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Original scientific paper

Impact of Temperament Types and Anger Intensity on Drivers' EEG Power Spectrum and Sample Entropy: An On-road Evaluation Toward Road Rage Warning

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Abstract: "Road rage", also called driving anger, is becoming an increasingly common phenomenon affecting road safety in auto era as most of previous driving anger detection approaches based on physiological indicators are often unreliable due to the less consideration of drivers' individual differences. This study aims to explore the impact of temperament types and anger intensity on drivers' EEG characteristics. Thirty-two drivers with valid license were enrolled to perform on-road experiments on a particularly busy route on which a variety of provoking events like cutting in line of surrounding vehicle, jaywalking, occupying road of non-motor vehicle and traffic congestion frequently happened. Then, muti-factor analysis of variance (ANOVA) and post hoc analysis were utilized to study the impact of temperament types and anger intensity on drivers' power spectrum and sample entropy of θ and β waves extracted from EEG signals. The study results firstly indicated that right frontal region of the brain has close relationship with driving anger. Secondly, there existed significant main effects of temperament types on power spectrum and sample entropy of β wave while significant main effects of anger intensity on power spectrum and sample entropy of θ and β wave were all observed. Thirdly, significant interactions between temperament types and anger intensity for power spectrum and sample entropy of β wave were both noted. Fourthly, with the increase of anger intensity, the power spectrum and sample entropy both decreased sufficiently for θ wave while increased remarkably for β wave. The study results can provide a theoretical support for designing a personalized and hierarchical warning system for road rage.

Keywords: anger intensity; driving anger; EEG; on-road experiments; power spectrum; road rage; sample entropy; temperament

1 INTRODUCTION

Road rage has nowadays gradually become a popular psychological issue influencing road traffic safety across international community. The psychological issue is also called driving anger which is usually induced by frustration or pressure due to adverse driving situations including traffic congestion and unfriendly behaviors around [1]. A report from National Highway Traffic Safety Administration revealed that 5% - 7% of 9282 investigated drivers in US were perpetrators of road rage [2]. Moreover, a report from China's Ministry of Public Security indicated that 83100 traffic accidents happened due to road rage in 2015 [3]. A driver's perception, identification, decision and volition will be weakened when the driver becomes angry during driving, finally leading to an impaired driving performance [4]. Consequently, some monitoring or warning measures toward road rage should be adopted to reduce its negative impact on road safety.

Up to now, the monitoring or detection of driving emotion is mainly based on observable indicators including facial/voice expression, behaviors as well as physiology [5]. Paschero et al. established a fuzzy neural network-based model to recognize a driver's happiness, anger and fear by extracting relative position between the driver's mouth and eyes [6]. Liu et al. constructed a road rage expression model based on principal components analysis (PCA) net with facial infrared and depth features [7]. Li et al. selected Mel-frequency cepstral coefficients features extracted from drivers' voice to identify driving anger state by optimized probabilistic neural networks based on firefly algorithm [8]. Wan et al. [9] built a support vector machine (SVM)-based driving anger identification model using time series features of driving behaviors consisting of lane departure and steering wheel angle (SWA). Boyce et al. [10] screened out aggressive and impatient driving status through cluster analysis on the data of vehicle speed variance, turn signal usage and following distance. Currently, driving emotion detection based on physiology has become increasingly common as physiological signals are spontaneous and difficult to be forged, leading to a reliable discrimination for human emotion [11]. Wang et al. [12] employed a factorization model to identify excitement, anger and sadness during driving with skin conductance (*SC*), skin temperature (*ST*), hear rate (*HR*), respiration rate (*RR*) and so on. Katsis et al. [13] proposed a combination model based on Naïve Bayesian and decision tree to differentiate drivers' dysphoria and euphoria through electrodermal activity (EDA), facial electromyography (EMG), electrocardiogram (ECG), and respiration collected in simulated racing environment. Malta et al. [14] selected EDA and gas/brake pedaling behaviors to recognize drivers' frustration based on Bayesian network. Lanatà et al. [15] applied nearest mean classifier with *HR*, *RR*, electrodermal response (EDR), together with SWA, velocity variance and reaction time to determine drivers' stress intensity. Wang et al. selected the time-frequency domain, waveform and non-linear characteristics of ECG signals to recognize drivers' anxiety and calmness based on BP network and Dempster-Shafer evidence [16]. Guo et al. found that there were significant differences between drivers with different gender, age and driving experience in terms of ECG characteristics in time and frequency domain as well as waveform under anxiety [17].

Amongst kinds of indicators selected for detecting driving mental state, EEG is usually considered to be the most reliable as it is a record of electric potential collected from human scalp, which is a result of inhibitory and excitatory components from postsynaptic potentials produced by pyramidal neurons [18]. Choi et al. [19] identified the participants' fear based on the change of ratio of power spectrum of δ and β wave extracted from EEG signal after watching scary movie clips. Wang et al. [20] selected Shannon entropy of α wave to identify drivers' fatigue state in actual traffic environment. Fu et al. [21] established a detection model of driving fatigue based on power spectrum of θ, α and β wave as well as root mean square of EMG. Chai et al. [22] utilized power spectral density of EEG signal to differentiate drivers' alert and fatigue states. Wanet al. [23] proposed a driving anger recognition model based on receiver operating characteristic (ROC) curve using SC, RR, HR, as well as relative power spectrum of θ and β wave. Fan et al. [24] established an identification model of driving emotion based on Bayesian Network considering driver personality and driving situations, along with relative power spectrums of δ, θ, α and β wave. Halim et al. proposed a driving-induced stress identification model based on SVM, neural network and random forest with different kinds of EEG features in time and frequency domain [25]. Habibifar et al. established a recognition model of negative emotion based on multi-layer perceptron and radial basis function neural networks using ECG, EMG, EDA and EEG signals collected during driving simulator experiments [26].

So far, most of the above-mentioned studies have focused on recognizing kinds of emotional states in simulated driving environments under laboratory condition. However, the emotional state induced in simulated environment is not valid as that induced in real traffic environment when considering demand characteristics and social desirability. Furthermore, in terms of emotional state recognition studies, most of current studies only roughly discriminate two confused states (e.g., fatigue or not fatigue), without considering subdivision of a specific emotional state according to its intensity which is not enough to take targeted intervening to address it. Additionally, when analyzing EEG features in different emotional states, drivers' individual differences, especially temperament types have not been deeply considered in most of those studies. As a matter of fact, some studies verified that EEG spectral characteristics had a close correlation with drivers' temperament types [27-29]. Aimed at those, firstly an elicitation approach for more authentic anger is proposed based on the irritative events which may naturally and frequently happen in real traffic environment. Secondly, drivers' EEG power spectrum and sample entropy characteristics will be respectively analyzed in anger states with different grade. Thirdly, the impact of temperament on those EEG spectrum and entropy characteristics will be deeply researched in this study.

2 EXPERIMENTAL DESIGNS

2.1 Scene

In order to obtain more authentic anger experience, a specific driving route with a large number of hectic sections across central area in Wuhan city (see Fig. 1), was chosen for conducting on-road experiment. The driving route was about 51 km long, containing three central business districts, fifty-nine pedestrian crossings as well as forty-two signalized intersections. Hence, when driving on the route, any subject would inevitably encounter many provoking situations or events, like traffic congestion, long red light, jaywalking, occupying road of non-motor vehicles, cutting in line or changing lane optionally of surrounding vehicles and so on, particularly during morning or evening rush hours (see Fig. 2). Consequently, in order to simulate true commuting experience in dairy life and obtain more anger elicitation, the on-road experiment was demanded to start at around 8:00 am or 5:00 pm. To further induce anger, each participant was responded to obtain extrinsic reward with 15 RMB/min if they could finish the driving route ahead of reference time, i.e. 120 minutes which was proved to be just enough for the test based on several pretests. It is noted that they would obtain only basic pay of 300 RMB without any deduction if they could not finish the experiment within the reference time. Moreover, all traffic rules and regulations were forbidden to violate, especially speeding during the whole experiment. Last but not least, the EEG related experiments on the subjects totally complied with Chinese law on scientific research.

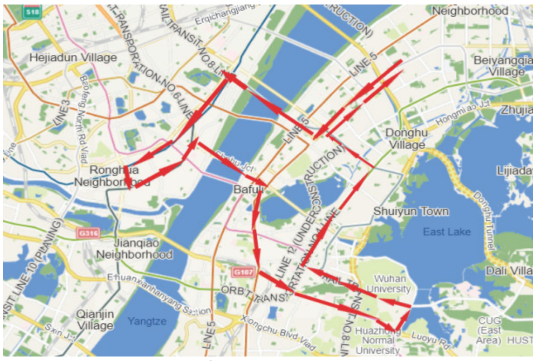


Figure 1 On-road experiment route

Figure 2 Real traffic environments for experiments

2.2 Participants

Thirty-two private car drivers possessing valid driving license were recruited as subjects from Wuhan to perform the experiments. The age of the subjects ranged from 22 to 54, with an average of 36.4 and standard deviation of 8.6. Meanwhile, the average of the subjects' driving years was 9.4, with a standard deviation of 5.2. Additionally, the number of the subjects with choleric, sanguine, phlegmatic and melancholic temperament was 6, 12, 12, 8 respectively, and in terms of each temperament type, the number of male subjects was equal to female. Particularly, each subject was medically checked to be in good physiological state without headache, cough, epilepsy or other brain-related illnesses, which was important for accurately extracting her or his EEG characteristics in different anger state. Moreover, considering the subjects' forgetfulness, concealment, and narrative impairment [1], an expert in driving behavior and traffic psychology field, with more than 20 years' driving experience, was enrolled to assess the subjects' anger level based on the replayed videos.

2.3 Apparatus

Firstly, an automatic transmission vehicle installed with controller area network (CAN) bus was employed for the on-road experiments (see Fig. 3). Secondly, an EEG signal acquisition system named NeuroScan 4.5 produced by Compumedics company from U.S. was adopted for the experiments. The EEG signal acquisition system was comprised of a 40 channel-electrode cap, a NuAmpamplifier and acquisition software (see Fig. 4), and the maximal sampling rate of the acquisition system could reach 1000 Hz. Besides, the electrodes distribution of the cap complied with standard of international society of EEG with double earlobe connection method. Moreover, the electrodes were distributed in four areas of the brain including frontal, parietal, temporal and occipital regions (see Fig. 5).

Figure 3 The on-road experimental vehicle

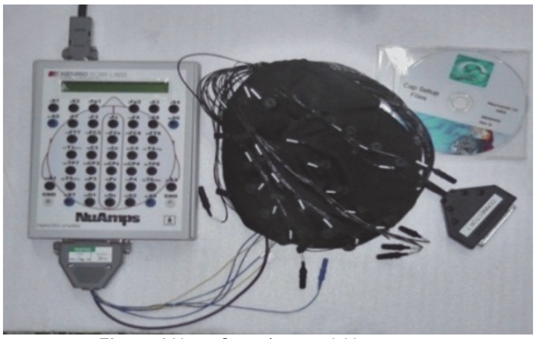


Figure 4 NeuorScan 4.5 acquisition system

Thirdly, three surveillance cameras with a frame rate of 30 were mounted on front windshield and right front door beam to record the subjects' facial/verbal expression, body gesture/limb movements/operational behaviors as well as driving situations including traffic congestion and irritating events around the experimental vehicle (see Fig. 6). In addition, a seven-level Likert scale from 0 (calm) to 6 (furious) was implemented for evaluating every subject's anger level. The replayed videos from those cameras would be utilized as direct and intuitive evidence to label anger level for each subject.

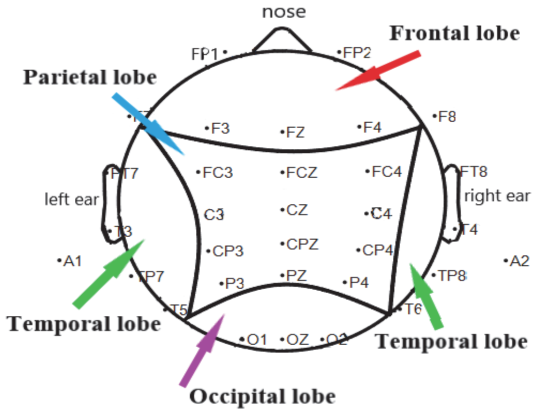


Figure 5 Distribution diagram of EEG cap's electrodes

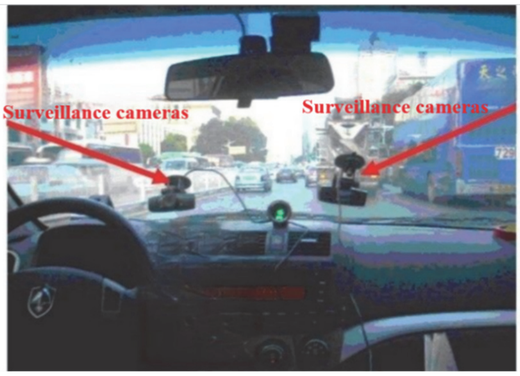


Figure 6 Surveillance cameras

2.4 Experiment Procedure

Firstly, an informed consent protocol including experiment requirements and payment was signed by each participant. Note that every subject was not allowed to make telephone calls, texting, drink water or other behaviors unrelated to driving when performing the experiment. Secondly, every subject's demographic characteristic like age, and driving years were collected and their temperaments were acquired through Chen Huichang Temperament Inventory [30, 31]. Thirdly, the EEG cap was worn on the subject's head (see Fig. 7), and then the conductive paste was injected into the electrodes and configured till all electrodes took on a good electrical conductivity based on acquisition software, as shown in Fig. 8 (black-best, red-worst). Fourthly, each subject was requested to conduct driving practice lasting 10 minutes to get used to the test vehicle and the EEG cap, so as to eliminate the possible tension or discomfort. Fifthly, each subject was required to complete the on-road experiment alone with their habitual driving style. Meanwhile, the EEG signals as well as videos from the three cameras were recorded simultaneously. Finally, after finishing the experiment, each subject immediately recalled and self-reported their anger level with the seven-level Likert scale every two minutes or any moment an irritant event occurred based on the replayed videos of the whole experiment. Simultaneously, two experts also evaluated the subject's anger level according to those videos, in order to correct obvious deviation of the subject's self-reports. The whole experiment procedure was shown in Fig. 9.

Figure 8 Configuration of conductivity of Electrodes of EEG cap

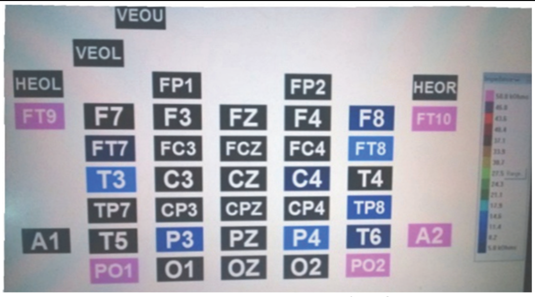


Figure 7 Wearing renderings of EEG cap

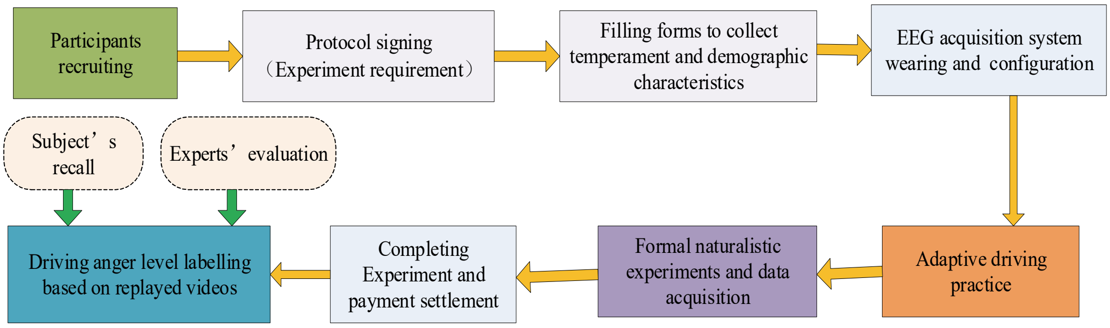
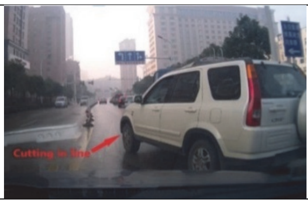
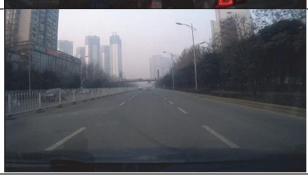


Figure 9 Experimental flow chart

Table 1 Stimulating situations and triggered anger levels

Stimulating situations	Video capture	Occurrence frequency	Sum of anger levels	Average anger level
Cutting in line of surrounding vehicle		129	658	5.10
Jaywalking		119	558	4.69
Traffic congestion		165	942	5.71
Occupying road of non-motor vehicles		146	567	3.88
Long waiting for red lights		72	281	3.90
Neutral		/	/	<3

3 ANGER INDUCED EFFECT AND INTENSITY CALIBRATION

3.1 Evaluation of Anger Induced Effect

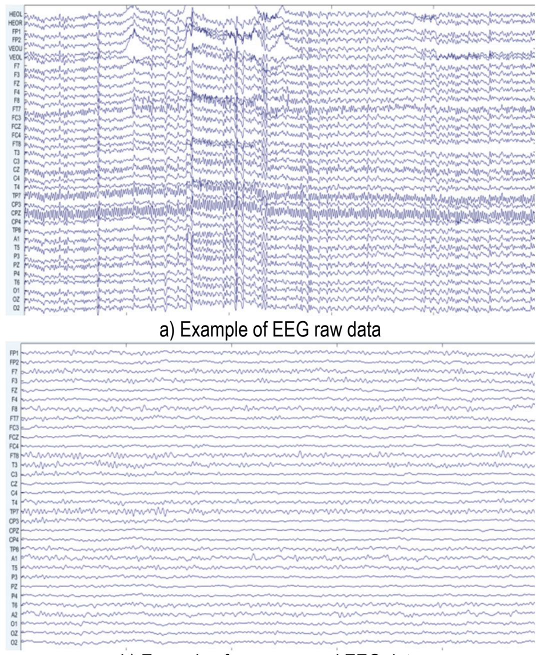
When labeling a subject's anger level, her or his self-reported anger level would be considered to be credible if the evaluation discrepancy between the subject and the expert was smaller than two. Otherwise, another expert with rich driving experience would be invited to evaluate the subject's anger level. After labelling all subjects' anger level during the whole experiment, it was found that the subjects' anger was indeed induced by sorts of provoking situations including cutting in line of surrounding vehicle, pedestrians' crossing the road illegally (jaywalking), traffic congestion, occupying road of non-motor vehicles, long waiting for red lights. For example, the average anger level triggered by traffic congestion was 5.71, reaching the highest among those typical provoking situations, which indicated that traffic congestion was most anger-provoking situation for the majority of subjects. Subsequently, the average anger level triggered by cutting in line of surrounding vehicles was 5.10, ranking the second among those situations. Additionally, the average anger level triggered by occupying road of non-motor vehicles and long waiting time for signals, was 3.88, 3.90, respectively.

Therefore, the anger induction approach proposed in this study was feasible and effective. Note that even the same provoking situations could induce different driving anger levels due to individual differences like temperament. The occurrence frequency of the typical stimulating situations and the average anger level triggered by those stimuli were listed in Tab. 1.

3.2 Data Preprocessing

To effectively analyze the subjects' EEG characteristics in different anger states, it was needed to calibrate anger intensity according to the subjects' anger levels. In this study, driving anger intensity was divided into four categories consisting of neutral (anger level = 0), low anger (anger level = 1.2), moderate anger (anger level = 3.4) and high anger (anger level ≥ 5). Therefore, 705 neutral driving samples, 410 low-anger driving samples, 318 moderate anger driving samples as well as 154 high-anger driving samples were acquired for analyzing the following EEG spectral and entropic characteristics.

As the experiments were performed on real urban roads, raw EEG data was mainly contaminated by atmospheric thermal noise, ocular movements, muscular activity and heart beats. Therefore, it was very necessary to preprocess the contaminated EEG signals. In this study, EEG data was processed by using EEGLAB toolbox embedded in Matlab software as follows: (1) Imported the raw EEG data into EEGLAB, as shown in Fig. 10a. (2) Previewed of the data, and manually removed abnormal segments. (3) Filtered the raw EEG data using FIR filter with cutoff frequency of 0.5 Hz to 35 Hz to remove the high-frequency noise. (4) Reduced the sampling rate from 1000 Hz to 250 Hz according to Nyquist's sampling theorem for improving efficiency of subsequent data processing. (5) Removed the low-frequency noise using ICA (Independent Component Analysis), and the denoised EEG data was shown as Fig. 10b.



a) Example of EEG raw data

b) Example of preprocessed EEG data

Figure 10 EEG data before and after preprocessing

3.3 Power Spectrum Estimation

3.3.1 Calculation Principle

According to the interview with all subjects, it was learned that most of subjects' anger level generally stayed the same for 3 to 6 seconds and it would gradually decrease if no new provoking events (situations) happened subsequently. Accordingly, the EEG signal lasting 4.5 seconds from the moment a provoking event started was selected for analyzing EEG characteristics under different driving anger states. Furthermore, in order to avoid the fluctuations of EEG signals due to the subjects' possible accommodations in the beginning of experiments, only the EEG signals generated 10 minutes after the starting moment of the experiments was chosen in this study. Power spectrum estimation has been widely used for spectrum analysis of the non-stationary random signal [32], and the auto-regressive (AR) model is often used for power spectrum estimation as its resolution ratio is independent of the amount of input data and Hanning window function is not needed when analyzing EEG signal in frequency domain in a limited amount of time [33]. Therefore, the AR model was adopted in this study, which could be expressed as follows:

$$x(n) = -\sum_{i=1}^{p} a_p(i)\, x[n-1] + e[n] \tag{1}$$

where, $x(n)$was the EEG signal, $a_p(i)(i = 1, 2, 3, ..., p)$was the AR model coefficient, $e[n]$was white noise sequence. This formula was a P-order model, the EEG signal sequence $x(n)$can be regarded as the output of the white noise sequence $e[n]$ through the AR model $H(z)$. The transfer function could be obtained by Z-transform. It was expressed as follows:

$$H(z) = \frac{1}{1 + \sum_{i=1}^{p} a_i z^{-i}} \tag{2}$$

Then the power spectrum estimation equation could be obtained by Eq. (1) and Eq. (2) as:

$$P_x(f) = \frac{\sigma^2}{\left|1 + \sum_{i=1}^{p} a_p e^{-\frac{j2\pi fp}{Fs}}\right|^2} \tag{3}$$

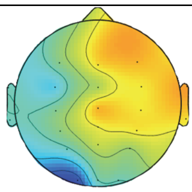
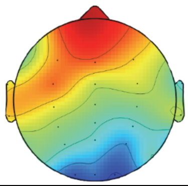
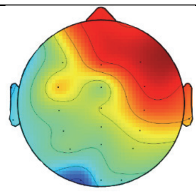
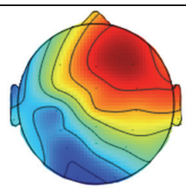
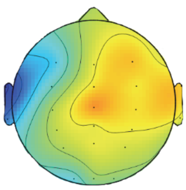
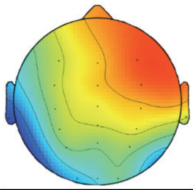
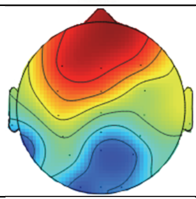
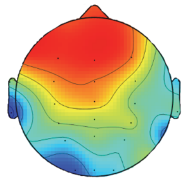
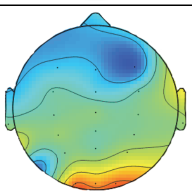
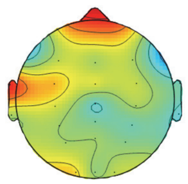
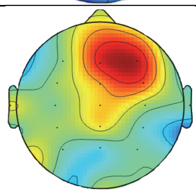
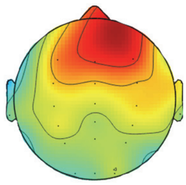
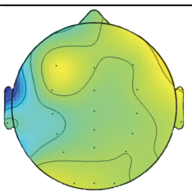
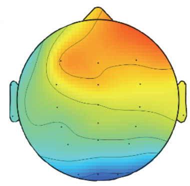
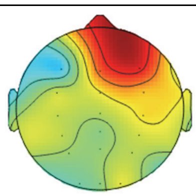
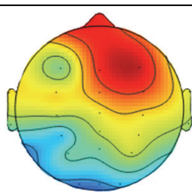
where, $\sigma^2$is the power spectral density of white noise, $P_x(f)$is the power spectral of EEG signal sequence $x(n)$. There are many methods to estimate AR model parameter $a_p(i)$, such as Levinson-Durbin method, Burg method and covariance method. In this paper, the Burg method, due to its high resolution, simple calculation and the best comprehensive effect [34], was used according to Pburg function in EEGLAB toolbox to estimate AR model parameters and thus the power spectrum of EEG bands.

3.3.2 Determining the Brain Region Closely Related to Driving Anger

Brain topography is a planar graph directly reflecting the activity of different brain regions based on power spectrum of EEG signals from all electrodes with different colors. Tab. 2 showed the brain topography based on power spectrum for the subjects with four different temperament types in four different anger states, respectively. For the brain topography, the red color indicated that the relevant brain region was active while the blue color represented inactive. As indicated, the frontal region was more active than other brain regions as the color in the region was much darker than other brain regions when the subject was in anger, illustrating that the frontal region was most correlated with driving anger states. Furthermore, it could be seen that the asymmetry between the left and right side of the frontal region became more pronounced with increase of anger intensity, and the right frontal region was more active than the left frontal region with the increase.

According to the replayed videos about the whole experiment process, it was found that the subjects with sanguine and choleric temperaments showed remarkedly more verbal aggressions and physical aggressive behaviors like fiercely gear shifting or frequent honking or flashing than the subjects with melancholic and phlegmatic temperaments. Coincidentally, according to the brain topography shown in Tab. 2, it can be seen that the frontal region of the subjects with sanguine and choleric temperament was more active than that of the subjects with melancholic and phlegmatic temperaments in anger state. However, both the differences between the former two temperaments and the latter two temperaments were not obvious from the perspective of the brain topography.

Table 2 Brain topography based on EEG power spectrum for different temperament types and anger intensity

Anger intensity / Temperament	Neutral	Low anger	Moderate anger	High anger
Sanguine				
Choleric				
Melancholic				
Phlegmatic				

3.3.3 Impact of Temperament Types and Anger Intensity on EEG Power Spectrum

According to brain topography based on power spectrum for the subjects in different driving anger states as shown in Tab. 2, it was found that the right frontal region in brain had close relationship with a driver's negative emotion. Therefore, the EEG signals collected from FP2 and F4 in the right frontal region were focused in the following study. In addition, it is well known that EEG signal is often decomposed into $\delta(0.5 - 4$ Hz), $\theta(4 - 8$ Hz), $\alpha(8 - 14$ Hz) and $\beta(14 - 30$ Hz) wave in frequency domain [35]. Moreover, based on the authors' previous research [36], the power spectrums of θ wave and β wave were both found to be significantly correlated with driving anger intensity. Hence, the two bands of wave were focused to analyze the impact of temperament types and anger intensity on EEG spectrum and entropy characteristics.

A multi-factor analysis of variance (ANOVA) was performed to study the impact of temperament types and anger intensity on power spectrum of θ wave, with the results shown in Tab. 3. The sum of squared deviations contributed by different temperament types was 39.628 with a mean square of 13.209, while the sum of squared deviations was 316.285 with a mean square of 105.428 for different anger intensity, indicating that the impact of anger intensity on power spectrum of θ wave was bigger than that of temperament types. From the perspective of concomitant probability, the main effect of temperament type on the subjects'power spectrum of θ wave was not significant (p = 0.063 > 0.05), while the main effect of anger intensity on the subjects' power spectrum of θ wave was significant (p = 0.000 < 0.05). However, it was noted that the interaction between temperament types and anger intensity on power spectrum of θ wave was not significant (p = 0.235 > 0.05). Further, post hoc analysis of power spectrum of θ wave for different temperament types and anger intensity was conducted, with the results shown in Tab. 4 and Tab. 5. According to Tab. 4, it was found that the differences of power spectrum between choleric and melancholic (p = 0.000 < 0.01), choleric and phlegmatic (p = 0.001 < 0.01), sanguine and melancholic (p = 0.006 < 0.01), sanguine and phlegmatic (p = 0.019 < 0.05) were all significant. However, the differences of power spectrum of θ wave between choleric and sanguine, melancholic and phlegmatic were neither significant. Based on Tab. 5, we could find that the differences of power spectrum of θ wave between any two of the four-intensity anger were significant, except for low anger and moderate anger which was marginally significant (p = 0.060). Moreover, with the increase of anger intensity, the power spectrum of θ wave decreased sufficiently.

Table 3 Multi-factor ANOVA and tests of between-groups effects for power spectrum of θ wave

Source	Type III Sum of Squares	d*f*	Mean Square	*F*	*Sig.*
Corrected Model	517.245^a	15	34.483	6.447	**.000**
Intercept	4782.474	1	4782.474	894.085	**.000**
Anger intensity	316.285	3	105.428	19.710	**.000**
Temperament	39.628	3	13.209	2.469	.063
Anger intensity × Temperament	62.816	9	6.980	1.305	.235
Error	1214.227	227	5.349		
Total	9667.822	243			
Corrected Total	1731.472	242			

Table 4 Post hoc analysis of power spectrum of θ wave for different temperament types

(*I*) Temperament	(*J*) Temperament	Mean Difference (*I-J*)	Std. Error	*Sig.*	95% Confidence Interval	
					Lower Bound	Upper Bound
choleric	sanguine	.646880	.4151593	.121	−.171179	1.464938
	melancholic	1.680920*	.4499394	**.000**	.794329	2.567512
	phlegmatic	1.730665*	.5255389	**.001**	.695106	2.766223
sanguine	melancholic	1.034041*	.3702277	**.006**	.304518	1.763563
	phlegmatic	1.083785*	.4591451	**.019**	.179054	1.988517
melancholic	phlegmatic	.049744	.4908182	.919	−.917398	1.016887

Note: $**p < 0.01$; $*p < 0.05$.

Table 5 Post hoc analysis of power spectrum of θ wave for different anger intensity

(*I*) Anger intensity	(*J*) Anger intensity	Mean Difference (*I-J*)	Std. Error	*Sig.*	95% Confidence Interval	
					Lower Bound	Upper Bound
Low intensity	Moderate intensity	.983877	.5213144	.060	−.043357	2.011111
	High intensity	2.060674*	.5343852	**.000**	1.007685	3.113664
	Neutral emotion	−1.356303*	.5322156	**.011**	−2.405018	−.307588
Moderate intensity	High intensity	1.076798*	.3819337	**.005**	.324209	1.829386
	Neutral emotion	−2.340180*	.3788921	**.000**	−3.086775	−1.593584
High intensity	Neutral emotion	−3.416977*	.3966839	**.000**	−4.198631	−2.635324

Likewise, a multi-factor ANOVA and hoc post analysis were also performed to study the impact of temperament types and anger intensity on power spectrum of β wave, with the results shown in Tab. 6 to Tab. 8. According to the mean squared deviation contributed by different temperament types and anger intensity as indicated in Tab. 6, it was concluded that the impact of anger intensity on power spectrum of β wave was bigger than that of temperament types. However, indifferent from the case of θ wave, there was a significant (p = 0.000) main effect of temperament types, as well as a significant (p = 0.000) interaction between temperament types and anger intensity on the subjects' power spectrum of β wave. Additionally, there was a significant (p = 0.000) main effect of anger intensity on the subjects' power spectrum of β wave. Further, as indicated in Tab. 7, it was also found that the differences of power spectrum of β wave between the extravert type (choleric or sanguine) and the introvert type (melancholic or phlegmatic) were significant. Based on Tab. 8, we could find that the differences of power spectrum of β wave between any two of the four-intensity anger were significant, except for low anger and neutral (p = 0.316), moderate anger and high anger (p = 0.503). Moreover, with the increase of anger intensity, the power spectrum of β wave increased sufficiently.

Table 6 Multi-factor ANOVA and tests of between-groups effects for power spectrum of β wave

Source	Type III Sum of Squares	*df*	Mean Square	*F*	*Sig.*
Corrected Model	314.052[a]	15	20.937	20.604	**.000**
Intercept	392.457	1	392.457	386.218	**.000**
Temperament	47.137	3	15.712	15.463	**.000**
Anger intensity	83.123	3	27.708	27.267	**.000**
Temperament * Anger intensity	53.761	9	5.973	5.878	**.000**
Error	230.667	227	1.016		
Total	1389.215	243			
Corrected Total	544.719	242			

Table 7 Post hoc analysis of power spectrum of β wave for different temperament types

(*I*) Temperament	(*J*) Temperament	Mean Difference (*I-J*)	Std. Error	*Sig.*	95% Confidence Interval	
					Lower Bound	Upper Bound
choleric	sanguine	−.096585	.1789046	.590	−.449111	.255941
	melancholic	1.364639*	.1878887	**.000**	.994410	1.734868
	phlegmatic	1.030014*	.1796075	**.000**	.676103	1.383926
sanguine	melancholic	1.461224*	.1872168	**.000**	1.092319	1.830129
	phlegmatic	1.126599*	.1789046	**.000**	.774073	1.479125
melancholic	phlegmatic	−.334625	.1878887	.076	−.704854	.035604

Note: $**p$ < 0.01; $*p$ < 0.05.

Table 8 Post hoc analysis of power spectrum of β wave for different anger intensity

(I) Anger intensity	(J) Anger intensity	Mean Difference (I-J)	Std. Error	*Sig.*	95% Confidence Interval	
					Lower Bound	Upper Bound
Low intensity	Moderate intensity	−1.749620*	.1858365	**.000**	−2.115805	−1.383435
	High intensity	−1.876924*	.1941315	**.000**	−2.259454	−1.494393
	Neutral emotion	.179888	.1790685	.316	−.172961	.532738
Moderate intensity	High intensity	−.127304	.1895548	.503	−.500815	.246208
	Neutral emotion	1.929509*	.1740963	**.000**	1.586457	2.272560
High intensity	Neutral emotion	2.056812*	.1829244	**.000**	1.696365	2.417259

3.4 Sample entropy estimation

3.4.1 Calculation principle

As EEG is a kind of chaotic, time-varying and non-stationary signal, the EEG characteristics cannot be accurately extracted by pure time-domain or frequency-domain analysis, several often-used entropy analysis methods including sample entropy, approximate entropy and Shannon's entropy, have been gradually applied for extracting EEG characteristics. Related studies show that sample entropy algorithm outperforms approximate entropy algorithm due to advantages of less data for effective analysis, better anti-jamming and anti-noise capability as well as faster computing [37]. Hence, sample entropy method was used to extract EEG nonlinear characteristics in this study. Sample entropy is often denoted by SampEn (m, r, N) (m is embedding dimension, r is similar tolerance, N is data length), the calculating process was taken as follows:

Step 1. For time series of N points, this can be expressed as $x = \{x(1), x(2), ..., x(N)\}$.Suppose the time series $\{X_m(i)\}$ were made up of m-dimension vectors: $X_m(1), X_m(2), ..., X_m(N-m+1)$

$$X_m(i) = \left[x(i), x(i+1), ..., x(i+m-1)\right] \tag{4}$$

where $i = 1 \sim N - m + 1$.

Step 2. The maximum difference between $X(i)$ and $X(j)$ defined the distance:

$$\mathrm{d}\left[X_m(i), X_m(j)\right] = \max_{0\sim m-1} \left|x(i+k) - x(j+k)\right| \tag{5}$$

Step 3. Based on the given threshold $r(r > 0)$, calculated the number of d[$X_m(i)$, $X_m(j)$]making (d[$X_m(i)$, $X_m(j)$] < r), the ratio of this number and ($N - m$) was defined as $B_i^m(r)$:

$$B_i^m(r) = \frac{1}{(N-m)} \text{ mm } \left\{\mathrm{d}\left[X(i), X(j)\right] < r\right\} \quad i = 1, 2, ..., N-m+1, i \neq j \tag{6}$$

Step 4. Computed the average value of $B_i^m(r)$ for every i, which was denoted by $B^m(r)$:

$$B^m(r) = \frac{1}{(N-m+1)} \sum_{i=1}^{N-m+1} B_i^m(r) \tag{7}$$

Step 5. Changed the embedding dimension from m to $m + 1$, repeating Step 1 to Step 4, then, $B^{m+1}(r)$ was acquired.

Step 6. Then, the sample entropy of the time series $\{x_i\}$ was:

$$SampEn(m, r) = \lim_{N \to \infty} \left\{ -\ln \left[\frac{B^{m+1}(r)}{B^{m}(r)} \right] \right\} \tag{8}$$

Step 7. If Nis a limited value, the estimated sample entropy is:

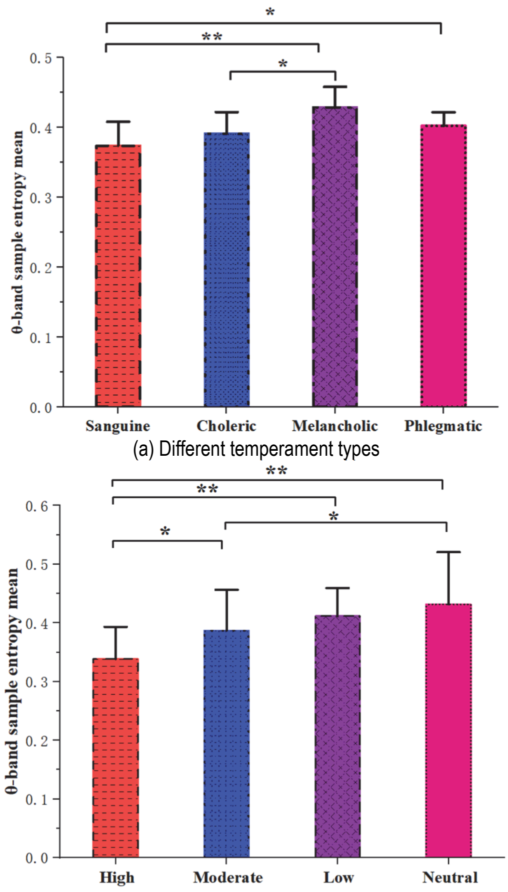
$$SampEn(m, r, N) = \lim \left\{ -\ln \left[\frac{B^{m+1}(r)}{B^{m}(r)} \right] \right\} \tag{9}$$

Generally, $SampEn(m, r, N)$ has reasonable statistical properties when $m = 1$ or 2, $r = 0.1 \sim 0.25$ SD (standard deviation of $\{x_i\}$) and $N = 100 \sim 5000$ [38, 39]. In this study, according to several pretests, both faster calculating and losing less useful information could be obtained if $m = 1$, $r = 0.2$ SD, $N = 1125$.

3.4.2 Impact of Temperament Types and Anger Intensity on EEG Sample Entropy

According to the calculation principle aforementioned for EEG sample entropy, the sample entropy was calculated for θ wave and β wave for the subjects with different temperament types in different anger-intensity states, with the results shown in Fig. 11 and Fig. 12, respectively. Based on Fig. 11a, it was found that there was no significant main effect ($F(3138) = 2.239$, $p > 0.05$) of temperament types on sample entropy of θ wave. Nevertheless, a significant main effect ($F(3138) = 69.697$, $p < 0.01$) of anger intensity on the sample entropy of θ wave was observed as shown in Fig. 11b. Additionally, no significant interaction ($F(138)) = 1.238$, $p > 0.05$) between temperament types and anger intensity on power spectrum of θ wave was noted. Further, posthoc analysis indicated that there existed significant differences of sample entropy of θ wave between high anger and moderate anger ($p < 0.05$), high anger and low anger ($p < 0.01$), high anger and neutral ($p < 0.01$), moderate anger and neutral ($p < 0.05$) as shown in Fig. 11b. However, posthoc analyses revealed that there were no significant differences of sample entropy of θ wave between neutral and low anger, low anger and moderate anger. Moreover, with the increase of anger intensity, sample entropy of θ wave decreased sufficiently. With regard to temperament types, posthoc analysis indicated that there existed significant differences of sample entropy of θ wave between choleric and melancholic ($p < 0.05$), sanguine and melancholic ($p < 0.01$), sanguine and phlegmatic ($p < 0.05$) as shown in Fig. 11a. However, no significant differences of sample entropy of θ wave between sanguine and choleric, phlegmatic and melancholic, choleric and phlegmatic were observed respectively.

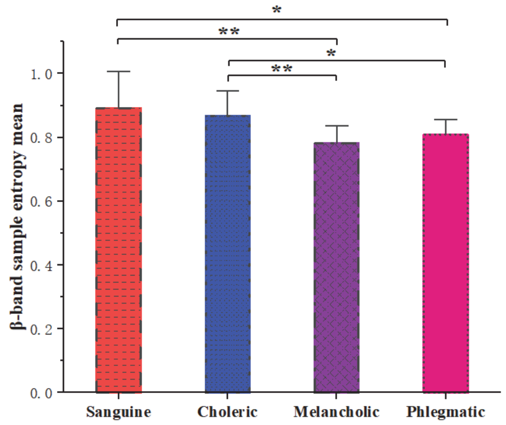
Similarly, Fig. 12 showed the sample entropy of β wave for the subjects with different temperament types in different anger-intensity states. A significant main effect ($F(3138) = 9.896$, $P < 0.05$) of temperament types and a significant main effect ($F(3138) = 27.240$, $P < 0.01$) of anger intensity on sample entropy of β wave was both observed as shown in Fig. 12a and Fig. 12b. Moreover, a significant interaction ($F(9138)) = 7.115$, $P < 0.05$) between temperament types and anger intensity on power spectrum of β wave was also noted. Further, posthoc analysis indicated that there existed significant differences of sample entropy of β wave between high anger and low anger ($p < 0.01$), moderate anger and low anger ($p < 0.01$), moderate anger and neutral ($p < 0.01$) as shown in Fig. 12b. However, posthoc analyses revealed that there were no significant differences of sample entropy of β wave between neutral and low anger, high anger and moderate anger. Moreover, with the increase of anger intensity, sample entropy of β wave increased sufficiently. With regard to temperament types, the same conclusion can be drawn for β wave, just like θ wave, as shown in Fig. 12a.



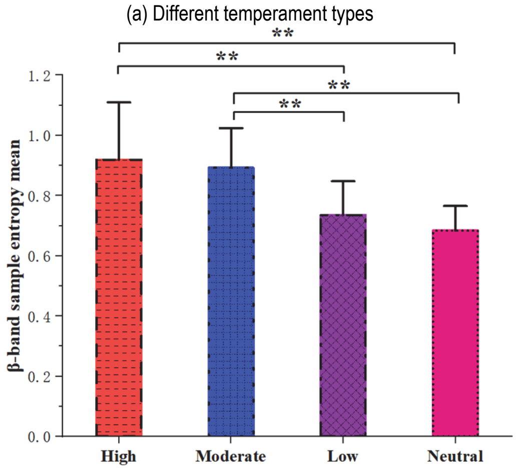
(a) Different temperament types

(b) Different anger intensity

Figure 11 The drivers' sample entropy mean of θ wave to different temperament types and different anger intensity
(Note: * $p < 0.05$; ** $p < 0.01$)



(a) Different temperament types



(b) Different anger intensity

Figure 12 The drivers' sample entropy mean of β wave to different temperament types and different anger intensity
(Note: * $p < 0.05$; ** $p < 0.01$)

4 DISCUSSIONS AND CONCLUSIONS

The main contribution of this study is to propose a novel inducing approach of driving anger in real traffic environment, to determine the brain region closely related with driving anger, to explore the impact of temperament types and anger intensity on drivers' EEG power spectrum and sample entropy. The study results can provide theoretical support for designing a personalized and hierarchical warning system for road rage in man-machine co-driving intelligent vehicles in future. For example, when the warning system detects that the driver is in a low-intensity anger, it can automatically play relaxed music through the human-computer interaction system to calm the driver's emotions. When high-intensity anger is detected, the warning system can assist or even take over the vehicle to prevent the driver from generating dangerous driving behavior. Except for these hierarchical intervening, for those extroversive drivers with sanguineous or choleric temperaments, the warning system can also release personalized intervening like relaxed conversations which can make them calm down

Firstly, in order to elicit authentic anger as much as possible in real traffic environment, aconsiderably busy route was chosen for performing on-road experiments. During the experiments, each subject encountered various provoking traffic events or situations such as jaywalking, occupying road of non-motor vehicle, cutting in line of surrounding vehicle, traffic congestion and waiting red lights. For the sake of more anger induction, the experiments were conducted during morning or evening rush hours. Moreover, the subjects could obtain extra bonus if they could complete the whole experiment ahead of reference time, which could further elicit the subjects' anger once they encountered traffic obstruction. The study results indicated that the proposed multi-intensity anger inducing approach was effective. For example, the average anger level triggered by traffic congestion was 5.71, the highest among those provoking events or situations, and the average anger level triggered by occupying road of non-motor vehicles was 3.88, the lowest among those typical provoking situations. Interestingly, the traffic congestion is found to be high anger provoking situation in this study, while the uncourteous behaviors from surrounding people was in some western countries like France [40] and U.S. [41]. The differences may be due to different culture background and safety awareness in different countries. Coincidently, Feng et al [42] discovered that the high anger provoking situation for bus drivers in China was traffic obstruction, particularly the lack of work sign reminding the road under reconstruction. In addition, according to the anger levels triggered by those provoking events or situations, some targeted anger management or intervening measures can be taken. For example, once those provoking events (i.e., uncourteous or illegal behaviors) are captured by electrical police or real police, or informed to traffic management authorities by the related sufferer, the perpetrator would be fined accordingly. Meanwhile, in order to alleviate traffic congestion, public transportation should be strongly advocated and advanced traffic guidance systems should be widely applied in busy road nets.

Secondly, according to brain topography based on power spectrum for driving anger states with different intensity, it was found that the right frontal region in brain becomes more and more active with the increase of driving anger intensity in this study. Consistently, Zeng also discovered that the subjects' right frontal region was more active than left frontal region when their negative emotions were induced through watching unpleasant photos [43]. Hence, it can be inferred that right frontal region has close relationship with driving anger.

Thirdly, as indicated by the authors' previous research [36], θ wave and β wave extracted from EEG signals were significantly correlated with driving anger intensity. Hence, the two bands were used to analyze the impact of temperament types and anger intensity on EEG characteristics. The study results showed that there existed a marginally significant ($p = 0.061 > 0.05$) main effect of temperament types on power spectrum of θ wave, while a completely significant effect on power spectrum of β wave. Post hoc analyses illustrated that the power spectrum of θ wave for the phlegmatic drivers was the lowest, while the power spectrum of β wave for the sanguine drivers was the highest among all temperament types. Coincidently, Nazarchuk et al [28] discovered that normalized powers of θ wave in cortical areas of patients of the phlegmatic group were significantly lower than those in patients of the choleric, melancholic and sanguine group. Gao et [29]. al also found that the average power of β wave of sanguine driver was significantly greater than that of the other temperament types. Moreover, the post hoc analyses indicated that there existed significant differences between the extravert group (i.e., choleric or sanguine) and introversive group (i.e., melancholic or phlegmatic) while no significant differences were found within the extravert group or within the introvert group. Additionally, in terms of anger intensity, a significant main effect of anger intensity on the power of θ wave and β wave were both observed. Moreover, with the increase of anger intensity, the power spectrum of θ wave decreased sufficiently while the power spectrum of β wave increased notedly. However, the differences of power spectrum of θ wave between low anger and moderate anger were marginally significant (p = 0.06), while the differences of power spectrum of β wave between low anger and neutral, moderate anger and high anger were not significant. The reason for this may be that the adjacent-intensity anger states were not accurately calibrated according to only the subjective self-reports of the recruited drivers.

Fourthly, considering the chaotic, time-varying and non-stationary characteristics of EEG signal, the sample entropy of θ wave and β was calculated in this study. The study results showed that there was no significant main effect of temperament types on sample entropy of θ wave while a significant main effect on sample entropy of β wave. The reason for this may be that the ratio of θ wave in all EEG bands for all temperament types of drivers in real traffic environment was a little bit low when compared with β wave. Moreover, it was indicated that there existed significant differences between the extravert group (i.e., choleric or sanguine) and introversive group (i.e., melancholic or phlegmatic) while no significant differences within the extravert group or within the introvert group for sample entropy of θ wave and β wave. Additionally, significant main effects of anger intensity on sample entropy of θ wave and β wave were both noted. Hence, anger intensity has remarkable impact on frequency-domain characteristics and nonlinear characteristics of EEG signals. Although the differences of the sample entropy were not always significant between any two intensities of anger for θ wave or β wave, the sample entropy of θ wave decreased sufficiently while the sample entropy of β wave increased notably with the increase of anger intensity.

However, considering some limitations existing in this study, further research is suggested as follows. Firstly, only temperament types were considered when recruiting the subjects, while a variety of common personal characteristics like age, driving age, personality (i.e., big five personality) would have impact on the subjects' anger intensity and even EEG characteristics [44, 45]. Hence, the impacts of these personal characteristics should be eliminated when focusing on the effect of temperament types. Secondly, the on-road experiments proposed were performed only in Wuhan which is a metropolis located in central China. Hence, the following experiments should be performed in other typical cities located in eastern, western, northern, southern China, respectively, considering anger intensity differences induced due to the differences of pace of life, driving style, traffic civilization in those different regions in China. Thirdly, as electrodes of the EEG cap were directly pasted to the drivers' scalp, leading to an inevitable interference of the drivers' regular mental states or driving performances, some non-invasive wearable devices for collecting EEG signals should be employed in future.

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