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Fractal Dimension and Power Spectrum of Electroencephalography Signals of Sleep Inertia State

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ABSTRACT Human brain functions and behaviors during the transition state between sleep and wakefulness are not similar to these at alert wakefulness state. The transition state, which is called sleep inertia, has many unpleasant and dangerous effects on many situations that require full attention and fast response, such as driving. Within 30 minutes after waking up from sleep, the driver's performance might be impaired due to the sleep inertia effects. Groups of drivers that may drive within a short period after waking up are: workers who travel early in the morning; secondary drivers of long distance bus who sleep in the bus before taking over the job from the primary drivers; night travelers; and long haul truck drivers who stop at the rest area to sleep for a while and continue driving. Previous research used subjective self-report measurement, eye tracker, and a driving simulator to analyze the driver's performance during sleep inertia state. The physiological measures of the drivers, such as their brain signals have also been studied. However, the brain signals which are recorded in Electroencephalography (EEG) are typically analyzed in perspective of the power spectrum. This study proposes a hybrid of EEG features, which are fractal dimension and power spectrum, supported by behavioral data which is the driver's reaction time. This study finds the features that significantly differentiate between normal and sleep inertia drivers based on the classification accuracy and p-value of the statistical ANOVA. This study compares the results with other features (power spectrum, variance, sample entropy), and between EEG channel. This study record the EEG from the Fz, T7, Cz, Pz, and O1 channels. This study uses subjective and behavioral measurements to support the results. The results show that the hybrid of fractal dimension estimated by Katz's algorithm at the O1 channel and delta power from the Fz channel, and alpha power from the O1 channel, have better classifications than the power spectrum alone. Furthermore, the reaction time recorded from the LED reaction time task shows a significant difference between drivers with sleep inertia and normal (alert) drivers.

INDEX TERMS Brain signal, EEG, EEG features, electroencephalography, fractal dimension, Katz's algorithm, power spectrum, sleep inertia, sleep offset, transport safety.

I. INTRODUCTION

In transportation, the safety of drivers and other road users is essential. Other than road environment and vehicle, human factors such as skill, experience, level of alertness and fatigue, largely contribute to road accidents. Driver's alertness can be affected by sleep. Within 30 minutes after awakening from sleep, human cognitive and behavioral performance are not as good as in a fully awake state [1]. The transition from sleep to wake is called sleep inertia. The impairment of some of the brain functions has a high impact on driver's safety. A lack of drivers' awareness of the effects of sleep inertia may lead to a road accident.

It was reported in [2] that there were 68 cases out of 467 sleep-related crashes which occurred in less than 15 minutes of driving and 83 drivers were awake less than five

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hours before the crash. Within this short duration, the drivers might have been in sleep inertia, in which the drivers started to drive after waking up from a nap or sleep in an unconscious state. The period of this transition state varies according to the complexity of the task undertaken upon awakening [1]. Reference [2] studied these sleep-related crashes and found that one of the factors contributing to the accidents is the total hours of sleep. The chances for the drivers to face sleep-related accidents versus non-sleep related accidents increase by five folds when the average of nighttime sleep is less than five hours.

For healthy people, the variation of sleep duration, prior sleep loss, wake time, the last sleep stage (before awakening) determine the severity of sleep inertia [3]. These factors might not contribute to the presence of sleep inertia for that narcolepsy patient, where they even experience sleep inertia following light sleep and brief episodes of drowsiness [4]. Meanwhile, idiopathic hypersomnia (poly-symptomatic) and delayed phase sleep sufferers have severe sleep inertia in the morning, however it absent after had a long sleep [4]. The drivers who sleep at the rest area may not aware of the effects of their sleep duration to the brain function impairments. The duration of sleep is related to the sleep cycle, which consists of 3 stages of non-rapid eye movement, NREM, (N1, N2, and N3) and a rapid eye movement (REM) stage. Sleep inertia is present after waking up from any stage of sleep. However, sleep inertia is more severe when waking up from stage 3, than REM stage of sleep [5], [6]. Also, sleep inertia usually happens when waking up in the first third of the night [4].

The lack of awareness on the brain function impairments due to sleep inertia, and the effects of sleep inertia towards drivers, as explained above, motivate this study to explore the drivers' brain activities during the state of sleep inertia. In previous research, many studies had evaluated sleep inertia subjects using both subjective and behavior measurements [5], [7]–[14]. In the subjective measurement, such as the Karolinska Sleepiness Scale (KSS) and Sleep Inertia Questionnaire (SIQ), the feeling of the subjects about the particular questions were rated by themselves. The behaviors of the subjects were evaluated based on the number of correct responses and the reaction time of the subjects when performing tasks, such as in reaction time, addition, and descending subtraction tasks. Besides subjective and behavior measurements, the brain activities during sleep inertia state have been analyzed using electroencephalogram (EEG).

However, most of the studies characterized the sleep inertia state only based on the changes in power spectrum obtained from the frequency analysis [3], [5], [15]–[20]. The findings were neither statistically tested nor classified. Other than that, the association between the EEG signals of sleep inertia state and the driving performances has never been discussed.

Therefore, this study explores more features of EEG signals that are recorded from sleep inertia and alert (control) drivers. This study aims to evaluate the feasibility of a fractal dimension technique, which is a measure of fractal-like signal, in differentiating EEG signals of these groups. Therefore, this study compares the fractal dimension with the power spectrum, which can be obtained from the frequency analysis, and other time-domain features such as entropy and statistical parameters. This study evaluates the significance of the fractal dimension technique based on the classification accuracy and statistical analysis. For driver's safety purposes, this study analyzes the association between the EEG signal of drivers at rest condition with eyes closed, and the behavior response while driving.

This article explores the time and frequency domain features of EEG and the behavioral responses to find the best features to classify drivers with sleep inertia and normal drivers. The main contributions of the article are as follows:

- A hybrid of Katz's fractal dimension and delta power of EEG signal, and the reaction time of drivers recorded from the reaction time task before driving. This feature combinations provide the higher classification accuracy than the other power spectrums and behavioral data.
- An association between EEG signals and driving performances found in this study contribute to future research to predict the consciousness state of the driver, whether the driver is in full alertness and is able to drive or the driver is still in the sleep inertia state. Furthermore, it contributes to the transportation industry and road safety—in improving vehicle safety, driving rules and regulations, or driver's warning system.

The rest of the article is organized as follows. Section II gives a review of the related works in evaluating sleep inertia based on subjective, behavioral, and physiological measurements. This section includes the past works on fractal dimension which has been used for EEG analysis of other applications, and also the evaluation of driver's performance. Section III explains the experimental design, the type of data, the criteria of data that need to be excluded from the analysis since they may contribute to outliers, EEG pr-eprocessing, the EEG features to be extracted, the classification, and statistical analysis. Section IV presents and interpret the results. In details, this section compares statistically between the EEG features and also the behavior task parameters. Section V discusses the results with a recommendation for future works at the end of the section. Finally, Section VI concludes the paper.

II. LITERATURE REVIEW

This section is divided into three subsections: literature review in sleep inertia evaluation methods, including the characteristics of sleep inertia described in previous research; followed by the fractal dimension technique that has been used in sleep-related research and also in other applications; and finally, the evaluation methods of driver's performance in motorist without sleep inertia.

A. SLEEP INERTIA EVALUATION

In the early days of sleep inertia studies, the sleepiness of the subject at the time was measured by the subjective measures such as Karolinska Sleepiness Scale (KSS), Stanford Sleepiness Scale, Visual Analog Scale (VAS) and Pseudo Analog Scale. Most of the self-report measures are simple and easy to administer. To analyze the subjects' feelings on themselves, these subjective measures need to be selected wisely. Many studies have used KSS in sleep inertia studies [7], [8], [12], [21], [22]; therefore, it is easily compared with other studies. Although the subjective self-report measurement is simple and quick, it is relatively easy to cheat, lacks face validity, and cannot be used alone. However, it can be used as supportive information to our study to validate the main findings since a subjective measure like KSS score was found to be associated with the accuracy of task performance [12], [23].

There are many tasks that requires a physical response used to assess someone's alertness, decision making ability, and motor functions. For most of the tasks, the subject's performances were evaluated based on the recorded reaction time (or performance speed) and the number of correct response (or performance accuracy). A simple reaction time task is a task that is designed specifically to measure the subejct's alertness at the time based on the reaction time and the correct responses. In sleep inertia studies, the reaction time decreased throughout 20 mins as reported in [24], and 90 mins as found in [8]. In [10], it was found that subjects responded faster after self-awakening than after forced-awakening and the pre-sleep session, based on the reaction time task. These findings show that a simple reaction time task is beneficial in evaluating circadian and homeostatic effects in sustained attention [7]. Other performance tasks which have been used in sleep inertia studies are fire chief, descending subtraction, symbol digit substitution, n-back, and finger tapping. However, these tasks are more complex and require selective attention, decision making, working memory, and other brain functions.

Previous research used wrist sensors [19], fMRI [20], visual evoked potential (VEP), event-related potential (ERP), and EEG to assess sleep inertia through the physiological responses of the subjects. EEG has been used earlier, and most of the EEG features that were analyzed and discussed was the power spectrum [3], [5], [15]–[20]. Based on the previous research, sleep inertia can be characterized by a gradual change of beta [25] and delta [3] power after waking up from sleep. At the posterior of the brain, beta power reduced, and delta power increased [17]. Meanwhile, at frontocentral [15], [18], both beta and alpha power decreased. When comparing the classification accuracy between the EEG features (delta, theta, alpha and beta at C3 and C4) and the features recorded from wrist wearable sensors (skin conductance, skin temperature and acceleration), the combination of EEG and reference [19] found that wrist sensors features produced accuracy at 85%, higher than the only wrist sensor features at 74%.

B. FRACTAL DIMENSION

Other than the power spectrum, there are many features that can be extracted from an EEG. Fractal dimension (FD) is one of the time domain features that measures the complexity of the signal. In the previous research, the fractal dimension has never been explored in evaluating the sleep inertia state.

There are only a few studies related to consciousness or sleep that used FD to detect the changes between two states, such as between sleep onset and stage 1 of sleep, between wakes, sleep onset and all sleep stages, and between wake and drowsiness. Reference [26] compared a huge number of parameters in differentiating sleep stages, including spectral powers and fractal dimension. It was found that the fractal dimension is the most promising classifier after the fractal exponent, and can significantly discriminate between wake and slow-wave sleep (stage 3) and between the individual sleep stages. In detecting sleep onset, [27] found that the combination of FD and spectral parameters (alpha and theta) provided higher sensitivity in detecting the sleep onset, as compared to the FD alone. However, the significance of the parameters were not statistically tested. In [28], it was found that FD has a correlation with alpha power, where the FD increased from the wake to drowsy state due to the reduction of alpha activity. In this study, the FD has significantly distinguished these two states by clustering the mean FD of multiple EEG channels.

FD also has been used in other conditions such as in differentiating between left and right-hand movement imagination [29], different handgrip forces [30] and two critical processes in acute stroke [31].

C. DRIVER'S PERFORMANCE EVALUATION

Sleep inertia has a high impact on the driver's safety, mainly between midnight and early in the morning. This transition state may affect the driver's alertness, concentration, reaction time, and decision-making abilities. Other than sleep inertia, another transport safety issue has been raised due to the fatigue condition of night shift workers. When their work ends early in the morning, it leads to drowsy driving, which consequently increases the risks of crashes. To evaluate the driver's performance on a particular condition, several studies are using driving simulators, which provide the driver's performance for real-time monitoring, as well as for offline analysis.

From the driving simulator, the performances are evaluated based on two types of measurements: vehicle and road-based; and, driver's physical and behavior-based. The vehicle and road-based measurements were analyzed in the perspective of lane deviation [32]–[35], speed maintenance [35], [36], car-following distance [35], and crash occurrences [33]. The sleepy and fatigued drivers had small variations of speed, as reported in [35]. However, the speed was higher in the sleep deprived groups, as compared to the normal sleep group [36].

Based on the driver's physical and behavior responses, the eye-tracking system has been used [35], [36] to record and track the driver's eye movement, which is associated with visual attention. From the eye tracker, the study was able to identify the eye fixation for the normal and sleep deprived groups, where the normal sleep group paid more attention to the direct sight (front), as compared to the sleep

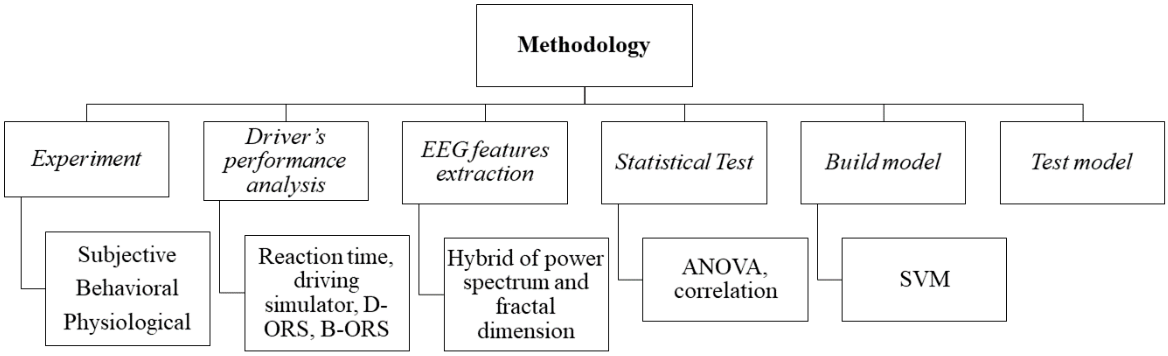

FIGURE 1. The proposed method.

deprived group. However, the information on the driver's behavior is limited to the eye movement. As performed in [33], a secondary task was added to the primary driving task to evaluate the ability of drivers to divide their attention to multiple tasks and driving at the same time. The addition of the secondary task, which was evaluated based on the accuracy and reaction time, increased the complexity of the task. Therefore, a selection of task is crucial in reducing bias and complexity.

III. METHODOLOGY

This study proposes a hybrid of time and frequency domain EEG features, as well as the behavioral parameter to classify drivers with sleep inertia and normal drivers. Fig. 1 illustrates the proposed method of this study. To evaluate the feasibility of the features in differentiating EEG signals of these group, we have designed an experiment to record the EEG signals, and collected subjective and behavioral data of drivers at sleep inertia and alert conditions. In this study, we tested the significance of the features and the EEG channel based on statistical analysis and classified the data using a SVM classifier. Finally, the association between the features of EEG and driver's performance was analyzed. The details of the proposed methods are explained below.

A. EXPERIMENT

Thirty two healthy subjects (28 female, 4 male) with mean age 22 were involved in this study. All of them are morning persons, and none was a smoker or caffeine consumer, as caffeine may produce harmful effects on subsequent sleep, hence causing daytime sleepiness [37]. Table 1 shows the experiment timeline where this study had two conditions, and it took eight days for Condition I (Session I) and four nights for Condition II (Session II). In Session I, which is for a full alertness condition, subjects underwent the Pre-experiment I before the experiment day. During the seven days of the Pre-experiment I, they wore a sleep tracker (Fitbit Charge HR) to monitor their sleep onset and offset. They monitored their sleep and wake hours and recorded it in the provided sleep diary by the National Sleep Foundation. For Condition II, which was the sleep inertia condition, they

TABLE 1. Experiment timeline (SI = Session I, SII = Session II, Pre-exp = Pre-experiment).

Condition	Day	Stage	Time
Condition I	Day 1-7	Pre-exp I (normal sleep pattern)	11 p.m. - 6 a.m.
	Day 8	SI (Full alertness)	8:30 - 10.30 a.m.
Condition II	Night 1-3	Pre-exp II (sleep restriction)	3 - 6 a.m.
	Night 4	Pre-exp III (1 hour sleep)	3 - 4 a.m.
	Night 4	SII (Sleep inertia)	4 - 5:30 a.m.

FIGURE 2. Sleep stages prior to forced awakening (N1 = Stage 1, N2 = Stage 2, N3 = Stage 3).

underwent four nights of sleep restrictions, where they were allowed to sleep only for three hours each night (3 to 6 a.m.) to induce sleep deprivation and therefore to cause severe sleep inertia. On the fourth night, the experimenter woke them up after they reach stage 3 of sleep. As shown in Fig. 2, before entering the sleep phase, the subject was at the transition of wake and sleep which is pre-sleep; the sleep onset were marked as they entered the stage 1 of NREM sleep (N1), where it varied between subjects. In this study, it took from 24 sec to 7 minutes to reach N2, transit to N3 within 3 to 30 minutes, and stayed in N3 for 8 to 32 minutes before woke up. The duration of N3 varied as they were awoken earlier than the target duration of N3 (1015 minutes) if they made a lot of movements during N3. This action was taken to avoid self-awakening which it may vary the effects of sleep inertia. The total duration of sleep were measured from the time they reach N1 (sleep onset) to the time they woke up, ranged between 19 and 96 minutes.

1) SUBJECTIVE MEASURE

Before performing the tasks, subjects were required to rate their sleepiness level based on the Karolinska Sleepiness Scale (KSS). As shown in Table 2, the KSS is a 9-point scale, ranging from an extremely alert to a very sleepy. They were required to rate their sleepiness level before the resting state,

TABLE 2. Karolinska Sleepiness Scale (KSS).

Score	Level
1	extremely alert
2	very alert
3	alert
4	rather alert
5	neither alert nor sleepy
6	some signs of sleepiness
7	sleepy but no effort to keep awake
8	sleepy and some effort to keep awake
9	very sleepy fighting sleep

reaction time task, and driving session. This study assumed that the subject was not alert in Session I if they rated their sleepiness level with a score of 5 to 9, and they were assumed alert in Session II if their score was 1 to 4. In this case, the EEG signals for the stated conditions were excluded from the classification.

2) PHYSIOLOGICAL DATA

From literature, EEGs of sleep inertia have been recorded at frontal [15], [18], [20], [38], central [15], [18], [20], [38], parietal [15], [39] and occipital [17], [20], [38], [39] lobes. As such, we recorded EEG signals from 17 active channels which covers frontal, central, parietal, temporal and occipital (Fp1, Fp2, Fpz, F3, Fz, F4, C3, Cz, C4, FCz, P3, Pz, P4, T7, T8, O1 and O2), with reference at CPz.

This work used an EEGOSPORTS (ANT Neuro, Hengelo, Netherlands) machine. This type of EEG system was chosen in this study because of several factors. The amplifier is not attached to the cap, hence comforts the subjects throughout the drive and sleep sessions. Besides, the electrodes wires are hidden, and the end of them were tied into one cable, hence making it neat and long enough for the movement of subjects while sleeping. The sampling rate used in this study was 1024 Hz. In Sessions I and II, EEG signals were recorded during two minutes of relaxed conditions with eyes closed. Before recording, the subjects were required to sit comfortably, and to avoid body movements and eye blinks during the recording to reduce the artifacts in the recorded signals. Besides Sessions I and II, EEG signals were also recorded during the pre-experiment III (sleep session) to monitor the subject's sleep stage prior to awakening.

3) PHYSICAL AND BEHAVIORAL DATA

To measure the driver's reaction time, a reaction time task (RTT) was conducted. In this task, four LEDs—two red and two green—were placed on top of the TV screen with 1meter distance, as shown in Fig. 3. This reaction time task was designed by following the oddball paradigm. Within 5 minutes, the red LEDs which were the target object, blinked for 40%, and the green LEDs which were the standard object blinked for 60% of the total number of flashes. They were not informed earlier about the time and frequency of the LED blinks. Whenever they saw the red lights, they needed to respond by pressing a button quickly. Meanwhile, the green LEDs required no response. The software recorded the reaction time of each subject.

FIGURE 3. Driving simulator with LED reaction time task setup and camera for video recording.

RTT was performed before the driving task to relate the real situation, where people normally do some activities that require motor and cognitive functions, before driving. After completing the RTT, subjects performed the driving task. We used Logitech driving simulator and STISIM Drive (Systems Technology, Inc. - STI, Hawthorne, California) software. One-third of the driving sessions was designed for monotonous driving; another one third was a curvy road with low traffic, and the rest was designed as medium-heavy traffic with decision-making situations. The drivers' performances, in term of accelerator and brake input, road excursion, speed deviation, and collision, were recorded by STISIM, and analyzed using the driving performance impairment by Observer Rated Sleepiness (D-ORS), explained in Section III-B. A Logitech webcam was placed on top of the TV screen that displayed the road scenarios, as shown in Fig. 3, to record the subjects' sleepiness behavioral signs during driving. The sleepiness level was identified based on the behavioral signs of sleepiness by observer rated sleepiness (BORS), explained in Section III-B. The experimenter scored both D-ORS and B-ORS after the experiment was completed.

B. DRIVER'S PERFORMANCE ANALYSIS

Driver's performances were analyzed based on the reaction time, measured by the RTT, collision and road excursion which occurred in the driving sessions and recorded in the STISIM software. Other than these parameters, the driver's performance impairment was evaluated based on the Observer Rated Sleepiness, which is called D-ORS. It was rated offline based on the driving speed, lane deviation and brake input, obtained from the STISIM software. The level of driver's alertness described by D-ORS is presented in Table 3. It consists of 3 levels of alertness-sleepiness. The driver was rated with level 0 (alert) if she drove normally and had a high and fast reaction, or level 1 if there were signs of sleepiness like driving with minor swerves but still had a relative normal to fast reaction, or level 2 (severe sleepiness) if the driver had significant problems to drive straight and had a bad and slow reaction.

TABLE 3. Driving performance impairment by Observer Rated Sleepiness (D-ORS).

Score	Description	
0	Level	*ALERT*
	Awareness	high and fast reaction
	Driving	normal
1	Level	*1st SIGNS OF SLEEPINESS*
	Awareness	relative normal to fast reactions
	Driving	minor swerving
2	Level	*SEVERE SLEEPINESS*
	Awareness	bad and slow reactions
	Driving	major problems to drive straight, major steering-wheel reversals

TABLE 4. Behavioral signs of sleepiness by Observer Rated Sleepiness (B-ORS).

Score	Description	
0	Level	*ALERT*
	Blink	normal
	Yawn	no
	Body position	sitting still
	Body movements	normal
1	Level	*1st SIGNS OF SLEEPINESS*
	Blink	Sporadic periods of long eyelid closure (followed by an increased level of blink frequency)
	Yawn	some
	Body position	some situation (stretch)
	Body movements	some (arms, legs, scratch)
2	Level	*SEVERE SLEEPINESS*
	Blink	Half-closed eyes, empty gaze
	Yawn	Frequent
	Body position	Frequent changes, stretching, slumped, hanging
	Body movements	Yes - head nodding

The alertness of the driver at the time was determined by the behavioral signs of sleepiness of the observer-rated sleepiness (B-ORS), described in Table 4. Three scores represent the subject's alertness state: score 0 is for being alert; score 1 is for first signs of sleepiness; and score 2 means the subject has severe sleepiness. The behavior signs of sleepiness such as eye blinking or heavy eyes (eyelid closure), yawning, body positions (e.g., stretching, frequent changes) and body movements (e.g., head nodding), were analyzed offline based on the video recorded during the session. From there, the B-ORS was rated. Here, the subject was assumed to be in the alert state if her average reaction time was earlier than 400 ms and had 0 score (alert) for B-ORS and was not alert if the average reaction time was later than 400 ms and had 1 or 2 ratings (first signs of sleepiness or severe sleepiness, respectively) for B-ORS.

C. EEG PRE-PROCESSING

The input signals were imported into the BESA Research 6.0 software for pre-processing. Firstly, the power line artifact was removed using a notch filter. Next, a bandpass filter with these parameters were applied: low cutoff with cutoff frequency 0.3 Hz, type forward, slope 6 dB/oct, and high cutoff with cutoff frequency 30 Hz, type zero phase, slope 24 dB/oct.

D. EEG FEATURES EXTRACTION

This study proposes to extract the fractal dimension of EEG and combine with other EEG features to improve the classification accuracy of the group of normal drivers and drivers with sleep inertia. For comparisons, other features of EEG that have been used in the existing research such as power spectrum, sample entropy [40] and variance [41], were also extracted. These features were obtained from the 100-sec (102,400 data points-) EEG signals for both the sleep inertia and control groups, using a 5-sec window. The details of the features extraction are explained below:

1) FRACTAL DIMENSION

The fractal dimension (FD) was chosen as it has significantly distinguished EEG signals of subjects with different activities or conditions in the previous research [26]–[29], [31]. FD is a measure of signal complexity. The dimension falls between 1 and 2. As the estimation of fractal dimension is directly from the time domain, it provides less computational time [31] and less computational complexity [42] than the frequency domain features. There are several algorithms developed to estimate the FD. In this study, we used two algorithms for estimating the FD: Higuchi and Katz.

Higuchi's algorithm is one of the conventional algorithm used to estimate the FD [43]–[45], where the accuracy was higher than Katz's and Sevcik's methods [46]. However, it is profoundly affected by noise [46]. The equation of Higuchi's algorithm is written as equations below [46].

Let X be an original series,

$$X = x(1), x(2), x(3), \ldots, x(N) \tag{1}$$

From (1), form k new series:

$$x_m(k) = \{x(m), x(m+k), x(m+2k), \ldots, x(m+|\frac{N-m}{k}|k)\} \tag{2}$$

m is the initial time value where and is the time delay. For each of the constructed time series $x_m(k)$ the length $L_m(k)$ is computed as:

$$L_m(k) = \sum_{i=1}^{\frac{m-N}{k}} |x(m+ik) - x(m+(i-1)k)|.\frac{N-1}{\frac{N-m}{k}k} \tag{3}$$

where N is the number of data points of the time series X and $(N-1)/\frac{N-m}{k}k$ is a normalization factor. An average length is calculated for all the time series with the same delay, k. This procedure is repeated for each k, which is from 1 to k_{max}. A total of the average length, L, for each k is expressed as in (4).

$$L(k) = \frac{1}{k}\sum_{m=1}^{k} L_m(k) \tag{4}$$

$L(k)$ is proportional to k^-D, where D is the fractal dimension by Higuchi's algorithm. In this study, we used $k_{max} = 10$.

In Katz's algorithm, let X be a time series,

$$X = x(1), x(2), x(3), \ldots, x(N) \tag{5}$$

The fractal dimension of a time series X generally is expressed as:

$$FD = \frac{\log L}{\log d} \tag{6}$$

where L is the total length of X and it can be obtained by adding the distance between two successive points, $a(i)$, as written in (7).

$$L = \sum_{i=1}^{N-1} a(i) = \sum_{i=1} N - 1\sqrt{1 + (x(i) - x(i+1))^2} \tag{7}$$

While d is the length of a straight line between any two points of X that provides the farthest distance, as written in (8).

$$d = max(dist(1, i)) \tag{8}$$

where $i = 2, \ldots, N$ The difference of distance between $a(i)$ produce different FDs. Therefore, Katz's algorithm created a general measurement unit (step), a, to average the distance, therefore:

$$FD = \frac{\log L/a}{\log d/a} \tag{9}$$

Let $n = L/a$, where n is the number of unit. Therefore, an equation of Katz's fractal dimension, FD, can be written as (10).

$$FD = \frac{\log n}{\log n + \log d/L} \tag{10}$$

2) SIGNAL VARIANCE

A statistical parameter, variance, is also estimated in the time domain. It measures the deviation from the mean, μ, value of a random signal and it changes over time. The variance of the signal $X = x_1, x_2, \ldots, x_n$ can be expressed as:

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \tag{11}$$

3) SAMPLE ENTROPY

Entropy estimates the regularity or randomness. The more complicated the number of sequence in a series, the higher the entropy value is [40]. Sample entropy (SampEn), developed by [47], is an improved function from approximate entropy (ApEn). SampEn can be described in term of space of dimension, the standard deviation of the time series and the length of the time series.

4) POWER SPECTRUM

In spectral analysis, waveforms with different amplitudes and phases are decomposed into a sum of sine waves at different frequencies based on Fourier Transform. Power at that frequency is obtained by squaring and summing the Fourier coefficient at each frequency. When we plot the power of each component frequency, it is called the power spectrum. This study estimated the power of delta, theta, alpha, and beta, at Fz, T7, Cz, Pz and O1 channels.

E. STATISTICAL TEST

The study hypothesizes that the fractal dimension of the EEG signals of normal drivers and drivers with sleep inertia are not equal. Firstly, the strength and direction of the association between the fractal dimension and other extracted features were measured statistically. The correlation coefficient varies from -1 to $+1$. A relationship between two features is perfect if the correlation coefficients equal to ± 1, and it is weak if the value goes towards 0. The value signs indicate the direction of the relationship. A positive correlation coefficient means that the fractal dimension increased as the other feature increased, and a negative value shows the opposite trends.

This study used inferential statistics ANOVA to analyze and measure the significance of the fractal dimension in differentiating between normal drivers and drivers with sleep inertia in comparisons to other EEG features and the behavioral measurement variables. A p-value, which is the output from the ANOVA, is equal or less than 0.05 if there is a significant difference between two variables.

F. DATA CLASSIFICATION

As well as statistical analysis, this classification of the EEG features in this study was performed to test the significance of fractal dimension in characterizing subjects with sleep inertia, whether this feature can improve the classification accuracy, as compared to the conventional method. In this study, we used SVM classifier to classify two groups based on RT, delta power, alpha power, and Katz's FD of EEG signals. The SVM is a popular algorithm that constructs an optimal hyperplane for a separation between two groups of data. It usually produces higher classification accuracy than KNN. However, in this study, we also tested other classifiers, such as KNN, decision tree, and ensemble classifiers for comparison. The built model was tested on 11 subjects (8 females, 3 males) for each control and sleep inertia groups.

IV. RESULTS

A. KSS

Fig. 4 shows the sleepiness score (KSS) collected in both control (SI) and sleep inertia (SII) session. In SI, eight subjects rated the KSS with level 5 and above, which means they were not feeling alert, whereas they were expected to have high alertness at that time. Meanwhile, two subjects rated the KSS with score 1 to 4 at SII, where they were alert after waking up from sleep. These subjects might be outliers to the data distribution. Therefore, the EEG signal of resting state with eyes closed for subject 5, 6, 7, 8, 9, 15, 16 and 20 from SI, and subject 14 and 18 from SII were excluded from the data classification.

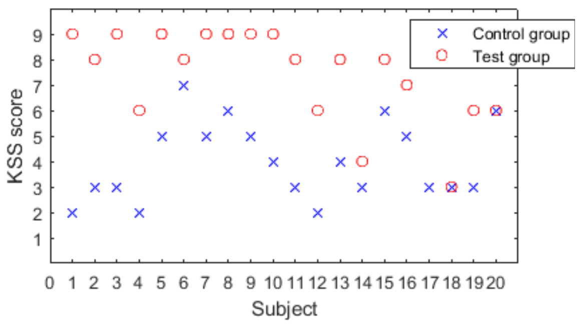

FIGURE 4. Sleepiness scores based on Karolinska Sleepiness Scale at full alertness condition (control group) and sleep inertia condition (test group).

TABLE 5. Correlation between the fractal dimension and power spectrum of the signals recorded during relaxation with eyes closed at full alertness condition (SI) and sleep inertia condition (SII) at O1 channel.

Channel	Features	SI	SII
Fz	KFD-Alpha	0.90	0.50
O1	KFD-Alpha	0.93	0.87
O1	KFD-Beta	0.82	0.71
T7	KFD-Beta	0.82	0.81
Cz	KFD-Alpha	0.96	0.89

B. CORRELATION BETWEEN EEG FEATURES

Table 5 shows the significant EEG features and EEG channels, which produced high correlation coefficients, in SI, SII, or both. The fractal dimension, FD, shows a high correlation ($r > 0.80$) with power of certain frequency and certain EEG channel. From the EEG signals of the resting state with eyes closed, the Katz's FD showed a high correlation with alpha power at Fz (control group only), O1 and Cz channels. Meanwhile, there was a high correlation between Katz's FD and beta power at O1 (control group only) and T7 channel. Other features or variables which were not presented in the table did not correlate with the Katz's FD.

C. DIFFERENCE BETWEEN SLEEP INERTIA AND CONTROL GROUPS

Table 6 presents the p-value of the ANOVA for the time domain and frequency domain features extracted from the EEG signals. This study only presents the results for the selected five EEG channels which are Fz, T7, Cz, Pz, and O1. A feature is significant in distinguishing between alert and sleep inertia state if the p-value is less than 0.05. The results showed that there was significant difference for Katz's FD which were extracted from the Cz and O1 channel, Higuchi's FD at the T7 and O1 channels, sample entropy at the T7 and O1 channels, delta power at the Fz, T7, Cz and O1 channels, alpha power at O1 the channel, and beta power at the O1 channel. However, there was no significant difference in the variance and theta power at all the EEG channels.

Table 7 shows the p-value of the ANOVA for behavior and physical response measurements. RT, B-ORS, and D-ORS showed significant differences between the control and sleep inertia group. Meanwhile, the vehicle collision and road excursion, which were recorded in the driving simulator (STISIM software) showed no significant differences between the groups, with $p>0.05$.

TABLE 6. P-value of the ANOVA for feature selection (EEG features).

Features / Channel	Fz	T7	Cz	Pz	O1
Katz's FD	0.70	0.07	0.04	0.28	0.03
Higuchi's FD	0.48	0.05	0.18	0.19	<0.01
Sample Entropy	0.43	0.03	0.08	0.30	<0.01
Variance	0.26	0.20	0.48	0.07	0.21
Delta	<0.01	0.01	0.03	0.92	<0.01
Theta	0.19	0.08	0.19	0.60	0.06
Alpha	0.29	0.24	0.14	0.16	0.01
Beta	0.79	0.69	0.98	0.51	<0.01

TABLE 7. P-value of the ANOVA for feature selection (Behavior responses and driving performances).

Behavior and driving performances	p-value
RT	<0.01
B-ORS	<0.01
D-ORS	<0.01
Collision	0.60
Road excursion	0.06

The differences between the control and sleep inertia groups estimated by the significant features of EEG can be illustrated as in Fig. 5. Briefly, the significant features of EEG signals are Katz's FD at the Cz and O1 channels, Higuchi's FD at the T7 and O1 channels, Sample Entropy at the T7 and O1 channels, delta power at the Fz, T7, Cz and O1 channels, alpha power at the O1 channel, and beta at the O1 channel. The box plots display the median of the data and the spread of the data, in term of the data range (between the lowest and largest value) and the interquartile range (between the first and third quartile). The range of data for each feature varied according to the EEG signals at the channels. As the fractal dimension falls between 1 and 2, Katz's FD extracted from EEG at the Cz channel is very small, as compared to Katz's FD at the O1 and Higuchi's FD at the T7 and O1, as shown in Fig. 5a. Next, the delta power has a smaller range at the Cz than at the O1 channel (Fig. 9e).

Although the control and sleep inertia groups were statistically differentiated by all the features stated before, the differences can be visually evaluated from the box plots. Based on the median line, there are likely to be a difference between the control (alert) and sleep inertia groups in Katz's and Higuchi's FD at O1, Sample Entropy at T7, delta power at Fz, T7, Cz and O1, and alpha power at O1. Katz's FD, alpha, and beta power are higher in the alert condition, as compared to the sleep inertia condition. Meanwhile, delta power is lower in the alert condition than in the sleep inertia.

D. CLASSIFICATION ACCURACY

The extracted features were classified using the linear SVM into two groups; alert (control) and sleep inertia (test). In this study, we combined both power spectrum and fractal dimension but they were selected based on the statistical test and visual analysis on the box plot. The proposed features in this model are delta power at the Fz channel, alpha power at the O1 channel, FD estimated by Katz's algorithm at the

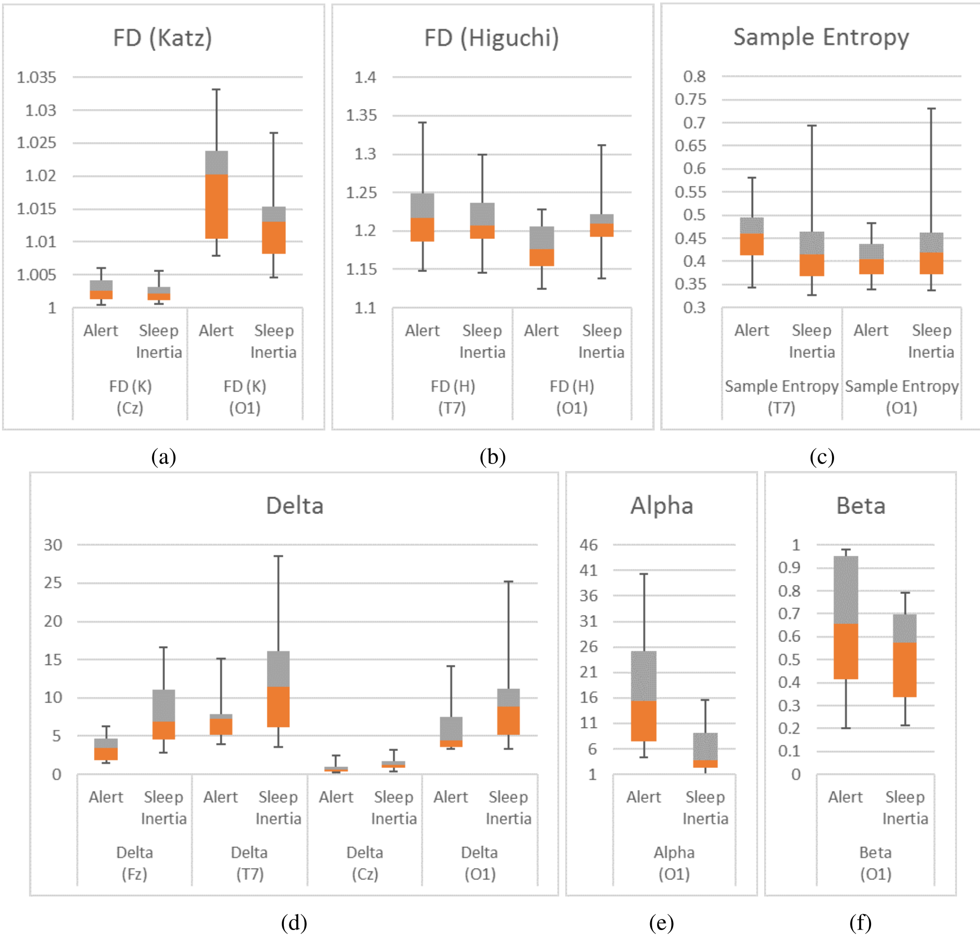

FIGURE 5. **The box plots of the significant features;(a) Katz's fractal dimension (FD), (b) Higuchi's fractal dimension (FD), (c) sample entropy, (d) delta, (e) alpha, and (f) beta power.**

TABLE 8. **Classification accuracy for 4 classifiers.**

Classifier	Accuracy
Decision tree	90.0
linear svm	93.3
KNN	90.0
boosted trees	60.0

O1 channel and RT. Table 8 shows comparisons of the classification accuracy between classifiers. The chosen linear SVM produced the accuracy of 93.3% with the precision of 85.7%, and the recall of 100%, and F1 score of 0.92.

Table 9 compares the classification accuracy between the power spectrum, which is the feature that is commonly extracted to analyze EEG of sleep inertia. This table present the power spectrum that were significant at Fz and O1 channels, which are delta and alpha power. The table shows that the classification which were solely based on delta, alpha and beta power produced 63.3%, 73.3% and 76.7%, respectively. The classification accuracy has increased to 80% when combining these three power spectrum: delta (Fz), alpha (O1) and beta (O1). Meanwhile, the proposed model produced a classification accuracy of 93.3%.

Fig. 6 shows a 2-d data distribution from Matlab, based on delta power at Fz channel and Katz's FD at O1 channel.

TABLE 9. **Comparison of the classification accuracy between the conventional features used in the previous studies and the proposed model (Delta (Fz), FD (O1), Alpha (O1), RT using the linear SVM).**

Features	Accuracy (%)
Delta Power (Fz)	63.3
Alpha Power (O1)	73.3
Beta Power (O1)	76.7
Delta Power (Fz),Alpha Power (O1),Beta Power (O1)	80.0
Delta Power (Fz),Alpha Power (O1),FD (O1),RT	93.3

The blue and orange dots are the classification results from three features; delta, FD, and RT. Blue dots represent the alert group, and orange dots indicate the sleep inertia group. As can be seen, the control group has low delta power, while sleep inertia group has low Katz's FD. In the perspective of RT, the data is illustrated in a box plot shown in Fig. 7. It shows that there is a difference between the groups, where the alert (control) group has RT faster than sleep inertia group.

E. CORRELATION BETWEEN EEG AND DRIVER'S PERFORMANCES

Fig. 8 and 9 show the distribution of both control and sleep inertia data in 2-axis scatter plots to visualize the association between the Katz's FD and delta power of EEG, and the driving performances at normal and sleep inertia conditions.

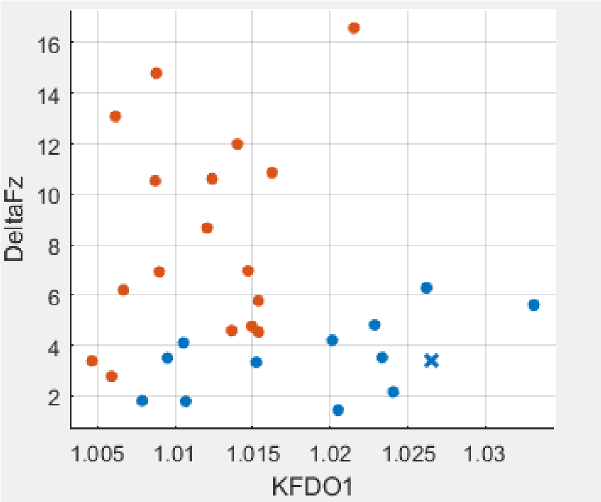

FIGURE 6. The distribution of alert (blue) and sleep inertia (orange) data based on Katz's fractal dimension (KFD) at O1, delta power at Fz channel and reaction time (RT).

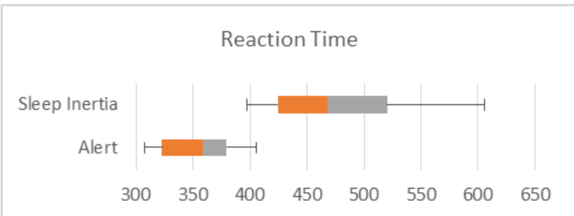

FIGURE 7. The box plot of the reaction time (RT) for both full alertness and sleep inertia groups. The x-axis represents the RT in miliseconds.

From Fig. 8a and 8b, it can be seen that most of the subjects with high FD of EEG have the D-ORS and B-ORS score of 0. Meanwhile, most of the EEGs with low FD have scores 1 and 2. In term of speed exceedance counts, as shown in Fig. 8c, most of the subjects have less than 12 counts of speed exceedance, and the FDs of their EEG are lesser than 1.025. There are 3 EEGs which have higher FDs, and their amounts of speed exceedance are larger than 14. Based on statistical analysis, Katz's FD and speed exceedance have a positive correlation with the correlation coefficient of 0.64. Fig. 8e shows that there is no correlation between the FD and the driving time as the time average is 17.74 min with a minimum standard deviation. From Fig. 8e, most of the low FD ($<$1.02) EEGs have longer reaction time (RT), while the higher FD ($>$1.02) ones have shorter RT.

As can be seen in Fig. 9e, the delta power with the range between 1.4 and 6.3 μV has D-ORS scores of 0 and 1. Meanwhile, the EEG with a higher FD has D-ORS scores of 1 and 2. It shows that there is a positive correlation between delta power at Fz channel and the D-ORS score (r = 0.60). As shown in Fig. 9b, all subjects in the control group were rated by the experimenter with 0's for B-ORS, except for one subject who was rated with score of 1. These subjects have lower than 8 μV of delta power. Meanwhile, all subjects in the sleep inertia group were rated by the experimenter with score of 1 or 2 for B-ORS. However, half of them have lower and higher than 8 μV of delta power, respectively. Fig. 9c presents a distribution of data in delta power and speed exceedance, and it shows that there is no correlation between the variables. However, five subjects have low delta power and higher counts of speed exceedance. From Fig. 9d, there is no association between delta power and the driving time, as found between Katz's FD and the driving time. Lastly, the RTs of the subject were longer than 400 ms for EEGs with high delta power, which is above $> 8\mu V$. For delta power lower than $8\mu V$, about 50% of them have lower than 400 ms of RTs, and the other 50% have higher than 400 ms of RTs.

V. DISCUSSION

A relationship between driving performance and EEG signals of the driver at sleep inertia state has never been discussed. To investigate the association between these variables, the current studies have limitations where the sleep inertia state was mostly characterized by the changes in the power spectrum of EEG [3], [5], [15]–[20]. Therefore, this study extracted fractal dimension and other features from the EEG waveforms and tests it with a classification method and statistical analysis to find the most significant features for classifying and distinguishing between alert and sleep inertia drivers. This study analyzed the correlation between the classified group and the driver's performances. The significant findings of this study are that the classification of the alert (control) and sleep inertia groups based on Katz's fractal dimension (FD) and alpha power at the O1 channel, delta power at the Fz channel, and the reaction time of the drivers, produced higher accuracy as compared to the other features and variables.

This study used the Karolinska Sleepiness Scale (KSS), as the first stage of sleepiness identification. This scale is a self-rated sleepiness scale, where the subject rated what they felt at the time. Data were excluded if they were not feeling alert during Session I or control condition, and not feeling sleepy in Session II (sleep inertia) as scored using KSS. This scale is essential to be used in this study at the early stage of data collection to reduce outliers. The extracted features of EEG were analyzed in term of the correlation among them. This analysis is needed to avoid the redundancy of features. A high correlation between the features might show a redundancy of features. This study needs to select the best features that can be used to determine the state of the driver. To find the significant features in distinguishing between normal or alert drivers and sleep inertia drivers, this study used the ANOVA. The p-value, which is the result of the ANOVA shows the significance of the features. If the p-value is higher than 0.05, it shows that the features cannot be used to differentiate between alert and sleep inertia drivers. A classification was applied to all the possible feature combinations. However, only the significant features, which were determined by the statistical analysis, were included. The classification provides the accuracy which can determine the best combination of features in differentiating between alert and sleep inertia drivers. Any misclassified data from this classification step

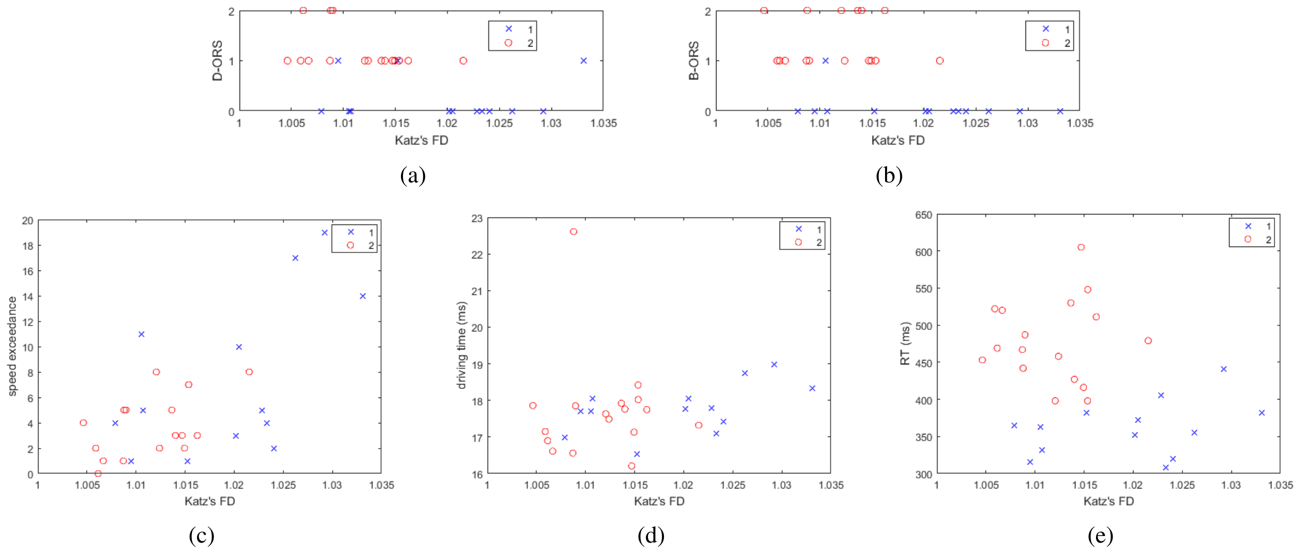

FIGURE 8. **The distribution of control (1) and seep inertia (2) data in perspective of Katz's fractal dimension (FD) and; (a) D-ORS, (b) B-ORS, (c) speed exceedance, (d) driving time, (e) reaction time (RT).**

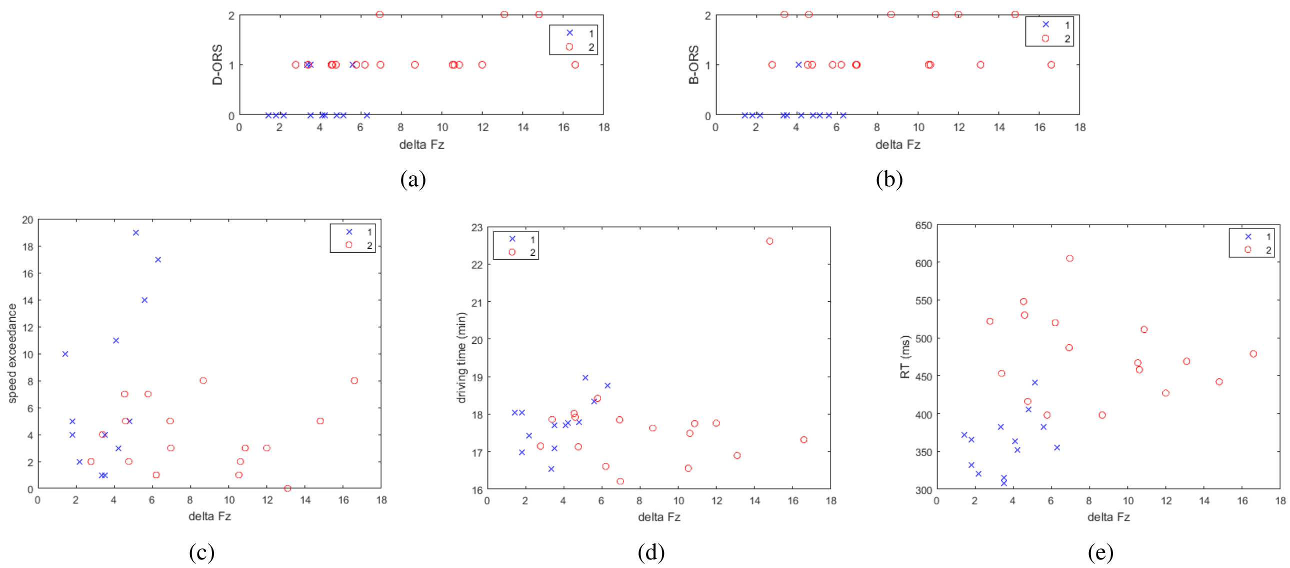

FIGURE 9. **The distribution of control (1) and seep inertia (2) data in perspective of delta power at Fz and; (a) D-ORS, (b) B-ORS, (c) speed exceedance, (d) driving time, (e) reaction time (RT).**

can be validated with the other collected data of the particular subject, such as the RT, driving performance, and KSS. This study examined the correlation between the selected features, which are Katz's FD and delta power (Fz), and the driver's performances. This analysis can show which parameters have a relationship with the EEG signals. It is important to find if EEG signals can provide sufficient information about the state of drivers, hence can be used to predict the driver's performance in the future.

This study found that the EEG signals of the condition of relaxation with eyes closed for both states, have a high correlation between the Katz's fractal dimension and alpha power at the O1 and Cz channels. The Katz's algorithm was found to be profoundly affected by the signal amplitude [44]. From our findings, it is suggested that Katz's FD correlates with the dominant frequency of the signals at the particular EEG channels. Even though FD has a high correlation with the alpha power and has a significant difference between the alert and sleep inertia groups, the inclusion of alpha power to the classification features with FD or delta power was not a redundancy, yet it increased the accuracy.

The higher power of delta in the EEG of sleep inertia group as compared to the EEG of full alertness group is consistent with the findings of the other sleep inertia studies [20], [39] where the EEG signals of sleep inertia group had higher delta power than the EEG of pre-sleep wakefulness. Furthermore, the low alpha power in the EEG of sleep inertia group found in our study is consistent with the EEG of the stress emotion [48], which is one of the sleep inertia effects besides drowsiness. Alpha waves are dominant at resting state, and it falls in a stressful situation [48] like a forced awakening from sleep. Meanwhile, a high theta power represents low vigilance [15], [49] or drowsiness [49], [50]; however, in our study, it was found that there was no statistical difference between the full alertness and sleep inertia groups involving the Fz, T7, Pz, Cz, and O1 channels. Other than that, the low beta power at O1 may represent the sleep-like EEG as compared to other power spectrum in other brain areas, as suggested in [39]. Low beta power also can show that the arousal mechanism is still not working optimally [15]. Besides, low beta power at the parietal and central areas of the brain may represent a drowsiness state [49], which is one of the effects of sleep inertia.

Fractal dimension has been used to measure the difference between two or more states, such as drowsiness, sleep onset, and sleep stages. A drowsiness state can be represented by a low Higuchi's fractal dimension [51]. The fractal dimension decreases as it enters the sleep stages, and the lowest value occurs at stage 3 of sleep or deep sleep [52]. Since drowsiness is one of the sleep inertia effects, it may cause someone to have difficulties in focusing and memorizing, to be restless and daydreaming or to exhibit disconnected thoughts. Other than drowsiness and stress, sleep inertia may reduce memory ability, the performance of a task (reaction time and speed), and productivity in the first part of the day. It also may cause drowsy driving, lateness at work, loss of concentration, impairment of the capability to make decisions, impairment of motor and cognitive functions, and slow reaction time. It was found in [7] that the performance speed was more affected than the accuracy, alertness, and sustained attention were more affected than cognitive throughput and working memory.

Therefore, this study included the driver's alertness state based on the average of reaction time or performance speed and her score on the sleepiness level based on the Karolinska Sleepiness Scale (KSS) which is the common subjective scale used to assess someone's sleepiness level. In many studies such as [53], [54], they observed the driver's behaviors as signs of sleepiness which include frequent blinking, heavy eyelids, nodding off, yawning, rubbing eyes, and frequent position changing. Besides, many studies evaluated vehicle-based performances such as speed variation, lane deviation [53] and steering wheel movement, as reviewed in [55]. In our study, two measurements have been used to identify the driver's alertness state during the driving session, which is vehicle- and behavior-based observer-rated sleepiness (DORS and B-ORS). These scales were rated based on the driver's physical and behavioral signs of sleepiness. This study showed that both D-ORS and B-ORS have an association with Katz's FD and delta power (Fz) of EEG signals. A high FD shows that driver was more alert, where the driver was driving normally, had a fast reaction, sitting still without any movement, blinking normally, and not yawning. Furthermore, a high delta power (Fz) indicates a sleepy driver, either there was a first sign of sleepiness or severe sleepiness. Some of the drivers had problems to drive straight, demonstrated slow reactions, blinked frequently, yawned, stretched their body, and fell asleep. The driver's RT measured in the reaction time task was also correlated with the FD and delta power. Generally, drivers with faster RT have high FD and low delta power of the EEG. Based on the driving time, the total time for all subjects has a minimal standard deviation, which means, the driving time did not significantly vary among the subjects.

From the classification, there was only one misclassified point (refer to the cross mark in Fig. 6) which is subject 6 from the sleep inertia group. The RT of subject 6 was 411 ms, which is closer to the minimum RT of the sleep inertia group and the maximum RT of the alert group. As shown in Fig. 7, the RT of the sleep inertia group falls between 398 and 605 ms, while the RT of the alert group ranges from 308 to 405 ms. Furthermore, the subject had only two times of road edge excursion (mean = 7.33) and had no collision during the driving session, although there were some signs of sleepiness based on D-ORS and B-ORS.

This study has some limitations, especially in term of data collection. The model of this study was trained using female subjects. However, we have tested the model using three male subjects and it produced 90.91% of the accuracy. The lack of male subjects in this study is because this study has been conducted in a university laboratory, and majority of the subjects who met all inclusion criteria were females. This study used a driving simulator to evaluate driving performance. However, the equipment that has been used is more suitable for gaming or racing, and the feeling and experience of driving using this simulator may not reflect the real driving.

For future research, more data, especially from males above 30 years of age, should be collected and analyzed. Instead of using gaming driving equipment, a regular vehicle cockpit simulator or a real vehicle in a safe environment (e.g., driving school) can be used. Furthermore, more driving performance parameters can be included to explore which parameters can be associated with the driver's EEG signals.

VI. CONCLUSION

This study combined features which are the fractal dimension estimated by Katz's algorithm at the O1 channel, power spectrum calculated in the frequency domain which are delta power obtained from the Fz channel and alpha power at the O1 channel, and the behavior response based on the reaction time. The combination of these four features was able to distinguish between the two groups of subjects having alert and sleep inertia states. It gave an accuracy of 93.3%, a precision of 85.7%, and a recall of 100%, and an F1 score of 0.92. The tested data also produced a high accuracy, which is 90.91%, a precision of 90.9%, and a recall of 90.9%, and an F1 score of 0.91. For future work, data from various type of subjects can be included to increase the sample size and to study the variations of their EEG and driving performances. Other feature selection methods can also be used to determine the best features to classify the alert and sleep inertia groups.

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