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Cognitive Vigilance Enhancement Using Audio Stimulation of Pure Tone at 250 Hz

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ABSTRACT In this paper, we propose a novel vigilance enhancement method based on audio stimulation of pure tone at 250 Hz. We induced two different levels of vigilance state; vigilance decrement (VD) and vigilance enhancement (VE). The VD state was induced by performing a modified version of the Stroop Color-Word Task (SCWT) for approximately 45 minutes. Likewise, the VE state was induced by incorporating audio stimulation of 250 Hz into the SCWT for 45 minutes. We assessed the levels of vigilance on 20 healthy subjects by utilizing Electroencephalogram (EEG) signals and machine learning. The EEG signals were analyzed using four types of entropies; Approximate Entropy (AE), Sample Entropy (SE), Fuzzy Entropy (FE), and Differential Entropy (DE). We then quantified vigilance levels using statistical analysis and support vector machines (SVM) classifier. We found that the proposed VE method has significantly reduced the reaction time (RT) by 44% and improved the accuracy of target detection by 25%, ($p < 0.001$) compared to VD state. Besides, we found that 30 min of audio stimulation has reduced the RT by 32% from the beginning to the end of VE phase of the experiment. The entropy measures show that the temporal profile of the EEG signals has significantly increased with VE. The classification results showed that SVM technique with DE features across all frequency bands can detect VE levels with accuracy varying between (92.10±02.24)% to (98.32±01.14)%, sensitivity of (92.50±02.33)% to (98.66±01.00)%, and specificity of (91.70±02.32)% to (97.99±01.05)%. Results also showed that the classification performance using DE has outperformed the other entropy measures by an average of +8.07%. Our results demonstrate the effectiveness of the proposed 250 Hz audio stimulation method in improving vigilance level and suggest using it for future cognitive enhancement studies.

INDEX TERMS Vigilance, enhancement, electroencephalogram (EEG), entropies, and SVM.

I. INTRODUCTION

Previous studies have highlighted the importance of maintaining high vigilance in multiple applied settings [1]. Vigilance, as part of the attentional networks model, is responsible for maintaining the required state of activation to facilitate the functioning of the attentional system, in order to appropriately detect and quickly react to stimuli in the environment [2], [3]. Deterioration in vigilant attention is the primary risk factor for accidents and injury when driving a vehicle, flying an aircraft, operating production line machinery and medical operations [4]–[6].

A consistent finding reported by several studies is that vigilance affects the user's reaction time causing a delay or even absence of an appropriate reaction to potentially dangerous events. To avoid the potential of danger and accidents during relatively long demanding cognitive process, vigilance enhancement is required.

Vigilance enhancement refers to the deliberate use of technological, medical, or therapeutic interventions to improve cognitive processing and attentional performance [1]. From a practical point of view, vigilance enhancement allows for

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maintaining an optimal cognitive performance and increased safety during a challenging work environment.

Researchers have utilized a wide range of traditional and computerized enhancement methods to improve sustained attention. These methods include: mental training [7], meditation [8], sports [2], caffeine [2], nicotine [9], herbal extraction [10], chewing gum (CG) [11], fragrances exposure [12], playing video games (VG) [13], applying transcranial alternating current stimulation (tACS) [14], or transcranial direct current stimulation (tDCS) [15], tactile and rhythmic haptics (RHP) [16], integrating of multiple tasks (IMT) [17], music [18] and binaural beat (BB) stimulation [19]. We have recently conducted a comprehensive review on the aforementioned enhancement methods on vigilance levels in the context of work, monitoring/surveillance, driving, learning, performing cognitive and memory tasks, typing, and sports [1]. We used the reaction time as a quantitative measure to assess the level of vigilance enhancement as reported in the findings of the collected studies. We found that when simple monotonous vigilance tasks were considered, the aforementioned enhancement methods showed a positive impact on vigilance. The techniques showed an average improvements varying between +8% to +18%. VG and tDCS reported the highest improvements on sustained attention with more than +15% on monotonous vigilance task. This was then followed by RHP, modafinil, IMT, caffeine, tACS, CG, music, binaural beats (BBs), and fragrance with improvements between +8% to +13%. However, in complex vigilance tasks, the above methods gave contradictory results. Auditory BB stimulation and tACS provided consistent improvements on vigilance levels at the monotonous and complex vigilance task. The consistent vigilance enhancement by BBs and tACS could be due to the permutation of physiological entrainment through frequency stimulations [1], [20].

In this study, we propose utilizing audio stimulation of pure tone at 250 Hz for vigilance enhancement. The selection of the 250 Hz was in line with a previous study using Magnetoencephalography (MEG), which demonstrated its effectiveness in minimizing the cortical contributions to the brainstem responses [21]. Typically, the frequency of 250 Hz is a good compromise between sensitivity and pleasing sounds. Besides, the 250 Hz had been used as the carrier frequency for most BBs in vigilance studies [1]. Audio stimulation has been of interest for a wide range of applications. Recent studies have suggested that audio stimulation can be used to modulate cognition [22], reduce anxiety levels [23], and enhance mood states [24]. Other clinical targets also include traumatic brain injury [25], anesthesia [26], reduced pain intensity [27], and attention-deficit hyperactivity disorder [28]. It is important to emphasize, however, that the results were usually presented based up on questionnaires, being therefore, subjective.

In this study, we investigate a more objective approach to analyze the impact of 250 Hz audio stimulation on vigilance levels by detecting certain features of interest in the signals acquired by electroencephalography (EEG). Traditionally, EEG signals have been studied through linear methods, mainly based on the computation of their power spectral density [29]–[31], as well as the symmetry between both brain hemispheres [32]. Studies have shown that spectral powers in typical frequency bands are closely related to vigilance decrement. Data analysis presented in this study involved five frequency bands, [delta (<4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz) and wide/full (0.1–30 Hz) frequency bands].The main findings of research using EEG vigilance level assessment suggest that low-frequency brain rhythms (4-12 Hz) increase during vigilance decrement. An increase in low-frequency rhythms is an indication of decreased alertness, corroborating with behavioral impairment of vigilance decrement [33]. However, these methods have reported some inter-subject inconsistencies [34]. Besides, it is well-known that non-linearity in the brain signals appear even at the cellular level, the dynamical behavior of individual neurons is governed by threshold and saturation phenomena [35]. Thus, a variety of non-linear metrics have been applied to analyze EEG signals in vigilance studies. For instance, differential entropy (DE) [36], wavelet entropy (WE) [37] and synchronization with directed transfer functions [32], [38], [39]. In most studies, the non-linear indices tested have reported more relevant information than common linear tools. Hence, the present work focuses on this incipient research area. We propose using four types of entropy, namely; Approximate entropy (AE), Sample entropy (SE), Fuzzy entropy (FE), and Differential entropy (DE) for EEG vigilance data analysis. Entropy is a nonlinear measure to reflect the degree of uncertainty in a given system, which is capable of characterizing the brain states from EEG signals. More importantly, the entropy measures have been successfully used to quantify the irregularity, randomness and complexity of EEG signals in many domains [40]–[43].

The main contributions of this work are as follows:

- Development of an experimental protocol to induce two different levels of vigilance state: vigilance decrement (VD) and vigilance enhancement (VE).
- Evaluation of the effectiveness of audio stimulation at 250 Hz on vigilance enhancement using EEG signals, RT and accuracy of target detection.
- Quantification of vigilance levels using EEG signals and machine learning.

The rest of the paper is organized as follows. Section II describes the methodology; covering participants, vigilance task, audio stimulation, data acquisition and preprocessing, data analysis methods, statistical analysis and classification. Section III presents the results of behavioral data, entropies and classification. Section IV provides a detailed discussion on the findings and provides suggestions for future work. Finally, section V concludes this paper.

II. METHODOLOGY

A. PARTICIPANTS

We recruited 20 healthy participants (16-males and 4-females, age: 22 ± 2 years, (mean ± standard deviation)).

All participants had normal or corrected to normal vision and no reported hearing difficulties. Besides, they had no history of neurological or psychiatric illnesses and had no current or prior psychoactive medication use. The experiment was conducted between 3.00 pm and 7 pm to avoid the influences of circadian rhythm on cognitive vigilance performance [44]. All participants were asked to give a written informed consent before participation in the study. The participants were asked to abstain from caffeine, exercise, energy drink, and tobacco use for 24 hours before testing. All methods performed to follow the Declaration of Helsinki. The experiment was approved by the Institutional Review Board of the American University of Sharjah.

B. VIGILANCE TASK

The vigilance task used in this study is a computerized version of the Stroop Color-Word Test (SCWT) implemented in a custom-made Graphical User Interface developed in MATLAB (Mathworks, USA). The SCWT consists of displaying six color words such as ['Blue', 'Green', 'Red', 'Magenta', 'Cyan', and 'Yellow'] in random order. One word is displayed at a time and the answers of the color word to be matched to are presented in random sequences in the computer screen monitor as shown in FIGURE 1(a). The displayed color word on the monitor screen is written in a different color than the word's meaning and the correct answer is the color in which the word is displayed (e.g.: if Green is written in Cyan then Cyan is the correct answer). The participants were instructed to pick their answers as quickly and accurately as possible by left-clicking the mouse on one of the six answering buttons. The answer to the color word is presented with random colored-background to maintain sustained attention to the task, as shown in FIGURE 1(b). The participants would also receive feedback, i.e. a message of ''Correct'' or ''Incorrect'' or ''Time is out'' on the monitor, depending upon answering correctly/incorrectly or failing to answer each question within the stipulated time.

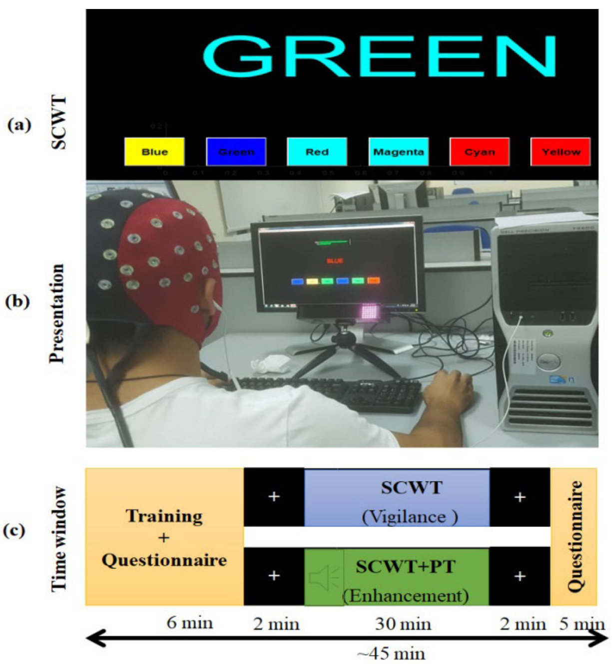

FIGURE 1. The experimental design a) Stroop color-word task (SCWT), b) shows the presentation interface and c) demonstrates the timing window. In the timing window, the plus sign in black background is for the pre and post-baseline. Thirty (30) min SCWT or SCWT+PT are for the vigilance task presentation.

Behavioral data such as reaction time (RT) to stimuli and accuracy of detection were collected while solving the vigilance task. The RT is measured as the average time it takes for the participant to respond to a target stimulus. Meanwhile, the accuracy was calculated based on the number of the color word correctly matched over the total number of the displayed color word targets. These metrics were then used to measure vigilance levels objectively. Different markers were sent to mark the start and the end of epochs in each SCWT question.

In this study, the participants were randomly assigned to one of the two groups (10 subjects for VD and 10 subjects for VE). The experimental protocol was conducted in two different sessions. One session for the vigilance decrement group and another session for the enhancement group. In the vigilance decrement group, each participant performed the SCWT continuously for 30 min, whereas, in the enhancement group, each participant performed the same SCWT while listening to an audio stimulation of pure tone (PT) at 250 Hz for 30 min. The overall experimental time frame for each session included 6 minutes for training and filling the questionnaire, 2 minutes pre-baseline, 30 minutes performing SCWT without audio/ with 250 Hz audio stimulation, 2 minutes post-baseline and 5 minutes for filling out another survey as demonstrated in FIGURE 1(c). The questionnaire used in this study was based on the Brunel Mood Scale (BRMUS) [45]. All participants filled-in the questionnaire before and after they performed the vigilance task. The BRMUS composed of 32 items. These items correspond to an 8-factor model including ''Anger,'' ''Tension'', ''Confusion,'' ''Depression,'' ''Fatigue,'' ''Happy,'' ''Calmness'' and ''Vigor.'' Each item has 5-point Likert scale ranges from '0' to '4' representing ''not at all'' to ''extremely'' depending on the participant's feelings.

C. AUDIO STIMULATION

We enhanced the vigilance level by utilizing an audio stimulation. We produced a pure tone of 250 Hz and presented into the right and left ears of participants using stereo headphones (MDR-NC7, Sony). The audio stimulation is developed using MATLAB software (R2020a). The volume of the auditory stimuli is set by the participants and delivered at minimum intensities of 50 dB. We presented the audio stimulation continuously with the task to avoid the impact of short rest on the vigilance level [1]. The audio tone was generated at a sampling rate of 48 kHz to ensure that the highest stimulus frequencies are well below the Nyquist rate. Stimuli were represented in memory as 32-bit integers so that the full dynamic range could be tested with minimal risk of quantization distortion.

D. DATA ACQUISITION AND PREPROCESSING

The EEG data were recorded using 64 Ag/AgCL scalp electrodes arranged according to the international 10–20 system (Waveguard, ANT B.V., Netherlands). The data were recorded at a sampling frequency of 500 Hz. Electrode impedance was maintained and kept below 10 kΩ throughout all the recordings and referenced to the left and right mastoids; M1 and M2. The main interferences were avoided by anti-aliasing with a band-pass filter (0.5-70 Hz) and a 50 Hz notch filter.

The EEG data were preprocessed using EEGLAB Toolbox [46] with the in-house MATLAB script [47]–[50]. The EEG signals were band-pass filtered with third-order Butterworth filters between 0.1 Hz to 30 Hz bandwidth to remove the unwanted spectral content such as power line interference, noise due to body movements, and other unknown sources. After filtering, Independent Component Analysis (ICA) was performed to remove noise components related to body movements, interference from other biological signals such as EOG, EMG, and electrocardiographic (ECG) modulation. The EEG signals were then re-referenced to the average of all channels and segmented into epochs in the range of 0- 1200 ms after the stimulus onset. Finally, all EEG epochs were visually double-checked to eliminate data segments contaminated with noise.

Then, we defined two types of vigilance states:

1) VIGILANCE DECREMENT

This include the first 5 min concatenated with the last 5 min of the EEG signals while 10-subjects performing the SCWT. There was 160 epochs in the two 5-min concatenated EEG data.

2) VIGILANCE ENHANCEMENT:

This include the first 5 min concatenated with the last 5 min of the EEG signals while another 10-subjects performing SCWT+PT. Similar to the vigilance decrement state, there was 160 epochs in the two 5-min concatenated EEG data.

Now for each vigilance state,, we investigated four types of entropy in each epoch to quantify the level of vigilance decrement and enhancement. The proposed entropies are briefly described below.

E. DATA ANALYSIS

First, we adopted a bandpass filter to decompose the EEG signals into five bands, including Delta (0.1–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Wide band at full spectrum (0.1–30 Hz).Then, we processed the EEG signals using four types of entropy, namely; Approximate entropy (AE), Sample entropy (SE), Fuzzy entropy (FE), and Differential entropy (DE). Entropy measures have been successfully used to quantify the level of uncertainty of EEG signals in many domains [40]–[43]. Although the original EEG signals do not follow a fixed distribution, EEG signals can be assumed to obey Gaussian distribution after band-pass filtering from 2Hz to 44Hz by steps of2Hz.

APPROXIMATE ENTROPY (AE) is a method proposed by Pincus [51] to measure the regularity of time series and the variations of statistics. AE measures the complexity of a time series in multiple dimensions and is extensively applied in the field of EEG signal analysis. In particular, AE use positive numbers to represent the likelihood of data to quantitatively describe the complexity of time series. Thus, the results of the AE reflect the complexity of the analyzed signal, regardless of the amplitude of the signal. Consequently, the more complex the time series is, the larger the approximate entropy.

SAMPLE ENTROPY (SE is proposed by Richman and Moorman [52] as a measure of time series complexity. SE has been widely used in evaluating the complexity of physiological time series and diagnosing pathological status. It measures the predictability of consequent amplitude values of the EEG based on information about previous amplitude values, and its calculation is not dependent on the length of the data. Similar to AE, SE is less sensitive to changes in data length, with larger values corresponding to greater complexity or irregularity in the data. However, SE may yield imprecise estimation because its similarity of two vectors is dependent on the Heaviside function.

FUZZY ENTROPY (FE) is an improved algorithm based on SE and AP for overcoming the drawbacks of them [53]. FE achieved stable results for different parameters and offered better noise resistance using the fuzzy membership function [54]. It uses the Gaussian function to measure the similarity of two vectors instead of the Heaviside function. The jumping characteristic of the Heaviside function leads to the discontinuity of AE and SE. Due to the continuity of the Gaussian function, FE effectively avoids the drawbacks of the AE and SE [55]. The FE not only takes the advantages of sample entropy but also has less dependence on the length of time series and possesses better robustness to the noise signal. It is more suitable than the sample entropy as a measure of time series complexity. The calculation algorithms of AE, SE, and FE are clearly defined in [52], [56].

DIFFERENTIAL ENTROPY (DE): is used to measure the complexity of continuous random variables. The DE is related to the minimum description length [36]. It has been proven that, for a fixed length EEG sequence, DE is equivalent to the logarithm energy spectrum in an individual frequency band [57], [36]. DE is then employed to construct features in the five frequency bands mentioned above. The estimation of the complexity parameters for the aforementioned entropies are discussed below.

1) ENTROPY FUNCTION SELECTION

The complexity parameters such as the embedding dimension m, and tolerance r, of the three entropies, AE, SE and, FE were estimated according to previous studies [40], [41]. Previous entropy studies suggested that the values of m and r can be selected within the ranges: (m [2, 4] and r [0.1, 0.9]). It should be noted that the entropy tolerance r has a direct influence on the entropy value. Too-large tolerance would let in redundant signals that interfere with genuine features. If the selected r value is too small, feature sensitivity is increased so that the entropy value is disordered by the noise. Thus, in the present study, the variables $m = 2$ and $r = 0.2$ times the standard deviation of the EEG data were adopted. Additionally, for the FE index gradient n, we set $n = 2$ and $\tau = 1$ after applying several iterations. The variables were selected in such a way to fit with our type of experiment (our experiment is based on event related potential). FIGURE 2 shows the flow chart of the proposed method.

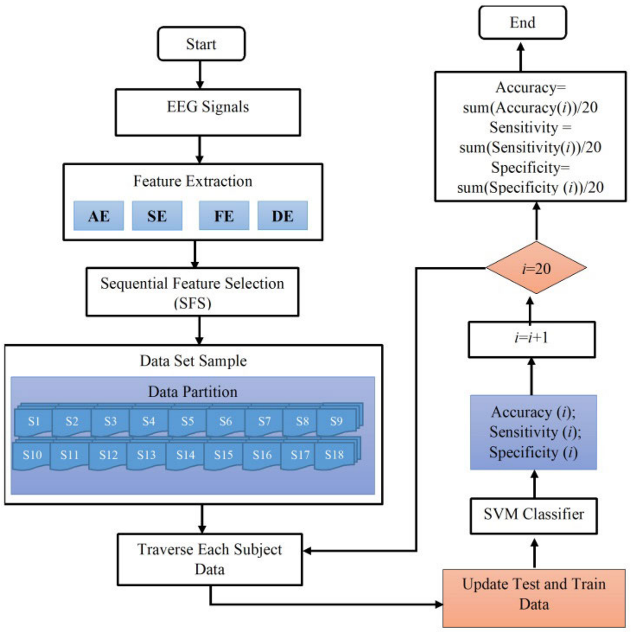

FIGURE 2. **Flow chart of the proposed method.**

F. STATISTICAL ANALYSIS AND CLASSIFICATION

A paired t-test was used to verify the effect of audio stimulation on subjective feelings, behavioral responses, and EEG variables (entropy values at VD vs VE). Before conducting the t-test, we used the Kolmogorov-Smirnov test to check if the data are normally distributed [58]. The Pearson correlation and simple linear regression were formed to verify the association between entropy measures and behavioral data measured by RT across the vigilance states. The statistical differences was assumed to be significant if p-value was less than 0.05, $p < 0.05$.

1) SUPPORT VECTOR MACHINES (SVM)

We classified the vigilance levels using SVM. The kernel function of SVM in this study was the Gaussian Radial Basis Function (RBF), and the learning method is minimal sequential optimization. We investigated the classification accuracy of vigilance states in the form of subject-independent classification. We adopt the leave-one-subject-out (LOSO) cross-validation strategy to evaluate the EEG vigilance level classification performance of the proposed methods. Prior to classification, we applied Sequential Feature Selection (SFS) algorithm [59] to reduce the dimensionality of the EEG features. The SFS generates a set of uncorrelated variables. Thus, it selects a sufficiently reduced subset from the EEG feature space without affecting the performance of the classifier. The EEG data of 19-subjects are used for training the classifiers, and the remaining EEG data of one subject is used as testing data. The classifications procedures are repeated such that the EEG data of each subject is used as the testing data.

2) PERFORMANCE MEASURES

We evaluated the SVM classifier based on the accuracy, sensitivity and specificity. The accuracy of a classifier is the percentage of the test set which is correctly classified by the classifier. The sensitivity is referred to the true positive rate which is the proportion of the positive set correctly identified. The specificity is the true negative average, which is the proportion of the negative set correctly identified. The following Eqs. (1)–(3) provide the definitions for the terms.

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Sensitivity(\%) = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity(\%) = \frac{TN}{TN + FP} \tag{3}$$

where TP is the number of true positives, TN is the number of true negatives and P and N are the positive and negative samples, respectively. The average classification accuracies, sensitivities, specificities, with their standard deviations corresponding to the entropy methods of analysis at the five frequencies are respectively calculated.

III. RESULTS

A. SUBJECTIVE AND BEHAVIORAL DATA ANALYSIS

We examined the changes in subjective feelings of vigilance states with the BRMUS scores and found significant effect of audio stimulation (SCWT vs SCWT+PT) in concentration. Two sample t-test comparing emotional states after performing SCWT for 30 min without audio stimulation and after the SCWT+PT revealed significant increase of engagement. The statistical analysis showed that anger, tension, depression, fatigue, and confusion, were significantly reduced after performing the SCWT+PT with $p < 0.05$, while, happy, and calmness significantly increased, $p < 0.02$. Table 1 show the BRMUS score at vigilance decrement and enhancement states with their corresponding statistical analysis.

The behavioral data such as the reaction time (RT) and accuracy for vigilance decrement (VD) and vigilance enhancement (VE) groups are shown in FIGURE 3. To reveal the development trend of behavioral measures with the time-on-task, the reaction time and accuracy were averaged within a 5-min bin and plotted against the time of the experiment (FIGURE 3). The results of the RT show a linear

TABLE 1. Comparison of brmus subscales Means ± SE after vigilance decrement and vigilance enhancement states.

BRMUS	Vigilance Decrement	Vigilance Enhancement	T-test result	
	(mean ± std)	(mean ± std)	t-value	p-value
Anger	2.15±0.34	0.50±0.31	2.31	<0.050
Tension	1.40±0.30	0.66±0.53	2.22	<0.050
Depression	2.50±0.31	0.40±0.32	2.68	<0.020
Vigor	2.00±0.28	2.62±0.48	1.40	0.076
Fatigue	2.84±0.20	1.32±0.41	2.88	<0.020
Confusion	2.12±0.50	0.63±0.51	2.66	<0.024
Happy	1.75±0.30	3.04±0.29	2.82	<0.020
Calmness	1.79±0.32	3.06±0.29	2.63	<0.020

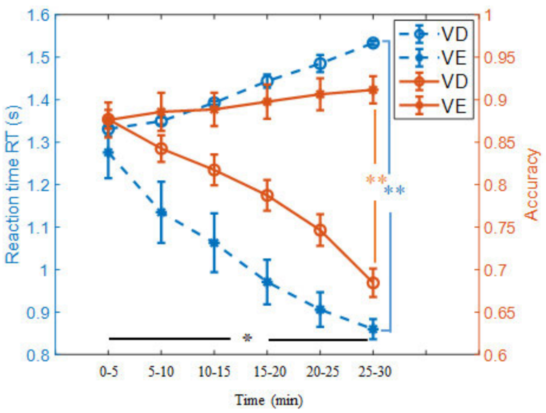

FIGURE 3. Reaction Time and Accuracy in 5-min interval for vigilance decrement (VD) and vigilance enhancement (VE). Error bars represent standard deviation of the mean across subjects. The asterisk '*' and '' indicates the differences is significant with p < 0.05 and p < 0.01.**

increasing trend with the time-on-task in the vigilance decrement group (with 13% increment from the beginning to the end of VD experiment) and show a linear decrement with the time-on-task in the vigilance enhancement group (with 32% decrement in RT). The statistical analysis showed significant decrease in the RT from vigilance decrement to vigilance enhancement with time-on-task, $p < 0.01$. Meanwhile, there was a significant increase in the accuracy from vigilance decrement to vigilance enhancement (with 22% improvements) with $p < 0.01$. Thus, the overall behavioral results indicate that listening to audio stimulation of PT at 250 Hz while performing SCWT for 30 min was effective in eliciting vigilance enhancement to all participants. Considering the increasing trend of the RT, the brain control ability decreased continuously, therefore, the first and last 5-min with the maximum interval and significant difference were defined as the alert and vigilance decrement states in the SCWT task.

B. ENTROPY ANALYSIS RESULTS

The complexity entropy (AE, SE, FE, DE) measured values for each EEG electrode and trial in all the frequency bands are shown in FIGURE 4 to FIGURE 8. For visualization, we plotted the entropy mean values for all EEG-electrodes at each trial (time window) to show their variation in the two mental states; the VD (trials labelled from 1-166) and the VE (trials labelled from 167-332).

In FIGURE 4 to FIGURE 8, we show the average complexity entropy of all subjects at Delta, Theta, Alpha, Beta, and Wide band for the VD and VE states respectively. The labels 'a', 'b', 'c', 'd' within each FIGURE depict the entropy complexity map of a) AE, (b) SE, (c) FE and (d) DE, respectively. As can be seen from the maps in each FIGURE (4-8), the entropy complexity for trials in the VE state are higher than that in the VD state at most electrodes. Specifically, FE and DE show the most discriminative complexity patterns across the two mental states, VD and VE. Through the analysis of entropy temporal profiles (series of trials) in the VD and VE, the results clearly and directly show that the entropy features are very informative to differentiate between the two vigilance states, VD and VE.

The statistical analysis for each type of entropy and band are summarized and depicted in FIGURE 9. FIGURE 9 shows the topographical statistical T-maps for each type of entropy in the five frequency bands. Positive value or red color T-map indicates that the entropy measured values increased from VD to VE states and negative value or blue color T-map indicates that the entropy measured values decrease from VD to VE state. The asterisk '*' within the topographical maps reveal that, the differences between the two mental states, VD vs VE, are statistically significant at $p < 0.05$. From FIGURE 9, we can clearly see that most electrodes located at the left frontal region show significant increase in all the frequency bands and types of entropy. Interestingly, when looking at each frequency band, we can clearly see that the higher frequency bands are more sensitive to vigilance levels than lower frequency bands as they show patterns that are more significant. Besides, when we consider the type of entropy, we can clearly see that the DE shows more significant electrodes than other entropies. Specifically, electrodes located at the left hemisphere and occipital regions show the most significant difference in the two mental states with higher T-values.

C. RELATIONSHIP BETWEEN BRAIN ACTIVITY AND REACTION TIME

The entropy complexity/values change with time varying and vigilance state. To study the correlation between vigilance state and RT, we first subtracted the entropy measures as well as the RT of VD from that in the VE state. Then, we correlated the changes/differences in entropy with the changes in the RT to stimuli in each electrode for all the frequency bands. To better visualize the correlation analysis at the scalp level, we depicted the correlation values in the form of heat map as shown in FIGURE 10. This will help to match it to the behavioral and statistical analysis maps in FIGURE 3, and FIGURE 9. We found that the entropy values in the electrode level negatively/positively correlated with RT as shown in FIGURE 10. The significance of the

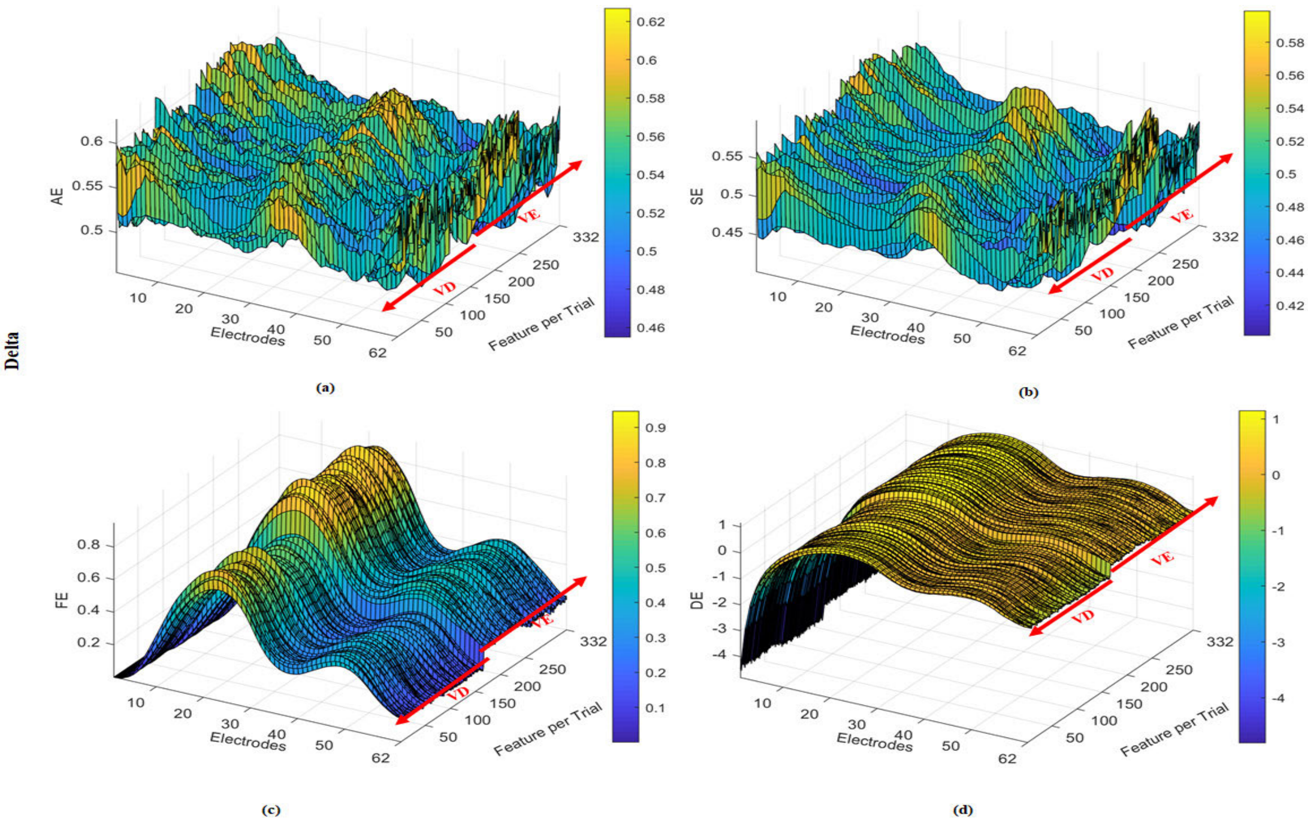

FIGURE 4. The average entropy complexity/values in EEG delta frequency band with 332 sliding window for 62-channel EEG signals of a) approximate entropy, b) sample entropy, c) fuzzy entropy and d) differential entropy in the vigilance decrement (VD) and vigilance enhancement (VE) states.

correlation (negative or positive) between the entropies and RT across the scalp is depicted by asterisk within the heatmap at $p < 0.05$. Significant negative correlation indicates vigilance enhancement and significant positive correlation indicates impairments. In this context, the negative correlation map shown in our analysis indicates that the entropy values increase with decreasing the RT (with VE). In particular, we found the highest negative correlation of $r = -0.78$, $p < 0.05$ at electrodes located within the left frontal region of the brain in all the frequency bands and types of entropy. The consistent negative correlations at the left frontal electrodes (AF7, AF3, F7, F5, and Fp1) across all the frequency bands and types of entropy demonstrate the effectiveness of audio stimulation in enhancing the vigilance state. When considering each frequency band alone, we can clearly see that the wide band and beta band show more enhancement distributed across the scalp for all types of entropy. Likewise, when we consider the types of entropy, we can clearly see that the DE and FE are the most sensitive method to vigilance enhancement as they show more significant electrodes at $p < 0.05$.

Meanwhile, the positive correlation map shown in FIGURE 10 indicates that the entropy values decrease with decreasing RT. From FIGURE 10 we can clearly see that the positive correlation is widely distributed across the brain but only few electrodes are significantly correlated as shown by the asterisk symbol. The overall correlation analysis depicted in FIGURE 10 is consistent with the statistical analysis in FIGURE 9. Taken the annotations from FIGURE 3, FIGURE 9 and FIGURE 10, we can clearly say that audio stimulation significantly alters brain activity and results in vigilance enhancement.

D. CLASSIFICATION

To differentiate between the two vigilance states; VD and VE, the entropy based features at each frequency band were used for classification. Taking the advantages of the feature dimension reduction, only the significant features selected by SFS were used to evaluate the proposed methods. The SFS resulted in 19-fetures distributed across the scalp. The selected features for all methods and bands were within the given EEG electrodes: AF7, AF3, F7, F5, F3, FT7, T7, C5, Fp1, Fp2, AF4, F8, F2, T8, C4, O1, O2, CP5 and CP3. The overall classification accuracy, sensitivity and specificity of the proposed methods are summarized in TABLE.2. The classification results are given as means±standard deviations. From TABLE 2, we obtain the following significant points:

- As regards the kind of entropy method, the best classification accuracy, sensitivity and specificity is achieved using DE. FE produced comparable classification performance to DE at delta band. The SE and AE produced

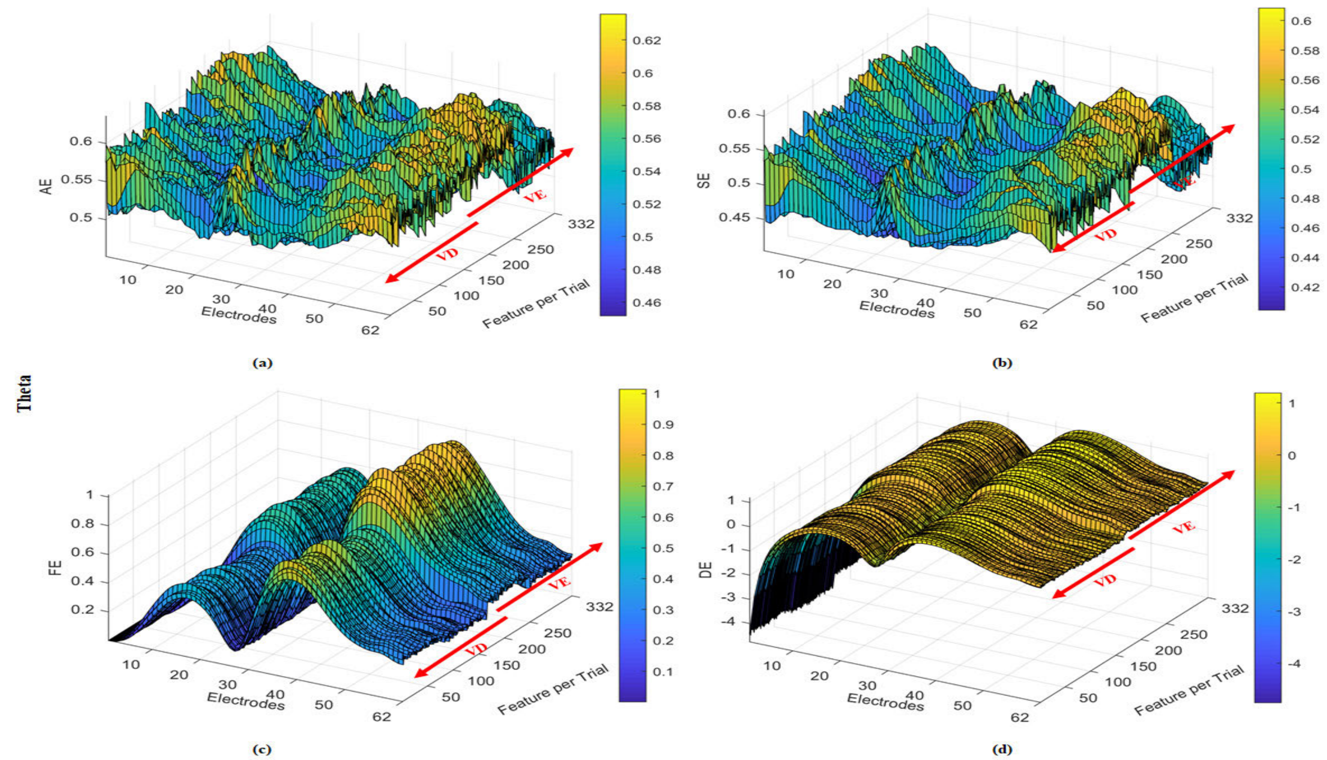

FIGURE 5. The average entropy complexity in EEG Theta frequency band with 332 sliding window for 62-channel EEG signals of a) approximate entropy, b) sample entropy, c) fuzzy entropy and d) differential entropy in the vigilance decrement (VD) and vigilance enhancement (VE) states.

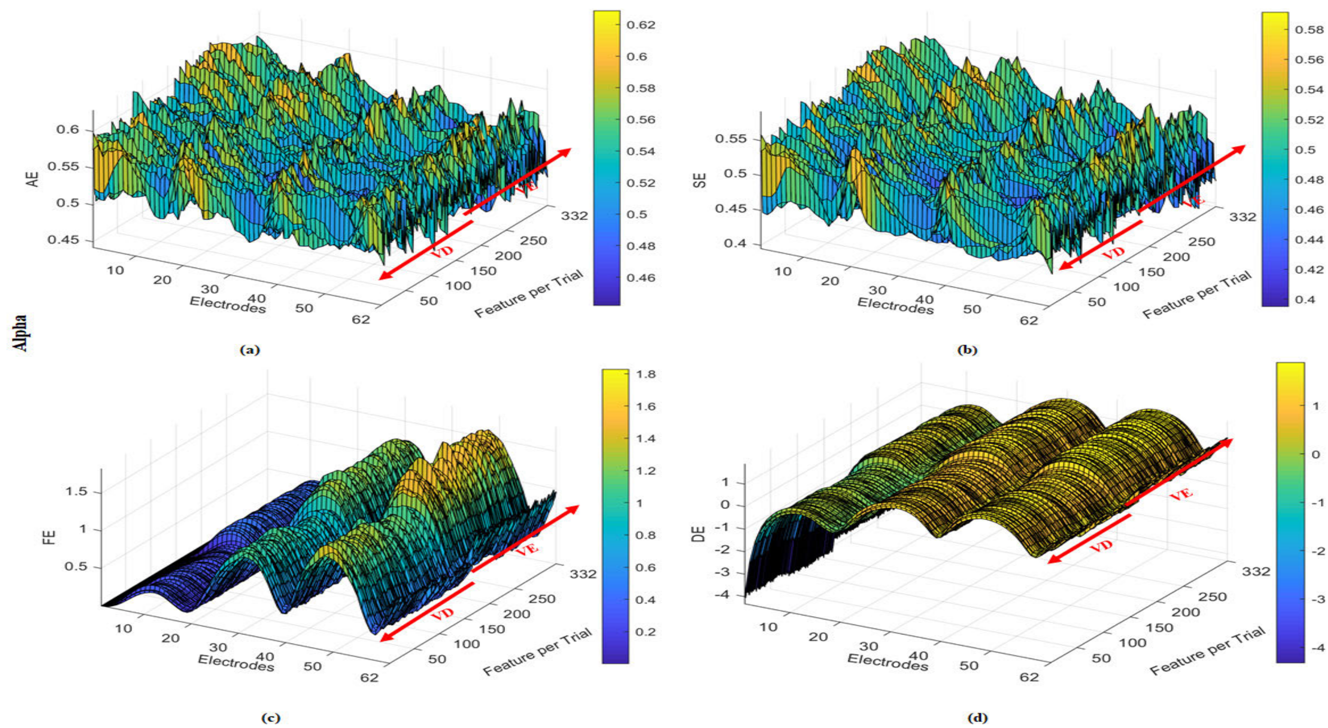

FIGURE 6. The average entropy complexity in EEG Alpha frequency band with 332 sliding window for 62-channel EEG signals of a) approximate entropy, b) sample entropy, c) fuzzy entropy and d) differential entropy in the vigilance decrement (VD) and vigilance enhancement (VE) states.

less classification performance in term of accuracy, sensitivity and specificity compared to DE and FE at most of the frequency bands. The ANNOVA test with multiple comparison showed that DE has significantly ($p < 0.0001$) outperformed SE and AP in classifying vigilance levels at all the evaluation metrics, see TABLE 2.

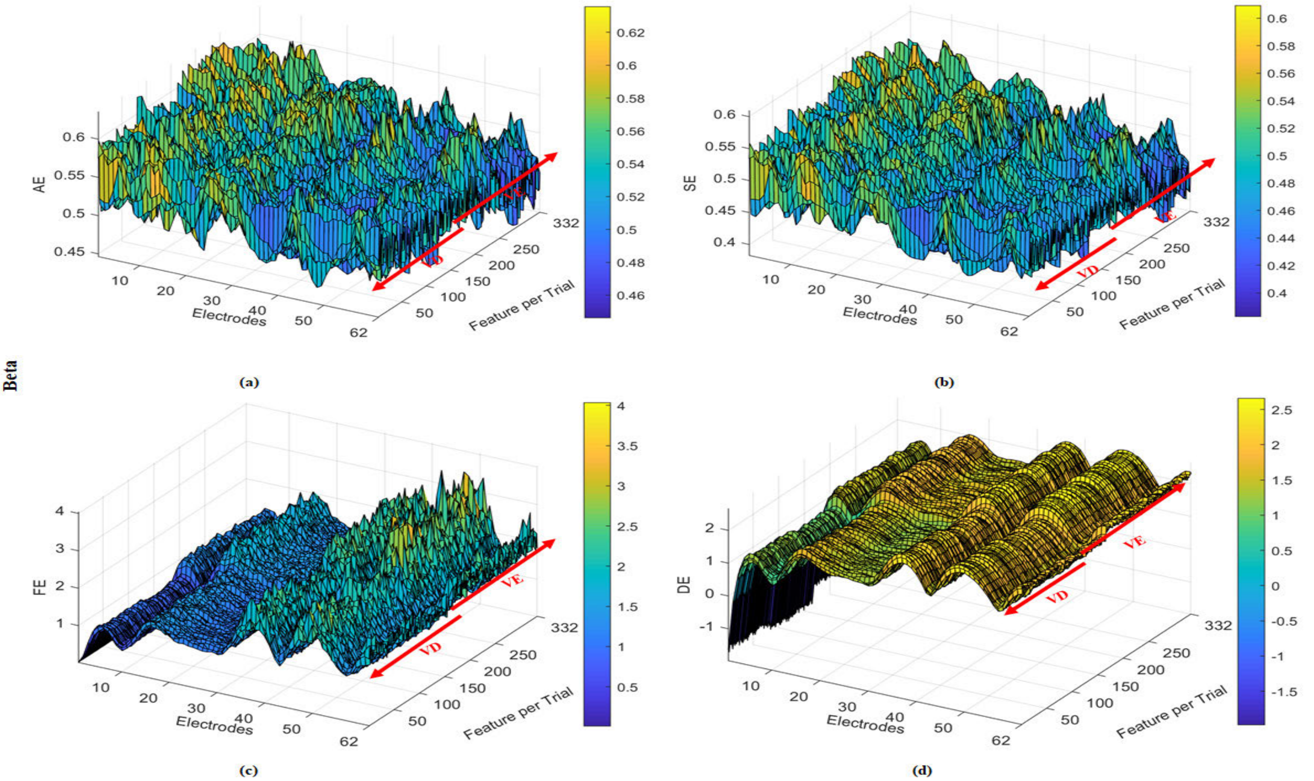

FIGURE 7. The average entropy complexity in EEG Beta frequency band with 332 sliding window for 62-channel EEG signals of a) approximate entropy, b) sample entropy, c) fuzzy entropy and d) differential entropy in the vigilance decrement (VD) and vigilance enhancement (VE) states.

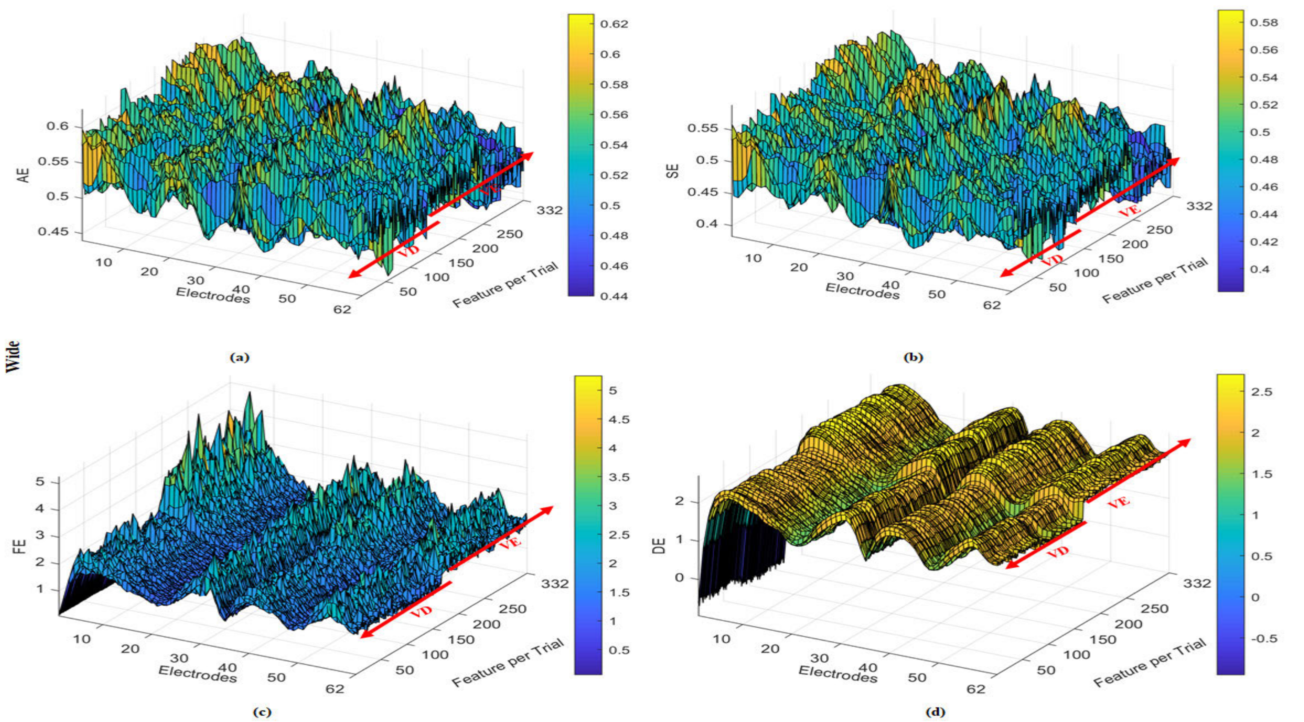

FIGURE 8. The average entropy complexity in EEG Wide frequency band with 332 sliding window for 62-channel EEG signals of a) approximate entropy, b) sample entropy, c) fuzzy entropy and d) differential entropy in the vigilance decrement (VD) and vigilance enhancement (VE) states.

It also showed that DE has significantly ($p < 0.0001$) outperformed FE in theta, alpha and beta bands but not in delta band, $p = 0.87$.

- For frequency bands, the highest classification performance in term of accuracy, sensitivity and specificity is achieved with the high frequency bands. Specifically,

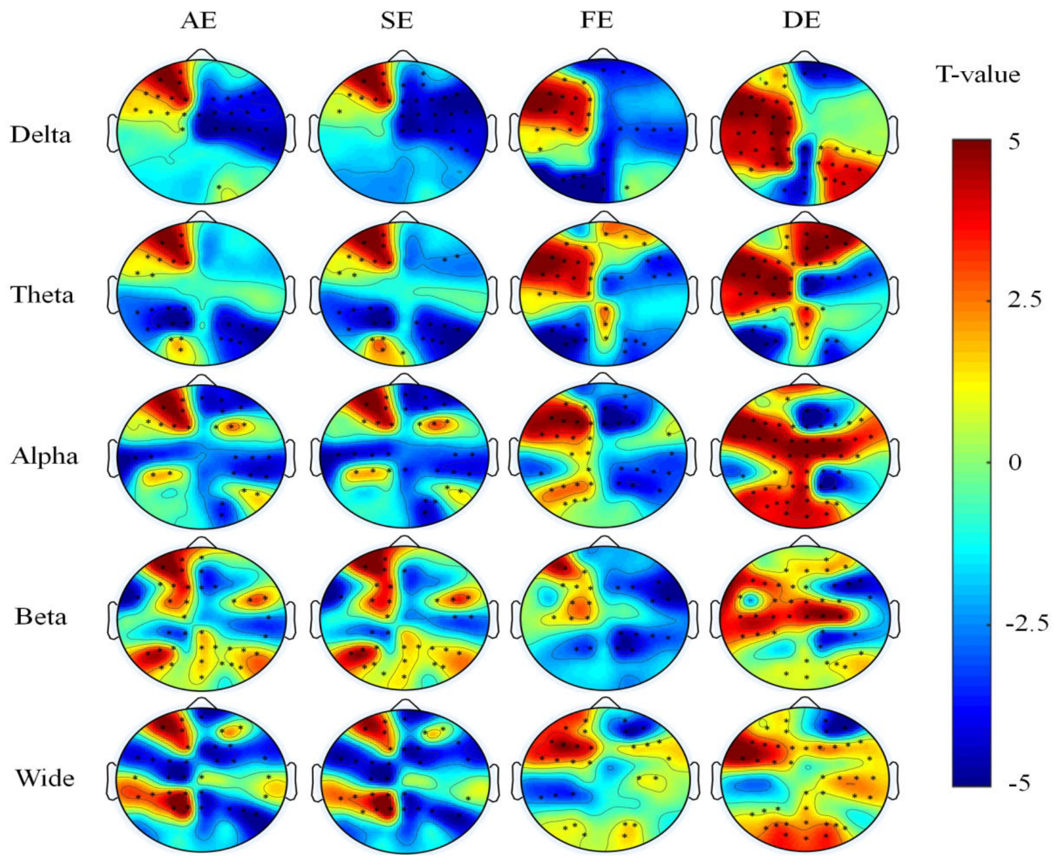

FIGURE 9. Statistical analysis of vigilance levels; VD vs VE in all types of entropy and frequency bands. Positive value in the T-map indicates increment in the entropy values from VD to VE and negative value indicates reduction in the entropy values from VD to the VE states. The star within the maps indicate that the differences between VD and VE is significant with $p < 0.05$.

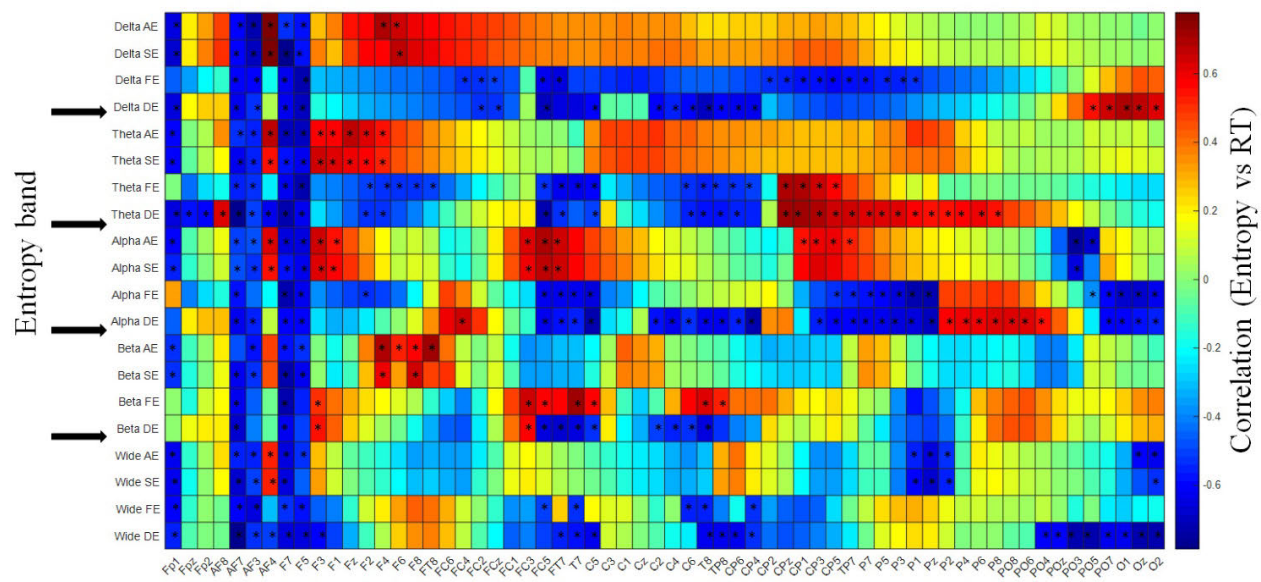

FIGURE 10. Correlation coefficient analysis between entropies at five frequency bands and the reaction time (RT). Positive correlation indicate that the entropy value increase with increasing the RT and negative correlation indicate that the entropy value increase with decreasing RT. The asterisk within the maps indicate that the correlation between entropy and RT is significant with $p < 0.05$.

we found wide frequency band at full spectrum and the beta band produced the highest classification performance in all the entropy methods except for FE. Wide band and beta band outperform other bands in classification accuracy, sensitivity and specificity with more than +4% in the DE, and +5% in the SE and AE methods,

TABLE 2. Comparisons of the average accuracies and standard deviations (%) of subject independent EEG-based vigilance and enhancement level classification among the various methods.

Performance	Method	Delta	Theta	Alpha	Beta	Wide Band
Accuracy	AE	67.23±03.95	70.34±03.12	74.39±03.94	79.68±02.19	81.05±02.90
	SE	71.15±02.66	74.89±03.69	79.35±03.07	84.87±02.27	86.91±02.86
	FE	91.43±01.96	89.49±02.59	88.95±02.36	83.70 ±02.56	82.29±02.93
	DE	92.10±02.24	92.20±01.91	94.21±01.50	97.47±01.35	98.32±01.14
Statistical Analysis	*DE vs All=P<0.0001;DE vs FE>p=0.87*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*
Sensitivity	AE	66.80±03.22	72.35±03.10	82.66±03.64	82.66±02.01	82.93±02.33
	SE	70.74±02.53	76.90±03.32	82.93±03.02	87.34±01.96	87.21±02.275
	FE	91.56±01.55	90.56± 02.42	87.55±02.22	80.85±02.23	82.32±02.56
	DE	92.50±02.33	91.63±01.75	93.17±01.33	97.52±01.10	98.66±01.00
Statistical Analysis	*DE vs All=P<0.0001;DE vs FE>p=0.91*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*
Specificity	AE	67.67±03.43	68.34±03.31	70.81±04.22	76.70±02.33	79.71±03.11
	SE	71.55±02.96	72.89±03.85	75.76±03.56	82.39±02.56	86.61±03.01
	FE	91.29±02.11	88.42±02.75	90.36±02.66	86.54±02.96	82.26±02.96
	DE	91.70±02.32	92.77±02.10	95.24±01.88	97.45±01.56	97.99±01.05
Statistical Analysis	*DE vs All=P<0.0001;DE vs FE>p=0.94*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*	*DE vs All=P<0.0001*

respectively. Delta and theta bands show +6% improvement in the classification performance compared to beta and wide frequency bands only in the FE methods.

- Taking the method and frequency bands together, DE at all the frequency bands produced the highest classification accuracy with 98.32%, 97.47%, 94.21, 92.20% and 92.10% in the wide band, beta band, alpha band, theta band and delta band, respectively. This was then followed by FE method at delta, theta and alpha bands with classification accuracy of 91.43%, 89.49% and 88.95%, respectively. Meanwhile, SE and AP achieved the highest classification accuracy only at the high frequency bands. Overall, our classification results show that DE is the best method in classifying vigilance levels at all the frequency bands with classification accuracy in the range of 92.1% to 98.32%.

IV. DISCUSSION

In this study, we investigated a novel enhancement method of pure tone (PT) audio stimulation at 250 Hz on vigilance levels. The PT was presented simultaneously to the ears of participants while performing SCWT for 30 min. We simultaneously recorded the electrical brain activity (EEG signals), self-reports and behavioral responses of the participants while performing the SCWT under vigilance decrement (VD) and vigilance enhancement (VE) states. In line with our previous studies [60], [61], and with the results of the behavioral responses of the participants we defined the VD state as the state in which participants performed the SCWT continuously for 30 min.

Meanwhile, the VE state was defined as the state in which participants performed the same SCWT while listening to the PT audio stimulation of 250 Hz for 30 min. Behaviorally, all subjects that performed the SCWT for 30 min showed vigilance decrement as reflected by the RT and accuracy of target detection and it is summarized in FIGURE 3. On the other hand, all subjects that performed the SCWT while listening to the 250 Hz PT audio stimulation showed vigilance enhancement. By comparing activity between VD and VE experiments, we found that PT did entrain the brain and enhanced the mood state of all participants. Furthermore, the machine learning model discriminates between VD and VE level with 98.32% accuracy. The significant findings of this study are discussed below.

A. VIGILANCE LEVEL AND BEHAVIORAL PERFORMANCE

In the VD, we found that all participants performed the SCWT for 30 min showed significant increase in the RT to stimulus associated with a decreased in the accuracy with time-on-task. Specifically, our analysis showed 13% increment in the RT and 21% decrement in the accuracy of target detection. The increase in the RT to stimuli in our study indicates that the proposed vigilance task is resource demanding with a high cognitive workload and stress. Thus, the increase in RT is an essential fact for vigilance level decrement. Other reasons of increased RT could be due to the increased level of confusion, discomfort, fatigue and loss of engagement with the task. The psychological feelings reported by the participants confirmed this claim. Intuitively, the subjective assessment had shown a significant increase in the scale of anger, fatigue and confusion after performing the SCWT for 30 min. In accordance with the present findings, previous vigilance and stress studies have demonstrated that the cognitive efficiency declines over time due to the effect of mental fatigue. The behavioral impairments observed in our study are also consistent with the decreased accuracy reported after 1 hour protocol to induce mental fatigue in [33]. Similarly to our experimental design, Naber *et al.* [62] reported that RT significantly increased with time-on-task after 5 min in Stroop color word task. Likewise, driving studies have demonstrated that driver behavior in post-congestion situations became more aggressive indicating that VD affects behavioral performance [63], [64].

Meanwhile, in the VE experiment we found a significant decrease in the RT associated with an increase in the accuracy as time passes. In particular, we found 32% decrement in RT and 5% increment in the accuracy indicating that the audio stimulation improves sustained attention and increases the cognitive efficiency. We anticipate that the decrement in the RT in our study might be due to the effects of multisensory process integration. Multisensory integration is apparent when input from one sensory modality enhances the perception of stimuli in another modality. In this case, listening to the audio stimulation while performing the visual stimulus of SCWT increased the cognitive processing and engagement in choice response time. The behavioral enhancement observed in our study is consistent with the decreased RT reported in multisensory enhancement studies [65], [66]. Nevertheless, perceptual sensitivity, accuracy, reaction times, memory, and learning; all had been shown to be enhanced by multisensory as compared to unisensory stimulation [67], [68].

Taking altogether, the VD and VE experiments, we found a significant decrease ($p < 0.01$) in the RT (the RT decreased by 44%) and significant increase in the accuracy of target detection (the accuracy of detection improved by 25%) with audio stimulation. It's worth noting that the linear decreasing trend in the RT with increasing the time-on-task in the VE experiment (in FIGURE 3) indicates that the audio stimulation reflects sensory dominant phenomena. Thus, we confirm that the proposed audio stimulation is very effective in enhancing the vigilance levels. The increased level of happiness and calmness in the subjective analysis also reflect mood state enhancement. Besides, the decreased level of anger, tension, fatigue, and confusion while listening to audio stimulation is another indication of vigilance enhancement.

B. VIGILANCE LEVEL AND ENTROPY MEASUREMENTS

The entropy measures (AE, SE, FE, and DE) in our study showed that the amount of complexity of EEG signals significantly increased from VD to VE experiment in most areas of the brain at all the frequency bands. There have been many compelling pieces of evidence demonstrating the effectiveness of entropy measures in clinical implications [69]. The complexity of the EEG signal in our study is reflected by the entropy values. The greater the entropy value is, the more active the brain is. Previous studies have found that higher entropy meant increased behavioral performance [70], [71]. In line with that, we found the entropy-measured values significantly increased across the left hemisphere and decreased in small regions within the right hemisphere when participants performed the SCWT while listening to the audio stimulation compare to that without audio stimulation. Specifically, left frontal, left-temporal, parietal and occipital regions were highly activated with audio stimulation. The increased entropy in the left hemisphere and across wide areas within the right hemisphere indicated that the audio stimulation enhanced sustained attention and decision making process. A previous study indicated that information processing in the brain involved multi-brain regions [72]. Under vigilance sate, frontal brain interactions would be changed to maintain sustained attention. Likewise, the increase in occipital brain region is related with visual task [73].

Meanwhile, decreased entropy in certain regions of the right hemisphere indicated that audio stimulus shifted the brain activation patterns from right to the left hemisphere [74]. These results suggest that the changes in the entropy features caused by audio stimulation is a good indicator of brain function enhancement. Previous studies have suggested that increased entropy was found to be related to performance improvement [75], [76]. The increased entropy value under vigilance enhancement is also consistent with the increased connectivity network measures reported in our previous vigilance studies [60], [61].

Interestingly, the entropy values in our study were maintained high throughout the temporal profiles with audio stimulation experiment (see FIGURES 4-8), which may reflect a state of excitement. In fact, we did not find any decrement in the behavioral responses; such as increased RT or decreased in accuracy with time-on-task in the VE experiment. One of the possibilities is that the pure tone stimulates the pituitary gland to release the dopamine hormone. Recent neuroimaging evidence supports the notion that dopamine may underpin the modulatory influence of audio stimulation on cognitive performance. Rausch and his colleagues [77] suggested that audio stimulation enhances dopamine release, thereby modulating brain activity and increased attention and memory formation. We thus, confirm that the higher entropy values across the cortex facilitate neural communication, promote neural plasticity, and enhance vigilance level. Consequently, the findings provide the impetus for additional research into the potential use of audio stimulation at 250 Hz as a non-pharmacological enhancement for people with low vigilance, and for people with learning difficulties, stress and anxiety.

C. MACHINE LEARNING AND VIGILANCE LEVEL ESTIMATION

We employed SVM to assess vigilance levels (classifying VE from VD state) based on entropy features. The SVM achieved the best classification accuracies in the range of

(97.47 ±01.35) % to (98.32±01.14) % using beta and wide band, and achieved (94.21±01.50) % using alpha band and (92.1±02.0) % using delta and theta band when utilizing DE learned features. Fuzzy entropy obtained similar results with the highest accuracies achieved at lower frequency bands with (88.95±02.36∼91.43±01.96) %. Sample entropy and approximate entropy features showed their highest classification accuracies at higher frequency bands with mean accuracy above 80%, as summarized in TABLE 2. The highest classification accuracy achieved at higher frequency bands in most types of entropy reflects the enhancement of sustained attention.

D. PERFORMANCE ENHANCEMENT CORRELATES WITH ENTROPY MEASURES

Combining the biobehavioral performance, we found the entropy measures co-vary with vigilance levels. Specifically, significant negative associations were observed with reaction time changes and entropy values. That is, the shorter the reaction time to stimuli the greater the cortical activations as measured by entropy. In particular, we found the maximum correlation of $r = \sim 0.78$, $p < 0.05$ between brain regions at electrodes AF7, AF3, F7 and F5 with decreasing reaction time. It is evident that when reaction time reduced due to the vigilance enhancement caused by audio stimulation, the entropy measures increased.

One could argue that pure tone does activate the peripheral regions of visual cortex and thus enhances the overall performance. We have also anticipated that that PT does increase the compensatory effort of participants, thus, they remain attentive to stimulus onset. Previous studies have suggested that real-time auditory feedback supports learning and retention of new skills [78]. Overall, the enhancement in the behavioral responses (reduced reaction time) and brain activities (increased entropy) by PT stimulation at 250 Hz is consistent with previous computerized vigilance enhancement methods summarized in [1].

The overall observed pattern of findings motivates the application of modern interventions from psychology and cognitive neuroscience to alert and enhance human judgment and decision-making in complex, real-world environments. For example, embedding the enhancement method into the vehicle driving fatigue detection system can improve the drivers' vigilance level and prevent accidents. Likewise, integrating the PT of audio stimulation into workstations can mitigate the level of stress on people at the workplace and may result in improving cognitive efficacy.

E. LIMITATIONS AND FUTURE WORK

This study investigated the use of PT audio stimulation at 250 Hz to enhance vigilance levels at the workplace. Although, the proposed PT demonstrated its effectiveness in enhancing cognitive performance and altering brain activity and mood states, the effects after stimulation on performance are yet to be explored. In future studies, we will investigate the effects of after stimulation as well as compare our proposed method with the well-established audio stimulation technique such as the binaural auditory beat stimulation. This will aid in understanding the effect of audio on neural mechanisms underlying vigilance levels. While, we used four entropy measures and machine learning approach to explore the effectiveness of PT stimulation on brain activity, combining cortical activations with functional connectivity network may provide full inspection on the effects and after effect of PT stimulation on sustained attention [50]. A potential candidate method is to combine entropy measures with functional connectivity network and graph theory analysis as suggested in [61].

V. CONCLUSION

This study investigated a novel enhancement method on vigilance levels and found significant improvements on the behavioral responses and cognitive performance. In particular, we found 44% enhancement in the reaction time and 25% improvement in the accuracy of target detection when participants performed the vigilance task for 30 min while listing to audio stimulation compared to that without audio stimulation. Besides, 30 min stimulation of the proposed VE method revealed 32% improvements in reaction time with time-on-task. The SVM classifier vigilance enhancement with 98.2 % accuracy using differential entropy learned features. Our findings provide new insights into the neural mechanisms of vigilance levels and highlight the importance of using audio stimulation of pure tone at 250Hz as a potential method of vigilance enhancement.

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