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A multidimensional EEG feature extraction attention detection for BCI System

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Abstract

Brain-computer interface (BCI) systems are highly valued for their applications in medicine and biology, where accurate analysis of attention levels and electroencephalography (EEG) data is crucial for the success rate of BCI systems. To improve this aspect, we propose to perform attention level determination prior to the execution of the BCI system. To accurately determine the level of attention, we propose a novel feature extraction approach that involves multidimensional feature extraction across multiple frequency bands of EEG data. The multi frequency band waveforms extracted using this method can be cross validated, thereby increasing the robustness of our research. We used publicly available datasets to train a Support Vector Machine (SVM) classifier to develop an efficient attention detection system, and developed a system for collecting EEG data to validate attention levels. The effectiveness and accuracy of the multidimensional feature extraction method was validated by classifying the data collected by the attention detection system. This study highlights the potential of integrating attention detection into BCI systems, pathways for advances in brain science research.

Keywords: Attention Detection, EEG, SVM, BCI, Feature Extraction

Introduction

Extensive research shows that attention can be effectively classified at several levels (Asadi et al., 2021; Wang et al., 2016). These classifications are significantly influenced by individual factors such as age and mental state (Al-Nafjan et al., 2017). The detection of attention plays a crucial role in practical applications. For example, a driver's physiological parameters including electrocardiogram (ECG) readings, electroencephalogram (EEG) signals and skin resistance undergo significant changes when fatigued (Jia et al., 2023). This highlights the potential for integrating attention detection into brain computer interface (BCI) systems (Cui et al., 2014; Ghassemi et al., 2009). Recent advances in BCI technology, ranging from medical rehabilitation to augmented human computer interaction (Asadi et al., 2021; Wang et al., 2016), emphasise the critical need for accurate interpretation and classification of neural signals, particularly in the monitoring and assessment of attention levels (Bedolla-Ibarra et al., 2022).

Our research presents a novel method for classifying levels of attention that significantly improves the accuracy of existing attention detection systems. This method exploits multi band, multi dimensional EEG features combined with both linear and nonlinear classification approaches, and integrates subjective data analysis (Acı et al., 2019; X. Zhao et al., 2018). We specifically analyse EEG wavelength characteristics at three different frequencies θ, α and β which serve as reliable indicators of attention levels. The set of ratios of these three waveforms is closely related to the hierarchical state of attention (Jing et al., 2020). To implement our approach, we use SVM classifier trained on a comprehensive feature set derived from public attention datasets. This classifier effectively blends linear and nonlinear methods with subjective analysis (Huang et al., 2023; Zhang et al., 2023), aiming to capture the complex dynamics of neural activity associated with attention (Jebelli et al., 2018).

We have rigorously validated our feature extraction methodology using a bespoke multi task attentional EEG acquisition system (Kirmizi-Alsan et al., 2006; Q. Zhao et al., 2011) inspired by the Mackworth clock test (Lichstein et al., 2000). This system provides a robust platform for applying the trained SVM classifier to accurately classify EEG signals based on attentional states (Poon et al., 2015). Our results demonstrate the effectiveness of our method in distinguishing between different attentional states, thereby significantly enhancing the classification capabilities of our EEG feature extraction technique (Blotenberg & Schmidt-Atzert, 2019; Sui et al., 2019).

Given the fundamental relationship between the level of attention and the signal strength detected by the BCI stimulator (Kirmizi-Alsan et al., 2006; Ko et al., 2017), our method holds great promise for improving the success rate of BCI systems. By preprocessing EEG signals prior to their analysis by the BCI system, we enable the system to effectively distinguish between periods of concentration and inattention. This proactive approach not only increases the efficiency of the BCI system, but also optimises the timing of its operation by activating BCI functions during periods of peak concentration. Such synergy offers significant potential for the development of highly adaptive systems that can intuitively adapt to the user's mental state. As a result, it opens the door to the creation of personalised and highly effective applications in a variety of fields.

Feature Extraction Methods

EEG has become an important tool for revealing the complex dynamics of the human brain, especially the parts related to consciousness. The classification of attentional states from EEG signals involves the analysis of different brain waves, specifically θ, α and β waves. The feature decomposition process used in this analysis is shown in Fig 1.

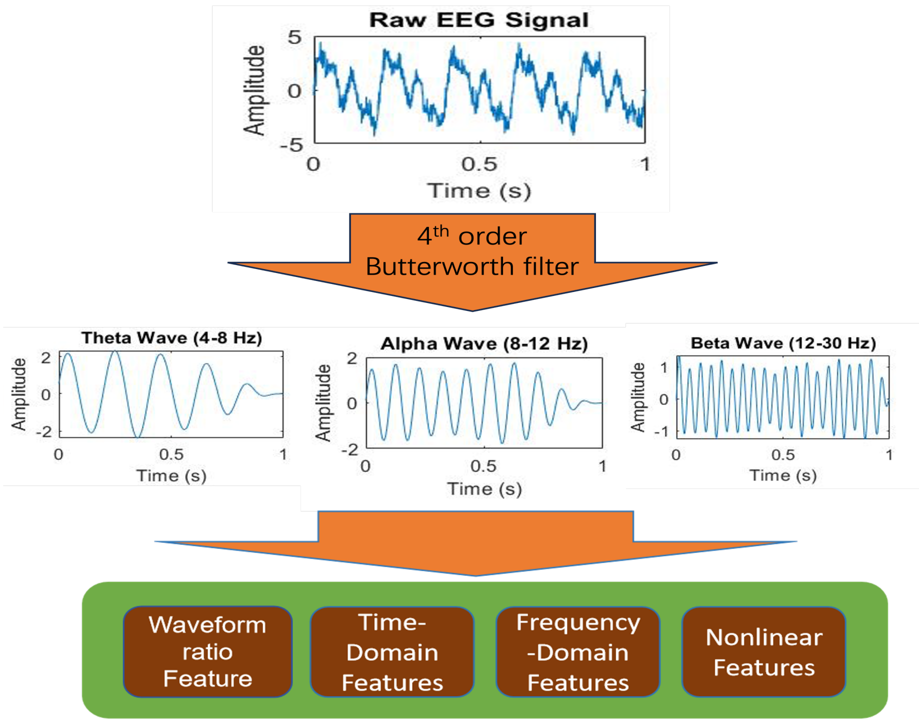

Figure 1. Attention level identification method based on multi dimensional EEG feature fusion

These waves, each characterised by different frequency ranges, serve as indicators of different cognitive states and processes. The α waves, typically between 8 and 12 Hz, are traditionally associated with states of relaxation and calm, but their significance extends further. In particular, fluctuations in α wave activity, particularly in posterior and occipital brain regions, correlate with varying attentional demands. An observable reduction in α activity, occurs during tasks, reflecting a heightened state of alertness and cognitive engagement. The β waves, which range from 12 to 30 Hz, indicate an alert and active mind, often seen during focused attention and problem solving scenarios. An increase in β activity is often seen during tasks that require active concentration, playing a critical role in decision making and problem solving. The θ waves, found in the 4-8 Hz range, are generally associated with sleepiness or the early stages of sleep. However, recent studies suggest a more complex role for θ waves in cognitive functions, including memory encoding and retrieval. This is particularly evident in attentional tasks, where increased θ activity is associated with improvements in sustained attention and working memory (Eoh et al., 2005).

a. Waveform ratio Feature

Due to the potential unreliability of single waveform data, ratios between different EEG waveforms have been introduced to improve the accuracy of judgement. High $\alpha - \beta$ ratios typically indicate relaxed, meditative or calm states, which are generally associated with lower levels of attention. In contrast, low $\alpha - \beta$ ratios indicate heightened levels of attention, as β waves are more prevalent in tasks requiring intense concentration. Similarly, a high $\theta - \beta$ ratio may indicate a relaxed, creative or meditative state, reflecting a shift of attention to internal or unconscious processes. Conversely, a low $\theta - \beta$ ratio indicates heightened attention, with β waves dominating during focused tasks. A high $\alpha - \theta$ ratio usually indicates a relaxed brain state, often associated with mild relaxation, rest or disengagement. On the other hand, a low $\alpha - \theta$ ratio may reflect increased brain activity and focus, characterised by a decrease in α waves and an increase in θ waves, which may be associated with increased attention, concentration or creative thinking. Power Spectral Density (PSD) is used to quantify the power within specific frequency bands, which is crucial for identifying the dominant EEG signal associated with different cognitive states. We calculate the first type of features by determining the PSD ratios: $\alpha - \theta$ (PAT), $\theta - \beta$ (PTB), and $\alpha - \beta$ (PAB). The PSD is calculated using the following formula:

$$\text{PSD} = \frac{1}{|f_n|} \sum_{k \in f_n} \|S(k)\|^2 \tag{1}$$

where n indicates the waves (θ, α, or β) and f_n is the frequency range corresponding to waves n. $S(k)$ is the power spectral density function of the signal as a function of frequency k.

b. Time Domain Feature

Incorporating academic theory into the analysis of EEG time domain features such as Time Domain Variance (TVAR), Time Domain Mean (TM) and Time Domain Root Mean Square (TRMS) deepens our understanding of neural dynamics. These metrics are central to the field of neural signal processing, which highlights the importance of amplitude variations in reflecting different cognitive states. In particular, the variance metric (TVAR) is crucial as it relates to signal variability and provides valuable insights into the responsiveness of the neural system (Tuncer et al., 2021). Where x_i represents the i-th data point in the data set. N is the total number of data points. $\bar{x}$ represents the mean of the data points in the first and second formulas.

$$\text{TVAR} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2 \tag{2}$$

TVAR measures the variability or uncertainty of EEG signals over time, and its relationship to attention can be seen by examining the brainwave variances across different attentional states. Typically, α wave variance is higher in relaxed, rested or eyes closed states. As attention increases, α wave variance tends to decrease due to more synchronised and stable brain activity. Conversely, β wave variance tends to increase during tasks requiring high levels of attention and decrease during relaxed or resting states. θ wave variance tends to be higher during states associated with relaxation, meditation or creative thinking, and lower during tasks that require intense concentration. The TM reflects the average signal level, indicating overall neural activation.

$$\mathrm{TM} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{3}$$

TM represents the average of EEG signals over a period of time, and its relationship to attention varies depending on the type of brainwave and the task at hand. Typically, the average amplitude of α waves is higher during relaxed states, whereas these averages tend to be lower during highly focused tasks. The β wave averages generally increase during tasks that require significant concentration and decrease in relaxed states. Similarly, θ wave averages are elevated during relaxed, meditative or creative thinking states, but decrease during tasks that require high levels of attention. TRMS includes both amplitude and variability, providing a comprehensive measure of the intensity of the signal. This metric is critical to our analysis because it provides a robust method for detecting attention related changes in brain activity, thereby increasing the reliability of our results in assessing cognitive state.

$$\mathrm{TRMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{4}$$

TRMS quantifies the strength or amplitude of EEG signals, and its relationship to attention varies across EEG bands and task demands. Typically, the TRMS of α waves can be higher during relaxed states, reflecting a less active cognitive state. Conversely, during tasks that require high concentration, the TRMS of α waves tends to decrease, indicating more focused and stable neural activity. For β waves, which are associated with active thinking and attention, TRMS levels tend to be elevated during tasks requiring intense concentration and lower during relaxation. Similarly, θ wave TRMS is generally higher during relaxed, meditative or creative states, when the brain may be engaged in deeper, introspective processes. In contrast, during tasks that require sustained attention, the θ wave TRMS tends to decrease, reflecting the brain's shift towards more goal directed activities.

c. Frequency Domain Feature

To extract features in the frequency domain, we first apply a Fast Fourier Transform (FFT) to the three primary EEG waveforms. Following the FFT, we calculate the Frequency Domain Energy (FE) feature, which is derived from the integral of the spectrogram. This measurement is critical in quantifying the power within specific frequency bands, a critical step in identifying the dominant EEG signals that correlate with different cognitive states. Frequency Domain Centre of Mass Frequency (FCF) provides crucial insight into the "centre of mass" of the power spectrum, facilitating a deeper understanding of the dominant frequency components during different attentional processes. Frequency Domain Frequency Variance (FFV) is an important metric that quantifies the variation and distribution of power across different frequencies.

$$\mathrm{FE} = \sum_{k=0}^{N-1} |S[k]|^2 \tag{5}$$

FE represents the total energy of EEG signals within a given frequency band. The relationship between FE and attention can be seen in the energy variations in brain wave frequencies during different cognitive states. Typically, α wave energy is higher in a relaxed state and decreases during tasks that require high concentration. Conversely, β wave energy increases in scenarios requiring intense concentration and decreases in relaxed states. θ wave energy, on the other hand, is generally elevated during relaxation, meditation or creative thinking, and decreases during tasks that require high levels of concentration. Where s denotes the raw time series of the EEG signal, the FCF is calculated as follows:

$$\text{FCF} = \frac{\int_0^\infty s \cdot S(k)\,dk}{\int_0^\infty S(k)\,dk} \tag{6}$$

The FCF of an EEG represents the concentration of brainwave energy at the centre of the power spectrum over a period of time. The relationship between FCF and attentional states can be explained by observing the centre of mass frequencies of brain waves under different cognitive conditions. Typically, in a relaxed state, the centre of mass frequency of the α wave is lower, reflecting more subdued cognitive activity. Conversely, during tasks that require a high level of concentration, the centre of mass frequency of the α wave tends to be higher. Similarly, the centre of mass frequency of the β wave tends to increase during activities that require a great deal of attention and to decrease during more relaxed states. For θ waves, the centre of mass frequencies are generally lower during relaxed, meditative or creative thinking states and may increase during tasks that require a high level of attention. FFV helps to illuminate the complexity and dynamic nature of brain activity during attentional tasks, providing insight into the variability of cognitive processes as reflected in EEG signals.

$$\text{FFV} = \frac{\int_0^\infty (s - FCF)^2 \cdot S(k)\,dk}{\int_0^\infty S(k)\,dk} \tag{7}$$

FFV measures the degree of variation in the amplitude of EEG signals over a given frequency range. This metric is important for understanding how attention affects the variability of EEG amplitude in different frequency bands during different cognitive tasks. In general, the frequency variance of α waves is higher in a relaxed state, indicating less uniform brain activity. Conversely, during highly focused tasks, the frequency variance of α waves tends to decrease, reflecting more stable and consistent brain activity. For β waves, frequency variance typically increases during tasks that require a high level of attention and decreases during more relaxed states. Similarly, θ waves show higher frequency variance during relaxed, meditative or creative thinking states, and lower variance during tasks that require high levels of attention.

d. Nonlinear Feature

The concepts of Approximate Entropy (ApEn) (Pincus & Goldberger, 1994), Sample Entropy (SaEn) and Fuzzy Entropy (FuEn) play a crucial role in the analysis of EEG signals, particularly in the study of neurological disorders such as epilepsy. These entropy measures assess the complexity or regularity of EEG patterns (Ahmed et al., 2011). ApEn, as a specific metric, quantifies the predictability of time series data. In the context of EEG analysis, a lower ApEn indicates greater predictability or regularity in the EEG signals. This characteristic may be indicative of specific neurological states or conditions, providing valuable insight into the underlying brain dynamics.

$$\text{ApEn}(m, r, N) = \phi^m(r) - \phi^{m+1}(r) \tag{8}$$

where

$$\phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C_i^m(r) \tag{9}$$

and $\phi^m(r)$ is likely to be a function depending on the embedding dimension m and a threshold r, N is the total number of data points in the time series, typically representing the fraction of vectors x in the time series that lie within r of a vector starting at position i, in m dimensional space. SaEn is an improvement on ApEn and measures the complexity of a time series of data. It is more consistent and less biased than ApEn, especially when dealing with smaller data sets. A higher SaEn value in EEG signals indicates more complexity, suggesting less predictability and potentially more disordered neural (Jie et al., 2014; Song et al., 2012).

$$\text{SaEn}(m, r, N) = -\ln \frac{A}{B} \tag{10}$$

Where A is the number of pairs $\{u(i)\}$ and $\{u(j)\}$ that are similar for $m+1$ points, and B is the number of pairs that are similar for m points. FuEn is an advanced form of entropy measure that incorporates the concept of fuzziness into the analysis of time series. FuEn is particularly useful in EEG signal analysis as it can provide a more nuanced understanding of the underlying neural dynamics, especially in the presence of noisy or artifact laden EEG data(Cao & Lin, 2017; Chiang et al., 2019). For a time series $x(i)$, the steps to calculate FuEn are as follows: Reconstruct the series into m dimensional vectors

$$X(i) = [x(i), x(i+\tau), \ldots, x(i+(m-1)\tau)] \tag{11}$$

For each pair of m dimensional vectors $X(i)$ and $X(j)$ in the sequence, calculate their similarity $D(X(i), X(j))$. The similarity is usually defined by a fuzzy function, such as an exponential decay function:

$$D(X(i), X(j)) = \exp\left(-\frac{\max_k |x(i+k\tau) - x(j+k\tau)|}{r}\right) \tag{12}$$

$$C_i^m(r) = \frac{1}{N-m+1} \sum_{j=1}^{N-m+1} D(X(i), X(j)) \tag{13}$$

$$\phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C_i^m(r) \tag{14}$$

FuEn is usually obtained by calculating the entropy difference between two different dimensions (m and $m+1$):

$$\text{FuEn}(m, r, N) = \phi^m(r) - \phi^{m+1}(r) \tag{15}$$

Entropy serves as a statistical measure of signal complexity or irregularity and is often used to analyse the complexity of EEG signals. The relationship between entropy and attention can be seen by examining the approximate entropy across different states of attention. During high attentional states such as during tasks that require a high level of concentration brain activity tends to be more regular and ordered. Consequently, entropy is lower, reflecting a reduction in signal complexity. Conversely, during low attentional states, such as during relaxation or distraction, brain activity tends to be more irregular and chaotic, resulting in higher entropy, indicating increased signal complexity. Therefore, entropy typically shows a negative correlation with attentional state: higher levels of attention are associated with more regular and predictable signals, whereas lower levels of attention correlate with more irregular and unpredictable signals.

e. Feature fusion & normalization

In our research, we faced the challenge of integrating a large number of feature values, 60,480 in total, derived from a multidimensional dataset containing 2 states, 60 data points, 14 channels, 3 waveforms and 12 different features per combination.Data availability is indicated at the end of the paper. The dataset included recordings from 34 subjects, with each subject providing 60 10s segments of both focused and unfocused data. The EEG data was sampled at 128 Hz on 14 channels, including AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4, as shown in Fig 2. To manage and integrate these features effectively, we used advanced data fusion techniques. First, we standardised the entire feature set to negate the influence of different scales between features and to ensure that each contributed equally to the Principal Component Analysis (PCA) process. Standardisation was achieved by subtracting the mean and dividing by the standard deviation for each feature, transforming them into a distribution with zero mean and unit variance.

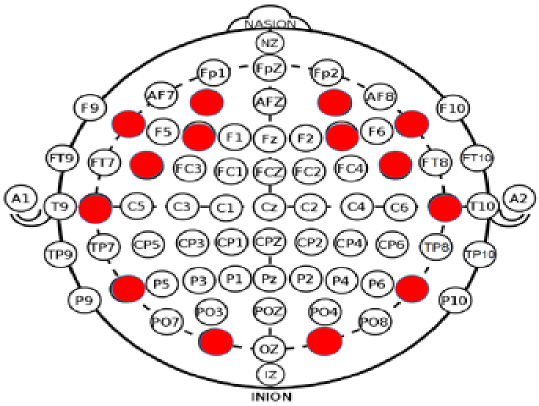

Figure 2. Channel location in international 10-20 EEG system

PCA was then used to analyse the principal components of the feature data. PCA works by calculating the covariance matrix of the data and extracting its eigenvectors and eigenvalues. The eigenvectors define the new coordinate system for the data, while the eigenvalues indicate the contribution of each principal component to the total variance of the data. In this study, we selected principal components that explained over 90% of the total variance of the original data, ensuring that the majority of information was retained while significantly reducing the dimensions. Through this process, we effectively compress the original 12 dimensional feature space, reducing model complexity and helping to improve the operating efficiency and classification accuracy of the subsequent SVM classification model.

Attention Detection System

We have developed an attention detection system inspired by the Mackworth clock Test. Our system enhances participant engagement through the use of dynamically changing images while simultaneously collecting EEG data over a predefined time interval leading up to user responses. Each image frame is displayed one second apart. To enhance the quality of our experimental data and to facilitate multi task analysis, we have incorporated a variety of colour options into the image presentation. Participants are instructed to respond by clicking the appropriate button when images of different colours are presented.

For data acquisition, we have set a sampling frequency of 256 Hz using four strategically placed EEG channels: two on the left and right foreheads and two near the left and right ears. The EEG system is connected to the computer using a dedicated interface key and a Software Development Kit (SDK), as shown in Fig 3.

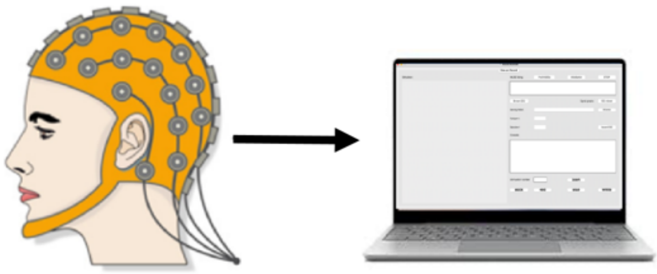

Figure 3. System Hardware device diagram

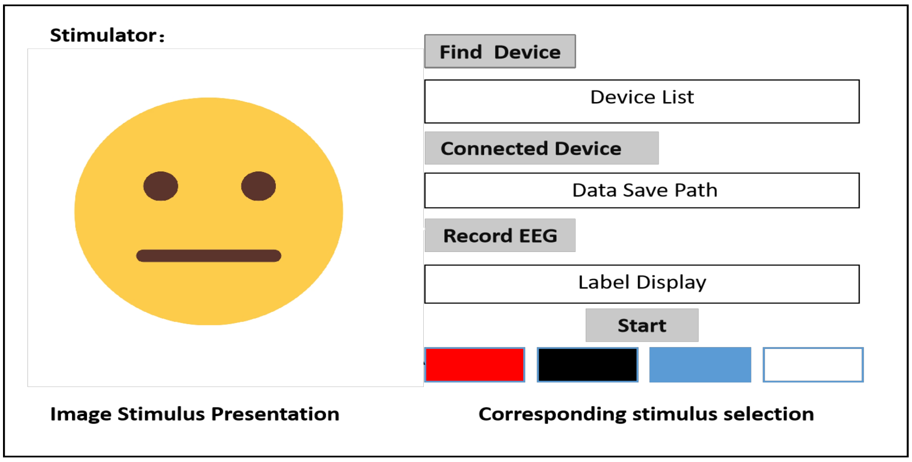

Figure 4. Attention Detection System GUI (emoticons without feedback)

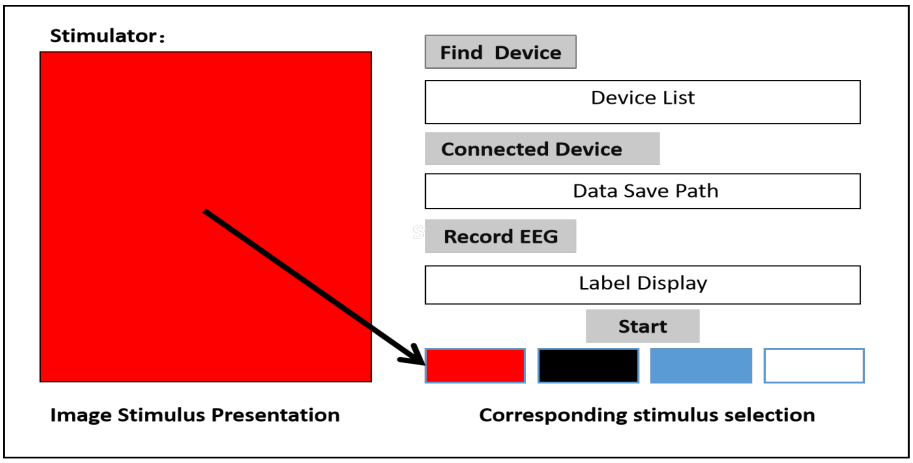

Figure 5. Attention detection system GUI (colour block stimuli requiring feedback)

The Graphical User Interface (GUI) of our system is designed for intuitive use during EEG experiments. First, users click the "Find Device" button to search for the electroencephalograph device. Once found, the "Connected Device" button allows the user to select the device for the experiment. The user must then enter the path, name and serial number where the EEG data will be stored.

Once connected, the experiment is started by clicking the "START" button. In the image stimulus area of the GUI, emoticons or solid blocks of colour (red, black, blue and white) are randomly displayed every second. Participants are instructed to refrain from taking any action when emoticons are displayed, as shown in Fig 4. However, when a solid colour block appears, participants must click a button corresponding to the colour of the block to label it accurately, as shown in Fig 5. The EEG data collected during the first 10 seconds of this labeling task will be used for analysis.

The EEG data collected by the attention detection system has time stamped labels that can be used to manipulate feature extraction for attention level analysis.

Results and Discussion

We used 30 of the 34 subjects as a training set and 4 subjects as a test set. Since attention corresponds to different areas of the brain, we selected channels that are more suitable for attention classification for the computation. In the study of attention, certain brain regions play a central role in shaping attentional processes, while others contribute less significantly. When designing experiments using the 10-20 EEG electrode placement system, careful consideration should be given to the selection of channels that capture neural activity relevant to attention.

Due to the highly nonlinear nature of EEG data, we choose the Radial Basis Function (RBF) as the kernel function for the SVM. This kernel function has been shown to be particularly effective in dealing with complex and nonlinear data sets and is suitable for the needs of our study. To ensure optimal performance of the classifier, we fine tuned two key parameters of the SVM: the regularisation parameter (C) and the γ parameter of the kernel function. Finally, the optimal parameters identified by cross validation were $C = 10$ and $\gamma = 0.01$. This set of parameter combinations achieved the highest classification accuracies on the validation set, suggesting that they are able to effectively process and classify attentional states in EEG data. Experimental results show that the SVM classifier using this parameter set achieves an accuracy of 94% on the test set, which is significantly higher than the baseline model with non optimised parameters.

Table 1: Comparison in detecting attentive states.

Ref.	Classifier	Accuracy
Liu et al., 2013 (Liu et al., 2013)	SVM	76.82%
Ke et al., 2014 (Ke et al., 2014)	SVM	85.24%
Peng et al., 2020 (Peng et al., 2020)	SVM	84.80%
Suhail, 2021 (Suhail et al., 2021)	SVM	92.98%
Al-Nafjan, A. (2022) (Al-Nafjan & Aldayel, 2022)	SVM	72%
Proposed Method	SVM	94%

Liu et al. aimed to improve classroom learning with an objective attention assessment system using EEG data. They used FFT to extract PSD features and calculated energy based on waveband dispersion. The α and β activation ratios were key to assessing alertness, with an accuracy of 76% using SVM classification. Ke et al. developed an attention detection system that distinguishes between attention, no attention and rest states. They explored linear and nonlinear parameters, favouring sample entropy over power spectrum, with impressive accuracies of 76.19% and 85.24% in two experiments. Peng et al. identified mental states using single channel EEG from the frontal region. HHT analysis and SVM classification achieved an average accuracy of 84.80% in distinguishing between attentive and relaxed states. Suhail proposed a neurofeedback system for cognitive state assessment based on EEG. They used various techniques, including Hjorth parameters, wavelet based features and spectral entropy, and selected features using Fisher's ratio and correlation analysis. SVM outperformed KNN and LDA, achieving 92.9% accuracy. Al-Nafjan, A. presented an SVM model with an outstanding 72% accuracy in distinguishing attention states, a significant advance.

In addition, our feature classification achieved 94% accuracy, demonstrating the effectiveness of our approach. Using different EEG and their features to assess attention has several advantages: 1, Different brain waves correspond to different brain states, providing a more comprehensive understanding of attention levels when multiple types are considered. 2, Integrating multiple brain wave characteristics provides a holistic view that overcomes the limitations of relying on a single metric. For example, combining the frequency and amplitude of α waves provides a nuanced assessment of relaxation levels. 3, Since tasks and individuals may respond differently to different frequency bands of brainwaves, using a range of them allows for adaptability to different contexts and individual differences. 4, The combination of multiple brainwave characteristics improves the accuracy of the assessment of attention. For example, observing both a decrease in α waves and an increase in β waves can more reliably indicate heightened attention. 5, The use of multiple EEG features increases the reliability of the assessment. In cases where one feature is influenced by certain factors, other features may provide complementary information, ensuring the overall accuracy of the assessment.

Conclusions

Given the widespread use of BCI systems in the medical field, our approach highlights the importance of focused attention in improving the success rate of BCI systems. In this study, we propose a novel method for classifying EEG data to determine the level of attention for publicly available datasets. This method decomposes the EEG signal into three waveforms θ, α and β using the 4th order Butterworth filter. Extracts waveform ratio features, time domain features, frequency domain features and nonlinear features, multidimensional features significantly expand the feature set, improve classification accuracy and increase the development potential. We use PCA to extract the principal component feature set from the features with a standardised variance of 90%. The feature set after dimensionality reduction and fusion can enable the SVM classifier to classify related features more effectively.

In order to explore the application of attention detection technology in human computer interaction, we developed a composite task EEG attention detection system based on the Mackworth clock test. This system can directionally collect time tagged personal EEG data. By classifying the collected personal attention EEG data, it can stably determine the level of attention of a specific person. Through the proposed classification method and the classification results of others on public datasets, it is shown that the proposed multi dimensional features have a higher classification success rate. The developed EEG attention detection system further verified the effectiveness and feasibility of the classification method. The EEG attention detection system can be used to preprocess the BCI system, demonstrating the practicality of machine learning technology in attention monitoring and significantly improving the performance of the BCI system.

Future research should aim to refine the accuracy and efficiency of EEG data processing and to categorise different levels of attention. The BCI system, which is directly controlled by the level of attention, has the potential to train an individual's attention and potentially address concentration problems in students with neurological difficulties. This approach promises not only to optimise the performance of the BCI system, but also to broaden the range of applications of this technology in various fields.

Data Availability (excluding Review articles)

A publicly available dataset was analyzed in this study. This data can be found here: https://www.kaggle.com/datasets/inancigdem/eeg-data-for-mental-attention-state-detection/data

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Conflicts of Interest

The author has no conflict of interest about anything in this article.

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