61 | 91.23 | 91.31 | 91.31 |

Table 1 shows the best performance achieved by the three selection methods. Unlike the ranking and sequential feature selection approaches, the proposed feature selection method is more flexible in representing channels, where not all channels have to be represented by the same rhythms. For example, with the selection of one feature per channel, the proposed method allows any of the five rhythms to be selected by a specific channel. It also allows channels not to be represented by any of the five rhythms. Similarly, when considering two features per channel, the method allows each channel to be represented by any two rhythms, one rhythm only or none of the five rhythms. The selected rhythm combinations confirmed the findings of the ranking and SFS approaches, where $\gamma$ and to a slightly less degree $\beta$, i.e., the high frequency rhythms, appeared to be more useful in discriminating between alertness states than the low frequency ones. Moreover, the algorithm selected a reasonable number of channels that were not concentrated in a particular region to achieve the highest accuracy. The improved performance of DEFS indicates that combinations of channels and rhythms (mainly containing $\gamma$ and $\beta$ as a common factor for any subset size between 1 and 5) can produce better performance than fixing each one of those. It is important to mention that the DEFS method is computationally more expensive than the ranking and SFS approaches, however, the objective here is to analyze the best subset of features for the classification problem at hand.

## 4 Conclusion

This paper investigated the EEG rhythms of subjects undergoing the cortical auditory evoked potential (CAEP) hearing test. It was shown that higher frequency EEG rhythms ($\gamma$, $\beta$) are better classifiers for the subject's alertness state than $\alpha$, $\theta$, and $\delta$ (lower frequency EEG rhythms). This can be explained physiologically, as higher frequency oscillations are associated more with active concentration and consciousness, which allows a clear discrimination between awake and drowsy states. Optimal combinations of different EEG rhythms have been described. The proposed differential evolution feature selection algorithm proved to produce better results than the ranking and sequential forward selection approaches. Obtained results suggest that best subsets are formed using combinations of channels and features that are influenced by high frequency rhythms.

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