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Computational Approach for the Real-Time Diagnosis of Attention Level and Focus State

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Abstract: ***The study of cognitive attention has become a major area of interest in the fields of education, neuroscience and psychiatry during the past several decades. Although the motivation behind these studies originated from the need to better understand mental disorders, such as ADHD, a growing desire to study attention and identify tools to assess the focus state has emerged. As the interest in this area has grown rapidly, computational academic tools are still lacking; the state-of-the-art tools that are currently available focus solely on either general retroactive detection of the focus state or discrimination between subjects diagnosed with various mental illnesses (mostly ADHD) and healthy subjects. To date, there is no reliable tool available to make a real-time diagnosis of the focus state. Due to the volatile nature of attention and unlike the common usage of general discrimination tools, real-time diagnostic tools enable actionable and practical event-driven responses. These event-driven responses include neurofeedback to tackle specific brain diseases and live notifications for helping subjects regain focus while carrying out critical daily tasks that require high levels of attention, such as flying a plane, supervising or even driving, to name a few. In this paper, we present the WBV ("Weighted-Band and Volatility") procedure, a novel methodology for real-time diagnosis of the attention level and focus state. The methodology showed excellent results in real-time focus state prediction, revealing the attention level of the subjects using less than 30 seconds of data and limited EEG input from only two frontal electrodes.***

Keywords: EEG, focus, attention, computational, prediction, machine learning, education, ADHD, WBV, real-time, game

1. Introduction

Focus state and cognitive attention are rapidly growing areas of interest and research. The importance of detecting and measuring these cognitive features varies and ranges from medical-psychological motivations, such as the diagnosis of the mental disorder ADHD, to general monitoring daily tasks, such as predicting and detecting decreases in the focus state. This type of monitoring can help prevent accidents and mistakes while significantly improving the efficiency of the activity.

Despite the importance of this vision, there are still no reliable computational tools available to identify the focus state and diagnose attention-related brain disorders. In addition, there is no solution at all, reliable or otherwise, for a real-time tool to measure and diagnose these disorders. Although non-real-time approaches may break with the traditional means as they are applied toward general diagnostic procedures for disorders, such as ADHD, real-time tools are required to enable the detection and prediction of short-term changes on the level of the focus state, initiating a relevant warning, neurofeedback or a proprietary notification event-driven mechanism.

The medical motivations that inspired this heightened interest in attention are associated with the specific cognitive illness of ADHD. This condition is considered to be one of the most common neurological disorders, affecting nearly 5% of school-age children on average, and it has been characterized in the professional literature as an inability to control the focus state for a substantial period of time in association with extreme behaviors, such as impulsivity (Biederman et al. 2005).

In addition, there are several common symptoms involving learning disabilities and irregular mental states, such as anxiety and depression (Biederman et al. 2005 ; Eldar, 2010).

Although the exact cause of ADHD is currently unknown, past studies have shown abnormal EEG waves in ADHD patients (Loo et al. 2005). Still, there is no objective test to diagnose ADHD, and the number of misdiagnosed children is high, with millions in the USA alone (Elder, 2010).

With respect to specific EEG bands and the efficiency of the spectral decomposition of the signal, studies have shown an association with the theta band wave (Barry et al. 2003). The beta band is also considered to be highly active when brain is "busy," whereas theta waves are related to a "dreamy" state. Theta power in non-ADHD diagnosed subjects, especially children, has apparently increased (Barry et al. 2003 ; Clarke et al. 2001 ; Lazzaro et al. 1998). Although these findings are the most consistent within the current literature, they were not obtained using computational analysis methodologies.

Few innovative computational approaches have been presented over the past few years to diagnose ADHD. One example involves event-related potentials (ERP) of the EEG signal to discriminate patients in an ADHD group from normal group subjects (Mueller et al., 2010). The reported approach was based on a feature extraction method followed by a support vector classification algorithm for discrimination. It exhibited high accuracy and required a few hours of data per subject.

Another state-of-the-art study focused on the feature extraction phase (Abibullaev et al, 2011). This research was based on the assumption that it is usually hard to find most discriminative features, especially when evaluating children, due to the high variability of the disorder. Therefore, the core of that work relied on finding an adaptive algorithm that could be used to make a reliable diagnosis of ADHD.

For this purpose, it showed improved detection results with a higher rate of specificity. In both cases, a general discrimination methodology was presented to allow retrospective discrimination based on substantial data from the subjects.

Relative to the specific goal of ADHD diagnosis, attempts to develop general focus state detection have even less of a computational background in the academic literature. Some work was published on focus analysis according to facial properties, such as impressions. For example, monitoring driver's fatigue using cameras was one attempt (Qiang et al. 2003), and a similar paradigm during meetings also showed significant findings (Rainer, 2009).

EEG-related work on attention became quite popular over the past decade. EEG properties, specifically gamma-band attributes, were already associated with mental disorders, such as schizophrenia (Lee et al., 2002), and with selective attention (Fell et al., 2003). An association between cognitive awareness and the gamma band was found (Ward, 2003) then later connected strongly with attention as a component of cortical computation (Fries, 2009). Much earlier findings revealed a connection between gamma band coherence and associative learning (Milter, 1998), and a strong connection between the gamma band and visual attention was established (Gruber et al., 1999). These connections were even tested in animals. For example, a connection between the local gamma activity and the attention of cats was found approximately a decade ago (Lakatos et al., 2004). In all of the above cases, a real-time computational approach was not presented.

2. Experiment Description

A proprietary Koi Fish feeding game was developed for the purpose of this study using Adobe Flash technology. The general purpose of the game is to feed the fish over a short time frame using a time-constrained ("charging") feeding mechanism. The challenge includes both planning (avoid feeding the same fish again before others) and execution (focus is required to accurately click on the fish).

Each game includes multiple sessions, segmented into a dual-phase game per subject: a training phase followed by a testing ("scored") phase. The goal of the training phase is to bring the subject to a challenging difficulty level in the game.

A screenshot of the game appears in figure 1 below.

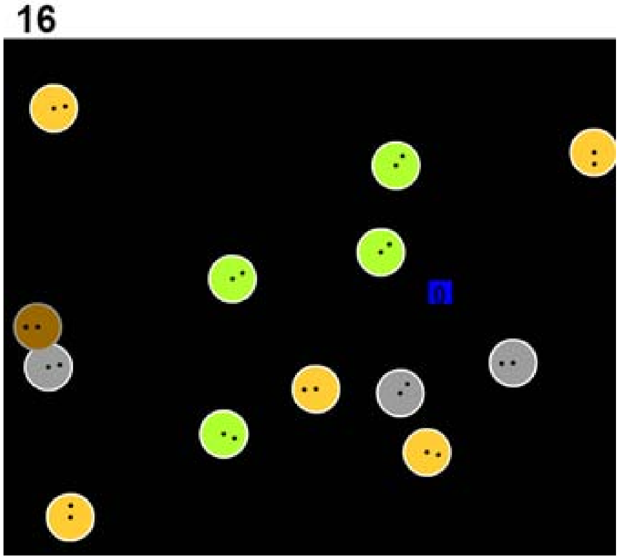

Figure 1: A screenshot from the propriety Koi Fish game. The blue cursor shows the time remaining for the next attempt to feed a fish. Yellow fish are several seconds away from "starving," and dark ones (such as the one on the left) are just a few seconds away from "starvation." Gray fish are already "dead" or simply "starved." Light green fish are included to confuse the user only and are not part of the player's practical mission. The timer above (in the top left corner, with a value of 16) specifies the time left in the current session, in seconds.

The main two parameters controlling the difficulty of the game are (A) the movement speed of the fish: higher speeds make it harder to click on them, and (B) the number of the fish: the greater the number, the harder it becomes to follow their movements and remember the correct sequence of the prior "feedings."

As mentioned above, the purpose of the training period is to adjust the game to the ability level of the player. The target level of difficulty was defined as either the most difficult level the user was able to finish successfully (meaning, without starving any fish) at least twice or simply the second difficulty level that was completed successfully. During the testing phase, "false-fish" were added to the game. Their number was set at half the number of "regular" fish. Their color was different (green rather than yellow) and they were only added to further confuse the player.

3. Data Acquisition

The full data set included 20 healthy subjects between the ages of 15-55 with no present indication of mental sickness or problematic cognitive behavior. All subjects signed a written consent form. A single EEG input was obtained from two frontal-central-located electrodes at a sampling frequency of 512 Hz. Each player was recorded for 8 minutes: the training phase lasted a total of 3 minutes, and the testing phase lasted 5 minutes. Each game session was played for approximately 20 seconds (the length of each session ranged from 16 to 46 seconds, depending on the number of fish).

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4. Methodology

The Weighted Band & Volatility ("WBV") methodology includes a few components: synchronization of the events and the EEG input, feature extraction, construction of classifiers and prediction, followed by a process of verification and validation.

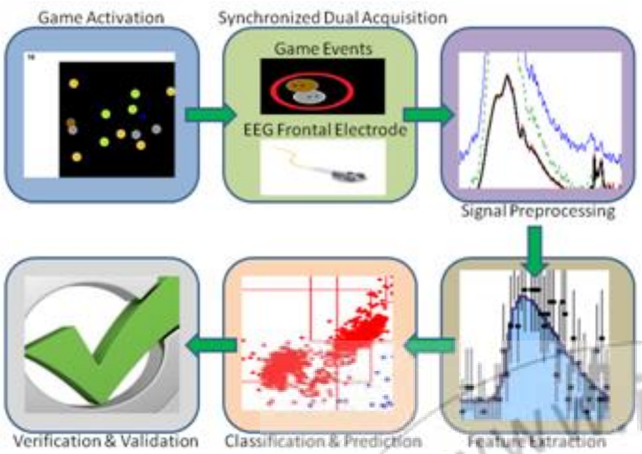

Figure 2: Overview of the WBV methodology

4.1 Preprocessing and Feature Extraction

During the preprocessing stage, a frequency band low-pass filter of 120 Hz was applied to the raw data. After being filtered, each recording signal was divided by its standard deviation for normalization.

The events, defined points of time when features were extracted, were defined according to the mouse clicks performed by the subject during the testing phase.

For the feature extraction phase, three sets of features were created per event E at a point of time $t(E)$. A 20-second window was initially defined prior to the event as W(E):

$$W(E) = \{Sig_x | t(E) - 20sec \le x \le t(E)\}$$

The feature sets included the following:

1) The absolute signal energy of the bands according to a classical decomposition: alpha/beta/theta/delta/gamma frequency bands. This decomposition was carried out in two phases:

(A) Activation of band-pass filters for 7-14 Hz, 14-30 Hz, 4-7 Hz, 0-4 Hz and 30-120 Hz, respectively, for the above-mentioned frequency bands. For alpha, this process can be described as

$$B(E) = band_{Alpha}(E) = PassBandFilter_{7Hz-14Hz} W(E)$$

(B) Averaging the absolute signal energy-adding feature $\{\int |X(B(E))|^2\}$, where $X\big(B(E)\big)$ denotes the Fourier transform of $B(E)$ (Boashash, B., 2003).

2) The band volatility, following the same process applied in feature set 1, except that the added feature is $\{Std_x | x \in \big(B(E)\big)\}$ rather than the energy variable.

3) From all features acquired in feature set 1, adding all possible pair divisions (i.e., gamma/alpha).

The results indicate that a total of 20 features were extracted per event, $Feat(E)$.

4.2 Classification and Prediction

For the classification and prediction phase, two target predictors were created:

1. A predictor of the accuracy of the user's next click, defined as the distance from the center of the entity that the user was attempting to click (assuming that it was the nearest one). Two variants were defined: (A) a single predictor that precisely predicts the distance and (B) 3 predictors that segment the events into 3 groups: weak, medium and strong, with each segment holding one third $\left(\frac{1}{3}\right)$ of the events from that subject.

2. A predictor of a "misclick" event (events for which the click accuracy was poor). This predictor comprises a binary prediction of whether the next event will be a misclick.

In both cases, the prediction is made in real-time using only the EEG features acquired from the 20-second window prior to the event.

4.3 Click Accuracy Prediction

The prediction was made by applying the "leave-one-out" technique (Halkidi et Al, 2002). For each subject, the EEG data and game events did not participate at all in the training dataset when activating the predictors from the data.

A supervised learning algorithm was then applied to create 3 classifiers of type 1(B) as described above, as well as one classifier per each segment of the relative subject accuracy (low-, medium- and high-accuracy click segments).
The prediction of new data was made using the following procedure:

1) Train each of the 3 classifiers. Within the training dataset, supervise using the target function of 1.0 if the event scores positive relative to the classifier's segment (i.e., weak indicates a low third accuracy click event and should receive a 1.0 trained target as the low accuracy predictor) and 0.0 otherwise. Each classifier served as a ridge regression predictor, with a Lambda value ranging from $(0.01 - 1000)$ for optimization purposes.
2) For new event E and its respective features $Feat(E)$, activate all 3 predictors for the new features.
3) Choose a prediction (low, medium or high) according to the classifier that claims the highest result.

4.4 Misclick Classification

The goal here was to classify and predict whether each event was a misclick. As before, the prediction is made by applying the "leave-one-out" technique, with the subject data not participating in the training set. The classification procedure is as follows:

1) Train a single ridge regression predictor of type 2 according to the above description, using the training dataset. Per event E, set $Feat(E)$ served as the event features, with a supervised target of 1.0 if the event was a misclick and 0.0 otherwise.
2) For new event E, generate feature set $Feat(E)$ and activate the predictor. If the result exceeds threshold T

within the range (0.005-0.995) for optimization purposes, choose a new event as a misclick.

5. Results

Results are presented in four sections. 1. The general methodology results included the prediction results of each of the accuracy predictors and the combined performance of the WBV methodology. 2. The results of the WBV methodology for multiple prediction variants. 3. Representation of the volatility as a factor of the subject's focus relative to the direct gamma activity. 4. Misclick prediction results.

5.1 General Methodology Results

Presented in table 1 below are the results obtained using each of the three predictors of type 1(B) as described above.

Table 1:

Averages-Prediction	*Weak Predictor Accuracy*	*Medium Predictor Accuracy*	*Focused Predictor Accuracy*
Prediction Weak (low third)	69.4% ± 6.3%	17.3% ± 5.1%	08.4% ± 5.7%
Prediction Medium (mid third)	18.5% ± 4.3%	61.2% ± 4%	22.1% ± 5.5%
Prediction Focused (top third)	12.1% ± 4.7%	21.5% ± 4.2%	69.5% ± 4.8%

Table 1: Each column represents one predictor, and each row represents one segment, which held one-third of the events according to the level of accuracy of the event. It is clear that the strong-state and weak-state predictors were able to predict their classes a close to 70% accuracy, whereas the "Medium Predictor," which predicted the middle 33.33% of accuracy clicks, predicted its own class at a greater than 60% accuracy.

Total prediction achieved when choosing the strongest predictor: **73.5% ± 5.8%** (relative to a random **33.33%**).

5.2 The results of the presented methodology for multiple prediction variations

Comparison graph: As presented below, figure 3 summarizes the prediction accuracy of the methodology when various feature sets were applied, demonstrating the significance of the volatility-based features and the contribution of the methodology as a whole compared with a single predictor implementation. Additionally, a gradual increase can be observed from random classifier accuracy to a fully feature-utilized WBV classifier.

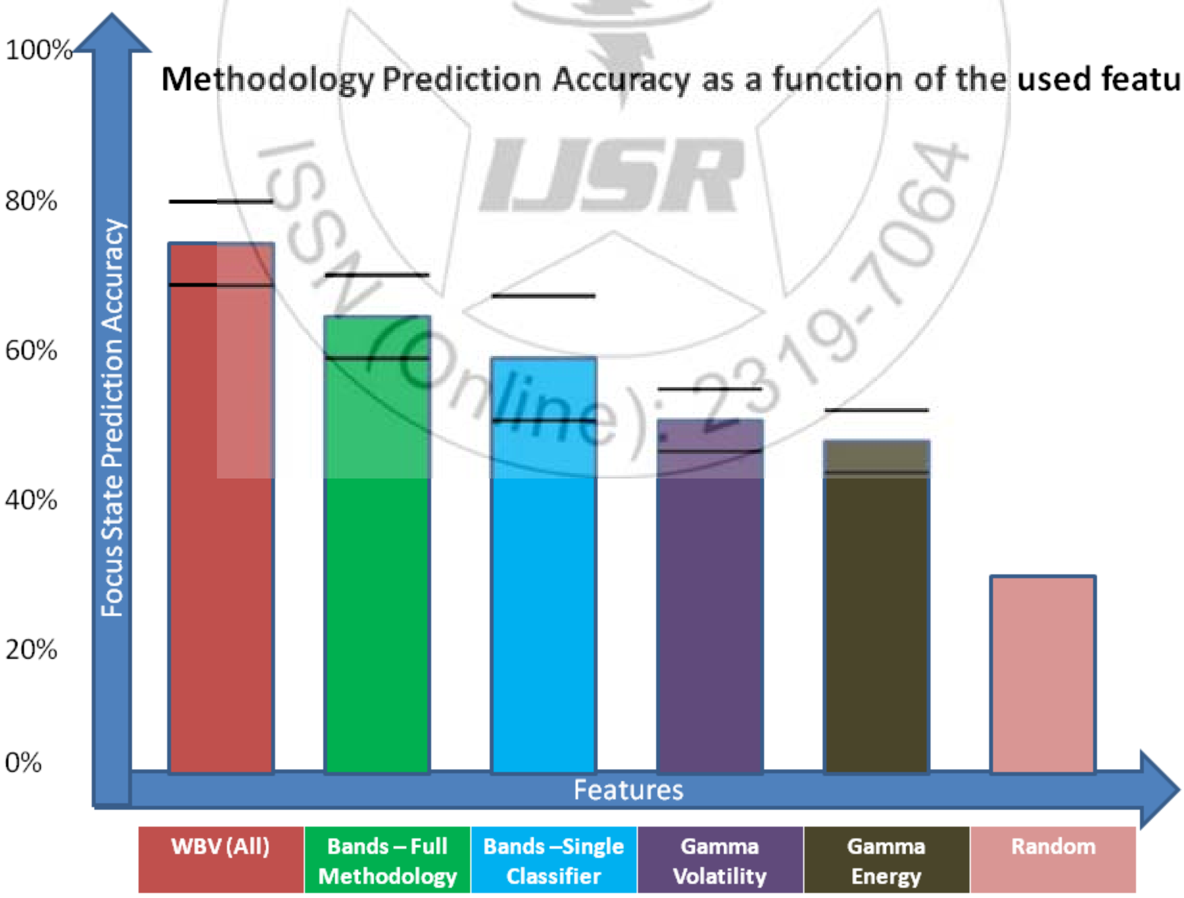

Figure 3: The prediction accuracy of the methodology is plotted as a function of the features being used. It is apparent that using all features was strongly able to predict the focus state, with a dramatic improvement achieved through using the volatility-related features rather than band energy-featured-only classifiers. Additionally, the contribution of the breakdown into three classifiers rather than one is also evident.

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Comparisons are provided in table 2 below, including a summary of the results with specifications of all variations for the methodology:

Table 2

Methodology	*Discrimination Accuracy Rate*	*Specificity Rate*	*Significance (p-Value)*
WBV (Weighted Band & Volatility Methodology)	73.5% ± 5.8%	82.3% ± 2.4%	0.0117
Weighted Band Only [A]	64.6% ± 5.0%	78.0% ± 2.8%	0.0382
Directed Band (Single Classifier) [B]	59.3% ± 6.3%	74.4% ± 3.6%	0.0755
Gamma Volatility Projection (Single Classifier) [C]	49.1% ± 5.7%	60.4% ± 4.1%	0.1304
Gamma Projection (Single Classifier) [D]	47.2% ± 5.9%	57.9% ± 3.3%	0.1469
Random Classifier [E]	33.33%	N/A	N/A

Table 2: Each row features an independent methodology applied to the data and its respective results, including the accuracy, specificity and significance according to the p-value. One can see that WBV (top row) showed the best results, using the full methodology described with all possible features. Variant **[A]**, second row, was identical to WBV except that it did not use the second set of features (volatility-based features), and this difference caused a major decrease in performance and more than tripled the p-value. Variant **[B]**, third row, is identical to variant **[A]** except that the predictors were of type 1(A) instead of 1(B), i.e., a single predictor only. Variant **[C]**, fourth row, used a single classifier with volatility (2[nd] feature set) only and showed better results than those of variant **[D]**, fifth row, which was like **[C]** except that it only used the gamma energy band. Variant **[E]** guessed the correct segment of the event, and by definition, this method had a 33.33% chance of being accurate.

5.3 Comparison of significance: gamma activity versus gamma volatility:

Figure 4 below presents a plot of the subjects' misclicks, both as a function of the gamma band energy and as a function of the gamma band volatility. Surprisingly, the association of a single feature indicated a higher chance of a low gamma band volatility than did the gamma band energy.

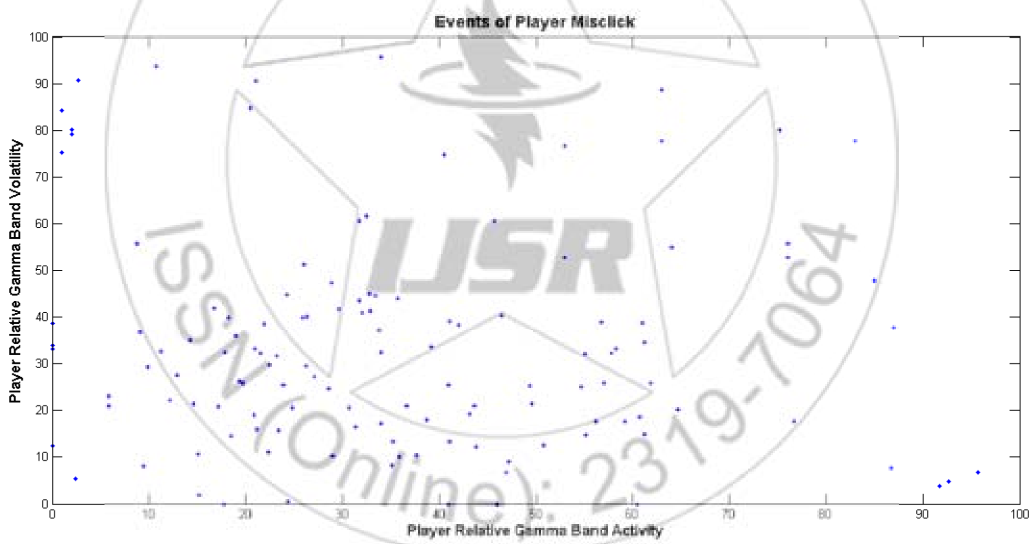

Figure 4: All misclick events are presented as a function of the relative gamma band, which is associated with focus, and the volatility of the gamma band. It is clear that the volatility (or lack thereof) of the gamma band is actually a stronger property of the misclick event than is the relative gamma band. As described above, all properties are the relative average of each player and were computed during a 20-second window prior to the event

5.4 Misclick Prediction:

The misclick predictor (type 2 in the predictor descriptions) is a stronger version of the "weak predictor" of type 1(B), as it addresses the set of most inaccurate click events. The total percentage of misclick events out of the total events was 12.65%.

The results are presented in table 3 below.

Table 3: Misclick single predictor results compared to a random classifier. Although the random classifier has a 12.65% chance of guessing a future misclick (as this is the statistical probability of all these events combined), the misclick single predictor achieved a greater than 37% accuracy with a p- value of less than 3%.

Methodology	Discrimination Accuracy Rate	Specificity Rate	Significance (p-Value)
Misclick Single Predictor	37.2% ± 4.6%	41% ± 5.8%	0.0285
Random Classifier	12.65%	N/A	N/A

6. Discussion

The results reveal interesting connections that had not been presented previously in the academic literature, both the general results predicting focus under real-time constraints and those in terms of the underlying results that revealed surprising findings.

1. Real-time prediction of the focus state. The results indicated that it was possible to reliably predict the focus state using a single frontal EEG electrode and less than 30 seconds of data acquired from the subject. These real-time results are absent from the existing literature on focus state analysis. It should be noted that the goal of the predictor was to predict the accuracy of classifying a single click event by a subject. This mission is much harder than predicting a general session of data from a large number of events (i.e., assessing the general focus of the subject during a long observation period). In other words, predicting whether the next event will indicate a low-focus state is much harder than giving a general score to a set that comprises hundreds of events. This ability is crucial for real-time applications. Educational applications might indicate exactly when a student begins to lose focus while studying, for example. This predictor can be used practically, unlike the general observation that the student was not highly focused on average throughout the course of the session.

A future direction would be to test the significance of the prediction using additional information from the subject, such as additional electrodes. Furthermore, it would be interesting to test the methodology using cognitive focus tasks other than the featured proprietary fish game, such as other massive attention simulations, or even more conservative assessment tools, such as the TOVA test.

2. Regarding the significance of the volatility of the gamma band compared with the significance of the gamma band, it was found that the gamma volatility features showed better discrimination properties compared with the gamma band energy features. Although gamma band activity was already known to show a strong connection with focus properties (Bauer et al. 2006), the volatility of the gamma band has not previously been considered a similarly important factor. Although prior research reported no conclusion regarding the connection of gamma volatility with the focus state, a general question had arisen in the past regarding a connection between temporary focus and evoked gamma oscillations (Fell et al. 2003).

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