Individual Alpha Peak Frequency Based Features For Subject Dependent EEG Workload Classification

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Abstract— **The individual alpha peak frequency (IAPF) is an important biological indicator in Electroencephalogram (EEG) studies, with many research publications linking it to various cognitive functions. In this paper, we propose novel Power Spectral Density (PSD) alpha features based on IAPF to classify 2 and 4 levels of EEG multitasking workload data. When optimized IAPF was considered, a 1.55% and 1.56% increase in average accuracy for 48 subjects' data, with 35 and 33 subjects showing improvement was observed for 2 and 4 class cases respectively. This trend suggests that individual specific features are able to improve classification performance compared to generalized features for subject dependent cases. The proposed features, which incorporates the biological meaning of the IAPF and provides subject specific information, can be considered as a viable alternative to the general alpha power feature when designing novel subject dependent feature sets for BCI workload recognition applications.**

I. INTRODUCTION

When analyzing EEG data, arguably the most well studied feature is the EEG alpha frequency (8-12Hz). The EEG alpha is proven through comprehensive research to be associated with cognitive performance and is a hallmark feature in EEG analysis. Recently, the usage of EEG is seeing a gradual shift from traditional medical applications such as detection of seizures and neurofeedback treatment to a plethora of non-medical applications ranging from BCI applications, training of cognitive abilities and gaming. Many new features that aim to improve classification accuracy have been developed to fulfil the needs of these new applications. However, the biological significance of the EEG power bands, especially the EEG alpha, remains important which is why studies usually consider them in their research as a benchmark feature.

Given the meaningful nature of the EEG alpha, there is motivation to develop new features based on the existing alpha feature for classification purposes. Therefore, in our study, we shall propose a new feature based on the individual alpha peak to classify an individual's EEG data, whist retaining the biological significance of the alpha feature.

The organization of the paper follows: First, a review of EEG alpha features and mental workload will be provided. Next, a description of our conducted experiment and data processing is given. A discussion of the experimental results and conclusion concludes the paper.

II. RELATED WORK

A. EEG Alpha Features

The general definition for the range of the EEG alpha band is 8-12 Hz. However, this band can be further split into two, namely the lower alpha (8-10Hz) and upper alpha (10-12Hz) bands. This splitting of the alpha band is performed as it is thought that these alpha bands, especially the upper alpha band, have correlations with human cognitive performances. For example in [1], it shows that the upper alpha band correlates significantly with semantic memory performances. In [2, 3], it was found that neurofeedback training of the upper alpha band resulted in improved performance during a mental rotation cognitive test.

The individual alpha peak frequency (IAPF) is also an important characteristic of the EEG alpha band and is defined to be the frequency at which the maximum power magnitude of the alpha band is found under eyes close condition. The IAPF can be used to split the alpha band into upper and lower alpha bands as shown in Figure 1. Similar with the upper alpha band, IAPF has also been found to be associated with human cognition. For example, [4] shows a relationship between having a high IAPF and performance in a memory test, while research in [5] shows how IAPF is related to cognitive preparedness. A study in [6] found that the IAPF is significantly correlated with the general latent factor of intelligence. Similar to upper alpha band, IAPF can also be trained with neurofeedback techniques. [7] proposed a neurofeedback protocol for the training of IAPF to enhance cognitive abilities in the elderly.

Given how significant the alpha band and the IAPF is to EEG studies, it is desirable to develop novel EEG alpha power features that are able to encapsulate the biological relationships of previous studies on the alpha band and also provide improved performance in classification tasks.

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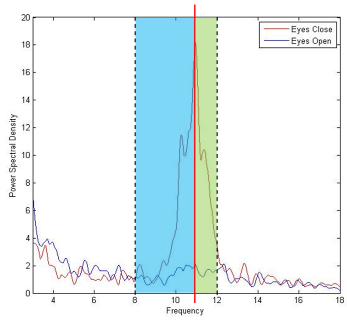

Figure 1. Individual Alpha Peak Frequency (red line) and corresponding lower alpha (blue) and upper alpha (green) bands along the defined 8-12 Hz of the general alpha band

B. EEG Mental Workload

Mental workload is loosely defined as the amount of mental effort a person requires when performing any task. The study of mental workload is gaining increased traction in the BCI community recently as there is a requirement that systems are to be able to monitor the user's mental fatigue whilst they are performing tasks. This is crucial for maintaining operator safety.

An EEG device is often used to measure mental workload and many studies on EEG features and classification for mental workload levels have been performed [8-11]. These studies often aim to induce different levels of mental workload through one of two methods: Arithmetic problems with varying levels of difficulty, or through a task battery type program where subjects are to attend to any number of tasks at one time. This second activity is commonly applied as a form of multitasking, with additional tasks to be performed in the task battery associated with a higher level of mental workload required. Some examples include the Multi Attribute Task Battery (MATB) from NASA [12] and the Simultaneous Capacity (SIMKAP) test developed by Schuhfried GmbH [13].

EEG classification can be either subject dependent or subject independent. Most EEG studies in workload classification consider the subject dependent case for application purposes as tailoring the classifier for subject specific classification often produces better results. In our study, as we intend to use the IAPF as a feature, we consider the subject dependent case only.

Besides power features, many other features derived from the EEG are able to classify mental workload levels with good performance. Features such as statistical, entropy and Higuchi Fractal Dimension features are often used in other studies [14-17]. In our study, we are interested in using the IAPF to propose novel alpha lower and alpha upper band features. We hypothesize that due to its subject specific nature, it should perform better than general alpha features for subject dependent classification.

In previous studies, when power features are considered, usually only the standard alpha band is considered as a feature. In this paper, we aim to propose a new alpha power feature that uses the abovementioned alpha bands as features, at the same time incorporating IAPF information by performing the splitting of the upper/lower bands at the IAPF. We hypothesize that these upper and lower alpha band features, separated based on the IAPF, should perform better than the general alpha band feature due to the added biological significance provided by the IAPF and splitting of the band as reviewed.

III. Method

A. SIMKAP Experiment

The experiment involved 48 post graduate students from the university. First, 1 minute each of open eyes and closed eyes EEG data was recorded with the purpose for calculation of the IAPF. This was followed by 3 minutes of EEG recording where the participant does not perform any task and serves as the first level of mental workload. Then, the SIMKAP test is administered, a screenshot of which can be viewed in Figure 2. The test involves a set of two baseline tasks with 3 minutes each followed by an 18 minute multitasking task. In the first baseline task, subjects are to perform item matching by marking out objects on the same row of the right panel based on those already marked out on the left panel. In the second baseline task, subjects are to respond to auditory questions by marking the appropriate answer on the screen. The questions include arithmetic problems, comparison questions and to identify similar objects from a set. The 3 minute EEG recordings from these baseline tasks form the subsequent 2 levels of mental workload.

In the multitasking condition, subjects are to perform the baseline tasks described above simultaneously. Additionally, subjects are also required to respond to auditory questions that require consultation of a virtual calendar and telephone book for the correct answer. Also, some auditory questions are now only to be answered at a specified time thus requiring subjects to monitor the timer on the top right of the screen as an additional task. The EEG recording for the final 3 minutes of this multitasking condition is used as the last level of mental workload data.

EEG signals are obtained with the Emotiv EPOC device, which has 14 electrodes at positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, according to the 10-20 international system and a sampling frequency of 128Hz with 16 bit A/D resolution. The device uses Bluetooth to transmit signals to a desktop computer and recording of data is performed using the Emotiv TestBench software.

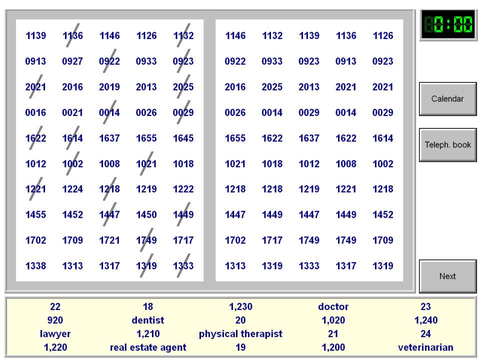

Figure 2. Screenshot from the SIMKAP multitasking test. Participants are to cross out items of each row on the right panel based on items already marked out on the same row of the left panel. At the same time, responses to auditory questions are to be made by selecting the appropriate answer from the bottom panel.

B. *Calculation of Individual Alpha Peak Frequency*

Individual alpha peak is the frequency at which the power spectral density of the alpha band is at its highest. For each subject, we utilized three methods to derive IAPF.

The first method (IAPF01), involves deriving the IAPF from all 14 channels of the recorded closed eyes EEG by peak frequency detection of the Fourier transform, and then taking the average of the 14 IAPF values.

In the second method (IAPF02), we follow the process proposed in [6], utilizing the average spectrum of the 4 parietal and occipital channels of the 1 minute eyes closed recording. Fourier transform is first performed on the EEG signals from the respective channels and the average spectrum is found. The maximum amplitude of the spectrum and its corresponding frequency, which is the IAPF, are located along the alpha band of 8-12 Hz.

Given the significance of the IAPF from review, we further hypothesize that, for each subject, there should exist an IAPF at which classification of mental workload EEG data is optimal. In order to test this hypothesis, we propose a third method (IAPF03) where we systematically test the individual values of IAPF from 9-11Hz for the best classification accuracy using a step size 0.25Hz. Feature extraction and classification is performed for each value of IAPF as detailed below.

C. *EEG Data Processing*

A 2-42Hz FIR band pass filter was used to perform artifact removal on the raw EEG signal. Then, the requisite 3 minutes duration of EEG data for each of the 4 designated mental workload levels were extracted from the continuous EEG signal. To reduce unwanted effects from pre- and post- task activity, the first and last 15 seconds of EEG data was excluded from each of the 3 minutes data. Each segment was then further divided into 5 portions of 30 seconds for the 5 fold cross validation process.

General α band (8-12 Hz) power feature is extracted with Fourier Transform for all 14 channels. For extraction of upper and lower alpha power features with inclusion of IAPF information, splitting of the α band is performed as upper α (x-12Hz) and lower α (8-xHz), where x is the value of the IAPF for the particular subject. Fourier transform is then performed to extract the features for the newly defined upper and lower alpha bands based on IAPF.

5 fold cross validation for both 2 and 4 levels of mental workload classification was performed using SVM classifier with the following parameters: Polynomial kernel, value of *gamma* set to 1, *coef* set to 1 and order d set to 5.

IV. RESULTS

This study seeks to compare the usage of 3 different methods for IAPF based separation of the alpha band into novel upper and lower alpha features with the original alpha power features for 48 subjects. Cases for 2 and 4 levels of mental workload from the SIMKAP multitasking experiment was considered.

For the 2 class case, the general alpha feature gave a classification accuracy of 90.88% with standard deviation of 14.70. Using average IAPF of all 14 channels in the IAFP01 method gave a classification accuracy of 90.46%. Using IAPF from the average spectrum of the parietal and occipital channels in method IAPF02 produced 90.90% classification accuracy. IAPF03, which used the best classification accuracy obtained for each subject across the 9-11Hz range of IAPF values, showed an average classification accuracy of 92.44%.

In the 4 class case, the general alpha feature gave an average classification accuracy of 63.64%. IAPF01 produced a classification accuracy of 62.39%, IAPF02 reported a classification accuracy of 62.38% and IAPF03 showed a classification accuracy of 65.19%. The classification accuracy for both 2 and 4 classes can be viewed in Table 1 with the reported standard deviation in parenthesis.

The number of subjects with improvement in classification accuracy and the average improvement is reported in Table 2 for 2 and 4 class cases with different method of IAPF considered. Classification accuracy of each subject from the general alpha feature is used as the baseline to perform this comparison. For the 2 class case, IAPF01 method resulted in 16 subjects showing improvement in classification accuracy with average improvement of 2.48%. IAPF02 gave 19 subjects with improvement of 2.40% average. IAPF03 showed 35 subjects with improvement and 2.50% average.

For 4 classes, IAPF01 gave 15 subjects showing improvement with an average of 2.26%. IAPF02 showed 14 subjects with improvement and a 2.24% average. IAPF03 showed 33 subjects with improvement and average of 2.78%.

TABLE I.
AVERAGE ACCURACY OF DIFFERENT IAPF METHODS FOR 2 AND 4 LEVELS OF MENTAL WORKLOAD CLASSIFICATION

No. of Classes	Method			
	Alpha	IAPF01	IAPF02	IAPF03
2	90.88% (14.70)	90.46% (14.72)	90.90% (14.68)	92.44 % (14.76)
4	63.64% (14.04)	62.39% (13.87)	62.38% (13.77)	65.19% (13.75)

TABLE II.
NUMBER OF SUBJECTS WITH IMPROVED CLASSIFICATION ACCURACY WHEN DIFFERENT IAPF METHOD IS USED

2 Class		
Method	No. of subjects improved (n=48)	Average Improvement
IAPF01	16	2.48%
IAPF02	19	2.40%
IAPF03	35	2.50%

4 Class		
Method	No. of subjects improved (n=48)	Average Improvement
IAPF01	15	2.26%
IAPF02	14	2.24%
IAPF03	33	2.78%

V. Discussion

In the experiment with 48 subjects, proposed novel IAPF based power features were compared with general alpha power features for 2 and 4 class mental workload classification problems. This study was done to investigate a first hypothesis that, due to the biological significance of the IAPF and the upper alpha band in cognitive tasks, together with the subject specific nature of the IAPF, a better accuracy can be achieved over the general alpha feature in subject dependent mental workload classification problems. This work was also performed to investigate a second hypothesis that an IAPF can be found for each subject that optimizes the classification accuracy for the mental workload classification problem.

The average classification accuracy of the IAPF based features calculated from the recorded EEG of 48 subjects for 2 and 4 class cases (IAPF01 and IAPF02) had similar performance with the original alpha band features. This could be due to the fact that only one eyes-closed EEG recording was performed. This might lead to cases where misreporting of the calculated IAPF occurs due to having only a single recording to derive the IAPF. It would have been more appropriate to perform a number of eyes-closed EEG recordings for each subject to determine the IAPF. No definite conclusion on the first hypothesis can be drawn from these figures.

However, if we consider only the subjects who showed improvement in Table 2, we observe an increase of around 2.2%. This result agrees with the first hypothesis in showing some indication that IAPF based features might be able to classify mental workload data better than the general alpha power feature.

The results obtained for IAPF01 and IAPF02 also suggests that classification performance is independent of the derivation procedure for IAPF from the EEG recording, as the reported accuracies for both 2 and 4 classes are very similar. The results from Table 2 also agree with this observation as the number of subjects who showed improvement and the average improvement is similar for both methods.

The result of using IAPF03 shows a consistent advantage over the general alpha feature, with average improvement of 1.56% for 2 classes and 1.55% for 4 classes across 48 subjects. The number of subjects who showed improvement is significant, with 35 subjects for 2 class and 33 for 4 classes. These account for about 70% of the 48 subjects considered. The average improvement for each of the 35 or 33 subjects is also consistent with findings from IAPF01 and IAPF02, with a value around 2%. These results agree with the second hypothesis of there being an IAPF value for each subject that optimizes the classification accuracy. The results also support the first hypothesis to some extent, as the observed improvement in classification performance can be attributed to the biological significance of the IAPF and upper alpha as well as the subject specificity nature of the IAPF.

Furthermore, by showing a consistent, better classification performance for the majority of subjects over basic alpha power, IAPF01 or IAPF02 methods; we can conclude that hypothesis 2, which states there being an IAPF that gives the optimal classification accuracy, can be substantiated. The results are indicative in showing that the majority of the subjects >70% show an improvement in classification performance when the optimal IAPF is known.

Our obtained results also show comparable performance with recent, state of the art studies on mental workload and multitasking tasks. This is true for both dual and multi-class classification problems. For the two-class problem, work in [18] for example, tested combination of features from Hurst exponent and Higuchi fractal dimension on EEG data from a MATB task using different classifiers, one of them being SVM. This study is very similar to ours in implementing a multitasking task to induce 2 levels of mental workload with SVM classification. The best reported result of average 92% accuracy for 20 subjects with SVM in this study is comparable with our proposed IAPF methods, obtaining an average classification accuracy of 92.44% for 48 subjects using IAPF03 with SVM classifier.

For the multi-class problem, work in [8] implemented a mental arithmetic task that induces up to 5 levels of mental workload and used 3 of these levels for multi-class classification. Spectral power features were used in this study, which are similar in nature with our proposed IAPF feature which can be derived from the spectral alpha power. Quadratic discriminant analysis was used as the classification method on EEG data for 16 subjects and an average accuracy of 62% was obtained for 3 classes. We were able to achieve similar results for 4 classes using IAPF01 and IAPF02 with 62.39% and 62.38% respectively. IAPF03 gave us the best result of 65.19%.

However, as the current calculation of optimal IAPF using IAPF03 is designed with the goal of testing hypothesis 2, the algorithm performs a brute force search for the IAPF over a range of predefined values. As a result, the current method is not optimized to derive the best IAPF intuitively and thus, is a limitation of the current study. Novel algorithms can therefore be developed in future work to search for this optimal IAPF. The optimal IAPF for each subject can then be implemented as an alternative feature in subject dependent mental workload classification problems.

VI. Conclusion

In this study, we proposed novel alpha features based on the IAPF, which incorporates the cognitive significance of the IAPF and its subject specificity. Given its individual specific nature, such features should provide better classification performance than generalized alpha features. This was observed in our mental workload experiment with 48 subjects to classify 2 and 4 classes of mental workload when we explored values of IAPF for each subject that optimizes classification performance. The results suggest that individual specific features like the IAPF can give better performance than a general feature like the alpha band power and this knowledge can be applied when designing subject dependent BCI applications in the future.

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