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*Research Article*

# The Induction and Detection Method of Angry Driving: Evidences from EEG and Physiological Signals

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*Introduction.* Angry driving has been a significant road safety issue worldwide. This study focuses on the problem of inducing and detecting driving anger based on the simulation and on-road experiments. *Methods.* First, three typical scenarios (including waiting for the red light frequently, traffic congestion, and the surrounding vehicle interference) which could cause driving anger were developed and applied in a driving simulator experimental study. The self-reported, biosignals, and brain signals of driving anger data were collected from the driving anger induction experiment. Second, in order to examine the difference of driving anger between simulation driving and real-life driving, 22 groups of on-road experiments were conducted. The typical scenes and self-reported data were recorded to distinguish normal driving from angry driving. Finally, a Hidden Naïve Bayes classifier was employed to detect angry driving during the on-road driving according to the four features (namely, BVP, SC, $\delta$%, and $\beta$%) from driver's biosignals and brain signals. *Results.* The evaluation of emotional differentiation degrees and emotional intensity indicates that the developed scenarios based on virtual reality were useful and effective in inducing driving anger. Meanwhile, the proposed angry driving detection approach achieves an accuracy of 85.0%. *Conclusions and Applications.* Due to possible crash and injury from the on-road experiments, the proposed approach of driving anger induction using a driving simulator is effective in exploring the causal relationship between angry driving, unsafe driving behavior, and traffic accident. In addition, angry driving detection approach can provide theoretical foundation for the development of driving anger warning products.

## 1. Introduction

Angry driving is quite common among drivers [1, 2], especially in China; the evidence from an online survey showed that 60.7% of the surveyed drivers had experienced anger during their driving process (Sohu, 2008). And it is regarded as one of the most prevalent factors implicated in road accidents [3]. The reason is that the emotional arousal labeled as anger has a negative influence on some cognitive variables, such as attention, perception, and information procession, which influencing the driver's control of the vehicle while driving [4]. In addition, it is also proved that the driving anger increased risk taking and had a negative impact on driving behavior [5].

According to Deffenbacher et al., driving anger can be defined as the propensity to become angry while driving and it is also defined as a specific situational form of trait anger. In their study, an evaluation scale which was called Driving Anger Scale (DAS) is developed to assess this construct [6]. Using this scale in the United States, Deffenbacher and his colleagues showed that drivers who score high on the DAS are more likely to become angry, engaging in more risky and aggressive behaviors, and are more often involved in accidents than those who score low [7, 8]. For exhaustive study, due to the fact that different drivers with the similar level of anger could express their driving anger with different behaviors, it is also necessary to analyze how this emotion emerged [9]. One of the questionnaires that have been created to explain this aspect is the Driving Anger Expression Scale (DAES) [10]. In this scale, six types of situations which were classified into "hostile gestures", "illegal driving", "police presence", "slow driving", "discourtesy", and

"traffic obstructions" were developed to measure driving anger. Previous studies also tried to find the relationship between driving anger and unsafe driving behavior [3, 11].

The impact factors of angry driving are associated with the driver, vehicle, road, and the environment. It had been found that younger males tend to have a more frequent reports and also recorded higher scores of anger level during driving [12–14]. Parker et al. found that experienced drivers become less irritated than novice drivers [12]. Other personal characteristics such as education, work stress, sensation seeking, and personality traits contributed to the occurrence of driving anger [3, 15]. Meanwhile, driving anger was also influenced by the driving environment and vehicle state. An evidence from an on-road experiment showed that slow driving, traffic violations, and traffic congestion can easily make drivers experience angry driving [16]. Smart et al. found that high performance vehicles tend to induce a more frequent angry driving [17]. In addition, the day of a week, time of a day, the weather condition, and road types would also influence the occurrence of driving anger [18].

Another important issue that has emerged from previous research is the method to induce anger during driving. Driving anger caused various risky behaviors on the road such as speeding, light flashing, and tailgating [19]. As a comparison, the simulation experiment is safer and simpler than on-road experiment. Prior laboratory anger inductions mainly relied on the induction materials. 16 groups of methods including self-statements, music, film, hypnotic suggestion, game feedback, social feedback, solitary recollection, imagery, empathy, and threat of shock were employed to induce different emotion in the psychological area [19, 20]. Similar methods are also adopted to induce anger during driving in current studies. Rotem Abdu et al. tried to use event recall to induce anger, and the driving simulation test results indicated that the participants' anger emotion is effectively induced [5]. Different types of music (including high/low energy in combination with both positive/negative valences) were regarded as the anger induction material by Juslin et al. In this study, 100 participants were split into five groups: the first four groups listened to different types of music (high/low energy in combination with both positive/negative valences) while the fifth group was used as a control group with no music stimulation. Results showed that anger induction level was highest during high energy negative music compared with positive music irrespective of energy level [21]. However, each of these methods has inherent defect. For example, the event recall method is sensitive to the external environment. A low-decibel noise will lead to a failure of the test. As another example, hypnotic suggestion methods may only work with a small portion of subjects, with the result that the findings may have little generalizability. In addition, the traditional emotion induction methods have significant biases compared with real-life driving in the aspects of emotion arousal and emotion duration.

Another concern of this study is the detection method to identify angry driving. As known, the evaluation of driving anger is a complex issue with the uncertainty of emotions. As a typical self-reported emotion evaluation scale, Driving Anger Scale (DAS) is widely used for the evaluation of angry driving. However, it is noteworthy that not all individuals are aware of and/or capable of reporting on their momentary emotional states. With the development of sensor technology and signal processing technology, many scholars tried to use biosignals and brain signals to classify different emotional states. For example, Schaaff et al. distinguished the happy and sad emotions based on the EEG characteristics, and the accuracy of the classification reached 66.7% [22]. As another example, Katsis et al. conducted a simulation experiment, and four features (including skin conductance, respiration, heart rate, and muscle conductance) were extracted as the vectors; the Support Vector Machine (SVM) and radial basis function network (RBFNETWORK) were employed to classify the different emotional states. The result showed that the accuracy of two different classification algorithms reached 79.3% and 76.7%, respectively [23]. However, due to the complexity of emotion measurement, little published academic studies focus on the detection of driving anger especially in China [24]. Thus, the primary purposes of this study were to explore the features which could express driving anger and develop an angry driving detection model.

To summarize, current studies has covered the following: how the driving anger emotion is expressed; some situations that could evoke driving anger; and how to evaluate the driving anger. Nevertheless, these researches also have many defects. How to continuously and effectively induce driving anger during the driving process is still a challenge. Furthermore, a standard evaluation method to measure driving anger is also a challenge which needs to be faced. Therefore, this study focuses on driving anger induction and detection via experimenting on driving simulator and real roads. First, three typical driving anger inducted scenarios were developed based on the virtual reality technology on a driving simulator. The participants' self-report, biosignals, and brain signals were collected to analyze the effectiveness of the inducting experiment. Then, four signals from drivers' physiological states and brain states were selected as the features for angry driving detection based on the on-road experiment. The Hidden Naïve Bayes (HNB) algorithm was employed to classify drivers' emotional states into two categories (normal driving and angry driving).

The technical route of the paper is presented in Figure 1 and the rest of this paper is developed as follows. Section 2 describes the driving simulating experimental design and driving anger induced scenarios evaluation. Section 3 presents the on-road experiment design, feature selection, the detection algorithm, and the evaluation of the detection model. Section 4 shows the general discussions about the two experiments in this study. The conclusion, limitations, and applications are also offered in this section.

## 2. Experiment 1: Based on Driving Simulator

In this study, the primary aim of the first experiment based on a driving simulator was to examine the effect of the designed scenarios on the induction of driving anger. It was expected that volunteers would report a higher anger level in an induced scenario than in a control scenario. This experiment also tried to examine significant differences of the driver's

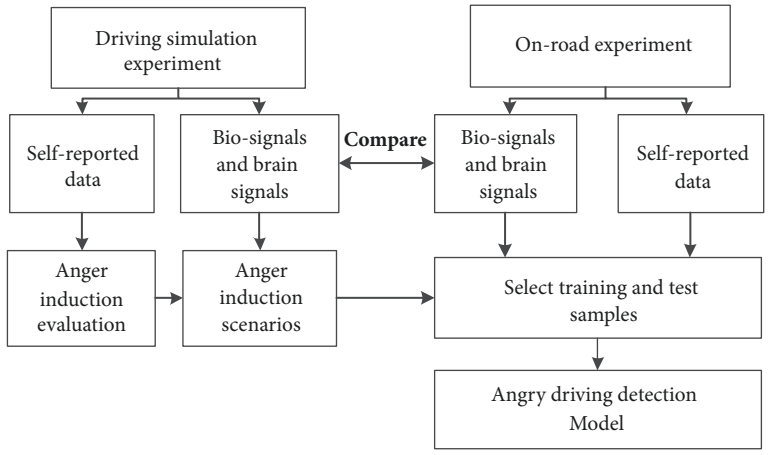



Figure 1: The technical route.

physiological states and brain states in different driving anger induction scenarios. It was hypothesized that those features would be influenced by anger induced scenarios and the difference would be regularly revealed.

### 2.1. Method

*2.1.1. Participant.* Fifteen healthy students, 13 males and 2 females, recruited via research leaflets from Wuhan University of Technology, with an average age of 24.6 years (SD=2.50 years), participated in this study. All of the participants had valid driver licenses for an average of 2.8 years (SD=1.50 years) and had experience of driving a simulator before. Each volunteer was paid 100 RMB for completing all experimental sessions.

*2.1.2. The Experiment System.* In order to keep the consistency of the experimental route and safe driving, a driving simulator was employed to imitate a real vehicle to conduct the experiments. As shown in Figure 4(i). The simulator consists of a Citroen vehicle, a 180° screen, and five network computers. It could provide a real-life steering wheel, a gear lever, accelerator–brake–clutch pedals, and a real-time virtual scenario. Moreover, the Biography Infiniti System (see Figure 2) and EEG recording equipment (see Figure 3) were also employed to collect biosignals and brain activities signals during driving.

*2.1.3. Variables Selection.* BVP (blood volume pulse): this index is used to describe the cardiac cycle in the process of driving; it refers to the number of heart beats per minute. Previous studies showed that when drivers are in a negative mood, large changes in BVP can easily be spotted [25].

SC (skin conductance): this index is measured in micro-Siemens. Some biofeedback systems display skin conductance in micro-mhos ($\mu$m)—a mho is the inverse of an ohm, which is the measure of resistance. These two measures, $\mu$S and $\mu$m, are equivalent. Normal readings, for skin conductance, in a relaxed state are around 20 $\mu$S, but readings can


Figure 2: The Biography Infiniti.

Figure 3: EEG recording equipment.

largely vary across different environmental factors and skin type.

$\delta$%: this index is the power percentage of $\delta$ wave; the frequency of $\delta$ wave is always in the range of 0.5 Hz to 4 Hz. It could be obtained by using the Fourier transform. It is

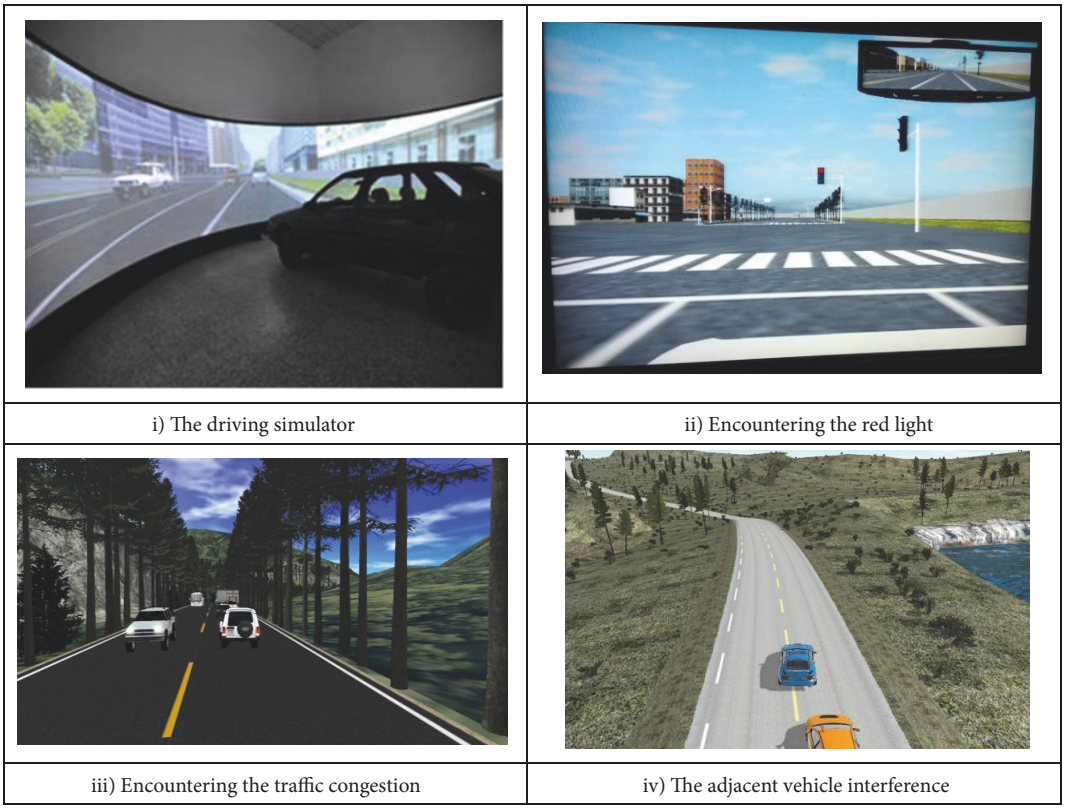



Figure 4: The induction scenarios of driving anger.

evidenced that the $\delta$% would have a significant change when people become angry.

$\beta$%: this index is the power percentage of $\beta$ wave. The frequency of $\beta$ wave is always in the range from 14 Hz to 35 Hz, and $\beta$% also could be obtained after using the Fourier transform. In previous studies, a significant difference has been showed between the neutral driving and angry driving.

Anger level: in order to independently assess the effects of the instructions on the participants' anger level, a self-report 5-point scale, scoring from 0 (not angry) to 4 (very angry), was used in this experiment, which is similar to the DAS. The participants were requested to report their anger level during driving.

*2.1.4. The Driving Anger Induced Scenarios.* It is ensured that the designed anger induced traffic scenarios is a subset of the inducing factors of "road rage" according to the national natural science foundation of China project. As described in previous studies [9, 25], the developed scenarios are presented in Figure 4, and the design parameters of three typical scenarios are showed as follows.

Scene i—encountering the red light frequently (see Figure 4(ii)): this scenario takes place on a 4 km (100,000 feet) two-way urban road with high traffic volume, pedestrian crossings, traffic lights, and three intersections. The speed limit in this scene is 60 km/h. The traffic light will turn red and last for more than 40 seconds when the subject vehicle arrived at 30 m away from the intersection.

Scene ii—encountering the traffic congestion (see Figure 4(iii)): this scenario takes place on a 2 km two-way rural road with a speed limit of 100 km/h. The road was composed of mountain scenery with many trees and few horizontal curves with high traffic volume. Each segment had 3 shallow curves with 4 vehicles traveling in the opposing lane. When the subject vehicle went through each curve, it almost comes to stop as the traffic flow became really heavy.

Scene iii—encountering interference from adjacent vehicle (see Figure 4(iv)): this scenario takes place on a 5 km two-way mostly straight rural road with a speed limit of 80 km/h. The road was composed of mountain scenery with many trees and few shallow curves with low traffic volume. After the subject vehicle (the yellow vehicle in Figure 4(iv)) traveled 1 km, the adjacent vehicle speed increases suddenly and surpasses the subject vehicle, making the subject vehicle reduce its speed to under 20 km/h.

*2.1.5. Procedure.* The Emotion Induction Programs (MIPs), which are a typical method of emotion induction test, were employed to induce the target mood in this study. The MIPs include three subprograms: the first and second step are used to simulate the natural environment, and the last step is used to review and check the effectiveness of mood induction. An experiment process was designed on the basis of this paradigm as presented in Figure 5.

Each participant needed to complete all six driving scenarios (A, A∗, B, B∗, C, and C∗). When participants first

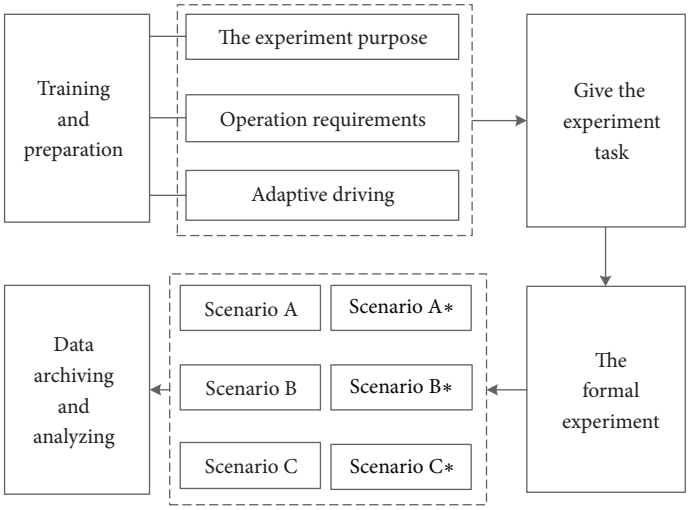



Figure 5: The induced experiment process. *Notes: A: normal driving; A∗: encountering adjacent vehicle interference; B: no need to wait for the red light; B∗: encountering the traffic light frequency; C: traffic flow is normal; C∗: encountering traffic congestion.*

Table 1: The emotional differentiation degree in different scenarios.

| | Total | Hit rate | Happy | Anger | Sad | Fear |
|---|---|---|---|---|---|---|
| A | 15 | 0.13 | 11 | 2 | 0 | 2 |
| A∗ | 15 | 0.87 | 1 | 13 | 0 | 1 |
| B | 15 | 0.13 | 10 | 2 | 0 | 3 |
| B∗ | 15 | 0.67 | 4 | 10 | 0 | 1 |
| C | 15 | 0.07 | 9 | 1 | 0 | 5 |
| C∗ | 15 | 0.73 | 1 | 11 | 0 | 3 |

arrived in driving simulator lab, they were asked to fill out the trait anger scale (TAS) and demographic questionnaire, and signed a labor contract. Then, in order to ensure that each participant can operate the driving simulator efficiently, a 5-minute adaptive driving is provided. Finally, all of the participants were asked to finish the whole driving route as they normally would do, and illegal behaviors are not allowed in this period.

*2.2. Results.* The emotional differentiation degree, the intensity of induced emotion, and physiological index were analyzed based on the results from the driving anger induction experiment (Scene i, Scene ii, and Scene iii).

*2.2.1. Emotional Differentiation Degrees.* The emotional differentiation degree is an important index to evaluate the accuracy of driving anger induction. It represents the matching accuracy between the target mood and the participants' reported. In this study, the hit rate was used to estimate the emotional differentiation degree. The result of participants' induced mood in different driving scenarios was shown in Table 1 based on the subjective self-reported questionnaire.

Compared to the control scenarios (A, B, and C), it could be observed that the participants are able to express anger mood easily after the experiment of three types of anger induced scenarios (A∗, B∗, and C∗) as shown in Table 1. The result indicates that it ranks best in the scenario of adjacent vehicle interference (A∗) with the hit rate of anger reaching 87%, and the worst scenario is the scene of encountering a high frequency of red light (B∗), with a hit rate of 67%. According to Table 1, it is verified that these three anger induced scenarios can actively induce drivers' anger emotion in the experiments based on a driving simulator.

*2.2.2. The Intensity of Induced Mood Analysis.* The intensity of induced mood is also an important index to evaluate whether the experiment is effective, and this index is mainly expressed by the score of a participant's self-report level. A higher average score means the emotional trigger is stronger. In order to find the significant variation in different scenarios, the self-report levels of anger before and after the experiment were recorded.

As shown in Table 2, the result of the paired-samples t-test shows that three control scenarios of A ($t=0.808$, $p=0.432$), B ($t=1.861$, $p=0.083$), and C ($t=1.000$, $p=0.333$) have nonsignificant influence on the induction of driving anger. However, these three induced scenarios (A∗, B∗, and C∗) have a significant impact on the induction of driving anger as the value of $p<0.05$. Under the scenario of the adjacent vehicle interferences, the highest anger level was induced, which was 2.625 and it was significantly higher than at the start of the induction experiment. In addition, the maximum of anger level also happened in scenario iii (A∗), which is 4. By comparing to the control scenarios, it is found that all of

Table 2: The paired-samples t-test of anger level between different scenarios.

| | Mean | Std. | 95% Confidence Interval of the Difference | | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | | | |
| A | 0.125 | 0.619 | -0.205 | 0.455 | 0.808 | 15 | 0.432 |
| A∗ | 2.625 | 0.957 | 2.115 | 3.135 | 10.967 | 15 | 0.000 |
| B | 0.188 | 0.403 | -0.027 | 0.402 | 1.861 | 15 | 0.083 |
| B∗ | 2.563 | 0.892 | 2.087 | 3.038 | 11.490 | 15 | 0.000 |
| C | 0.125 | 0.500 | -0.141 | 0.391 | 1.000 | 15 | 0.333 |
| C∗ | 2.000 | 0.894 | 1.523 | 2.477 | 8.944 | 15 | 0.000 |

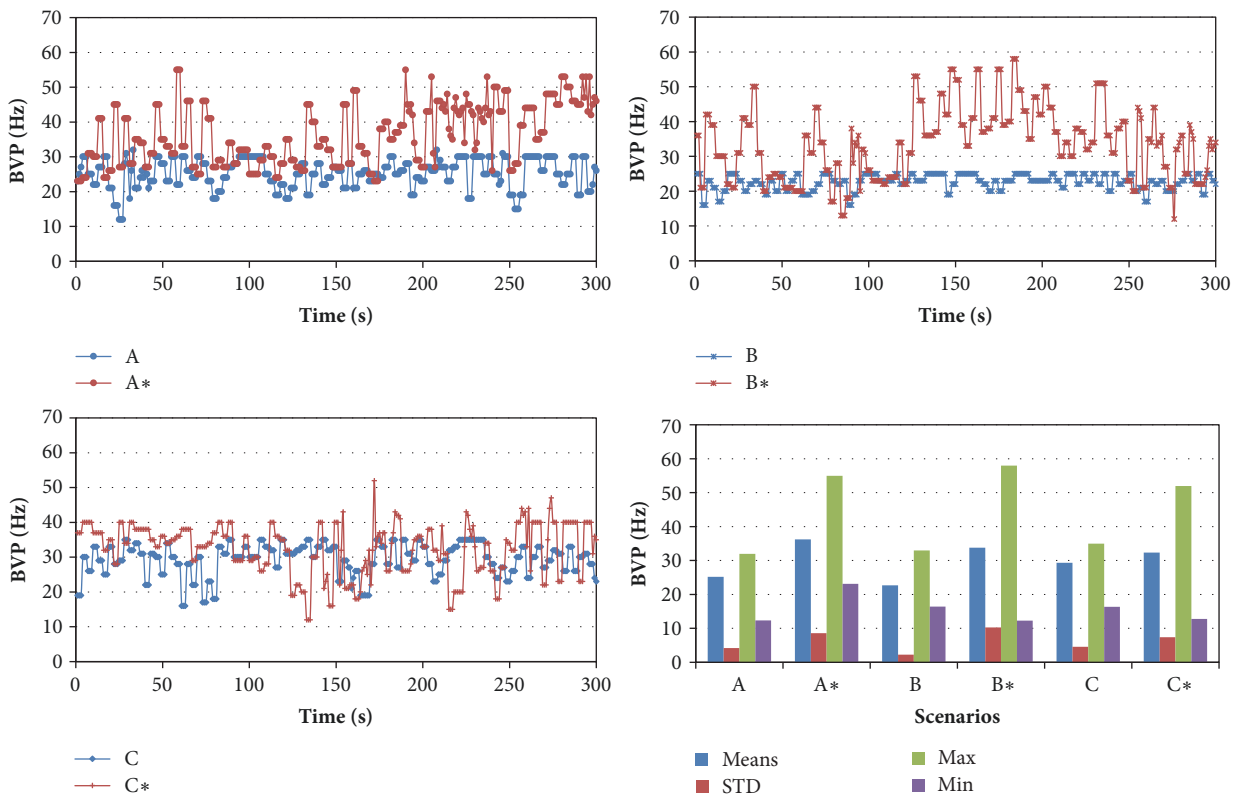



Figure 6: The value of BVP in different scenarios.

these three induced scenarios could induce different level of driving anger.

*2.2.3. Physiological Index Analysis.* It had been proved that the drivers' physiological states and EEG were significantly different in sensitivity when they were in a negative emotional state [26]. So four typical signals (including BVP, SC, $\delta$%, and $\beta$% described by Wan et al. [27]) from physiological states and brain states were selected to verify the effectiveness of the designed experiment. The significant differences of these four indexes between different simulating scenarios were also analyzed in this study as shown in Figures 7, 8, and 9.

As shown in Figure 6, the drivers' BVP has a significant volatility in the three induced scenarios; it is more sensitive in the scenario of encountering the red light frequently (B∗) compared with the other two induced scenarios. In addition, the maximum of the driver's BVP also happened in scenario (ii) (B∗), which is close to 58 bm. The similar result could be observed in the value of SC as shown in Figure 7; the mean and standard deviation of SC increased significantly in scenarios A∗ and B∗ compared with these two control scenarios (A and B). Figure 8 presents that it appears nonsignificantly different in the index of $\delta$% between induced scenarios and control scenarios, except for the scenarios of C and C∗. Statistical analysis shows that when compared with the control scenario (C), the mean and standard deviation of $\delta$% are decreased in the scenario of encountering the traffic congestion. Figure 9 shows that the wave of $\beta$% in scenarios A∗ and C∗ is more unstable than two control scenarios (A and C). The standard deviation of $\beta$% reached 6.75 and 6.89 in scenarios A∗ and C∗, which increased by 5.22 and 2.17, respectively, compared with scenarios A and C. In addition,

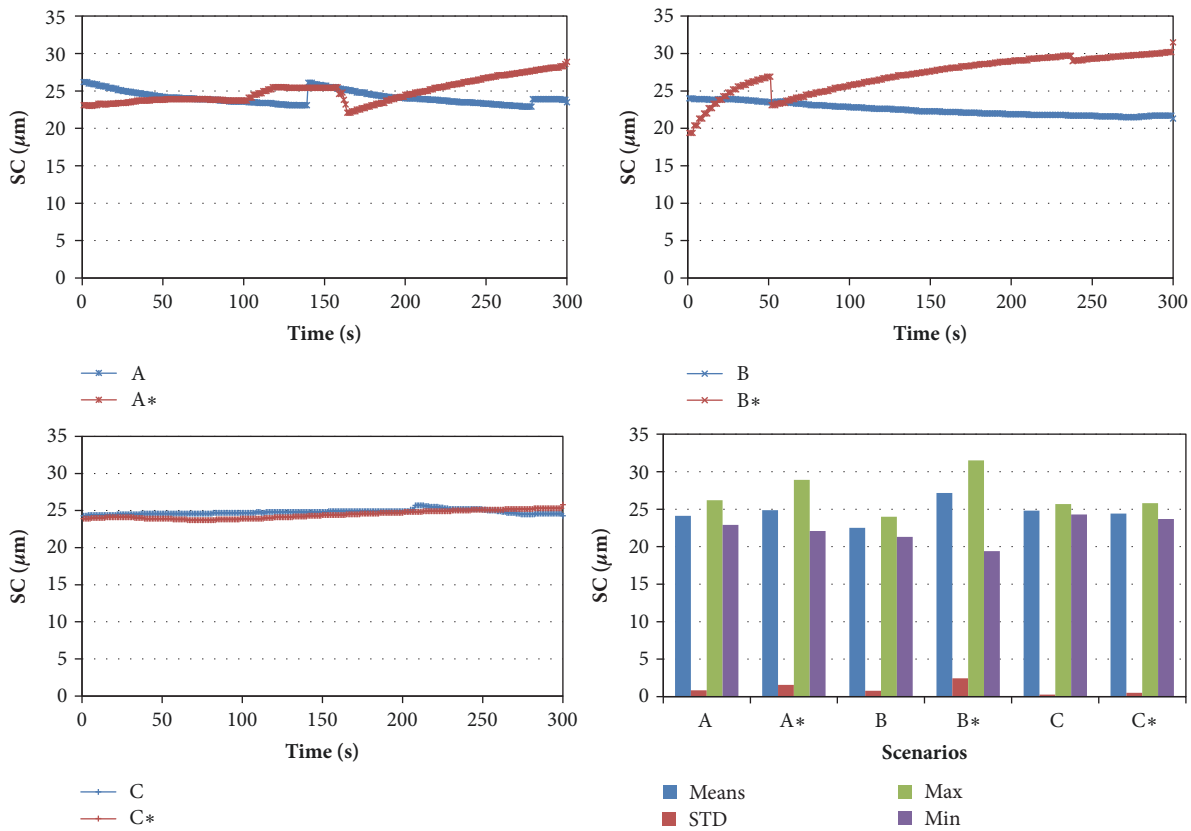



Figure 7: The value of SC in different scenarios.

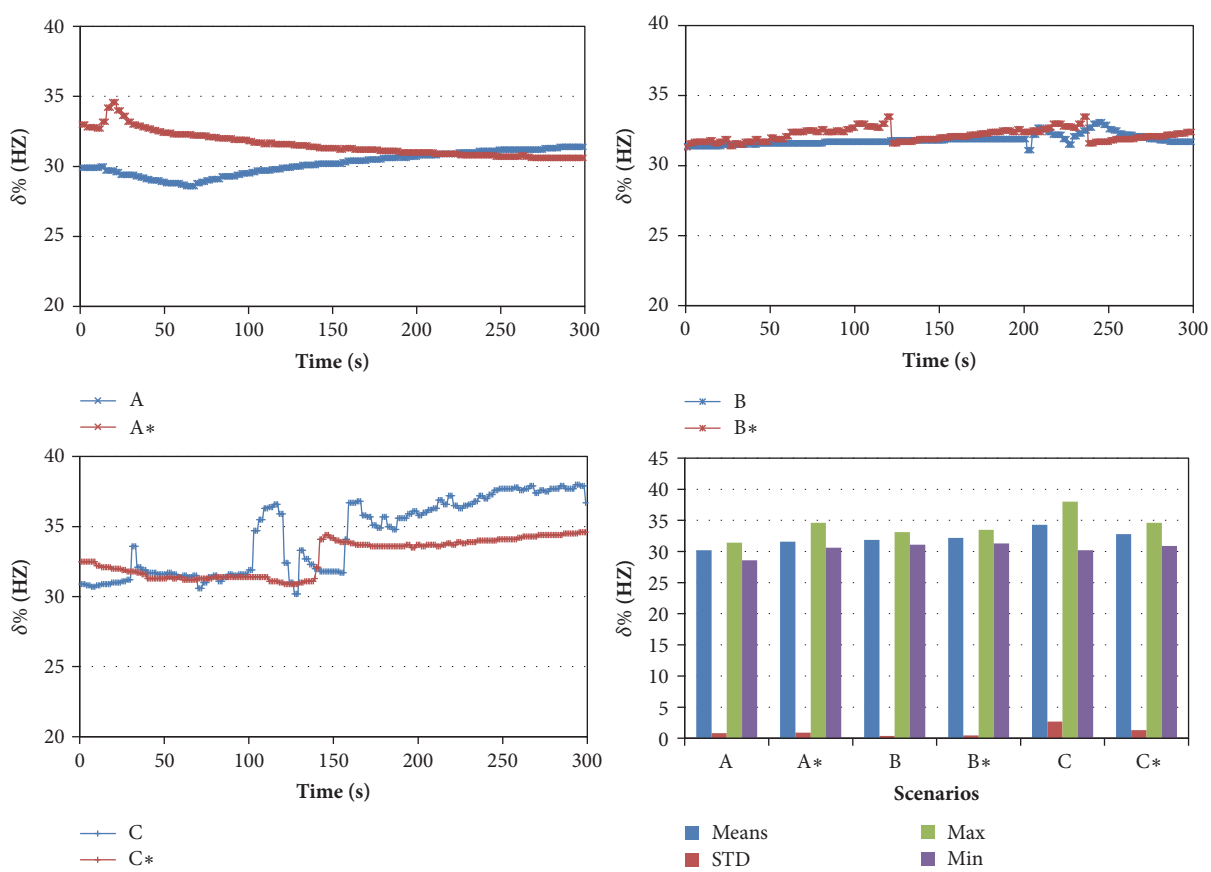



Figure 8: The value of δ% in different scenarios.

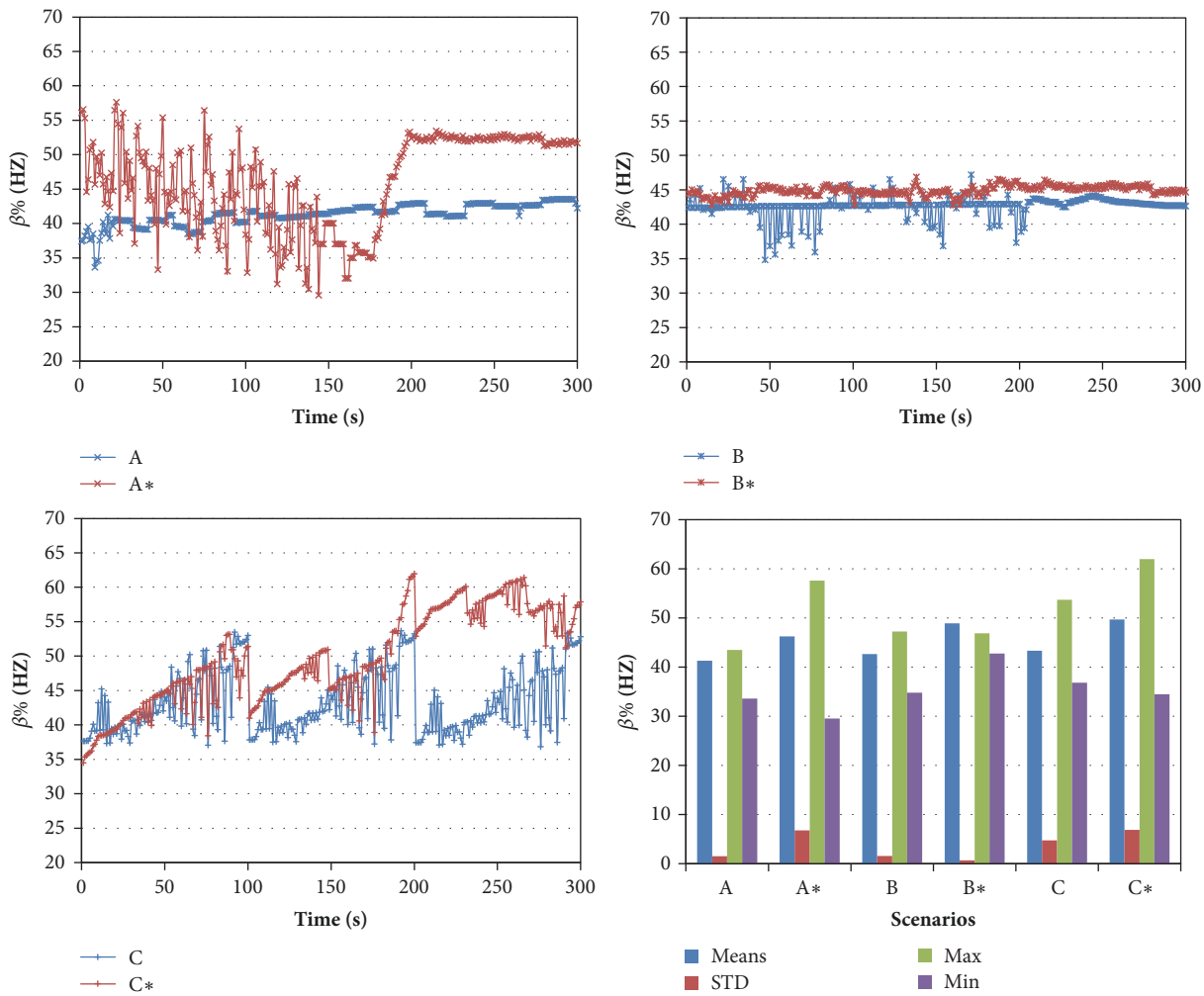



Figure 9: The value of $\beta$% in different scenarios.

by comparing to the control scenarios, the mean of $\beta$% in three induced scenarios is increased by 4.94, 6.26, and 6.37, respectively.

*2.3. Discussion.* Study results suggest that the three typical driving anger induced scenarios developed by the virtual reality technology in a driving simulator are efficient in inducing the anger emotion during driving. A statistical analysis of the subjective questionnaire shows that the participants' self-reported anger level has a significant increase in the induction scenarios compared with the control scenarios, especially in the scenario of encountering the adjacent vehicle interfere. This conclusion also coincides with the related literatures [24]. Meanwhile, the result of the drivers' emotional differentiation degree indicates that the effectiveness of driving anger induction is encouraged by three induced scenarios. The hit rate in the scenario of encountering the adjacent vehicle interfere is up to 0.87, which indicates that this induced scenario is ranking best to induce driving anger in all of these scenarios. In addition, the drivers' anger level has a significant difference in six scenarios. Compared with the control scenarios, these three induced scenarios cause higher level of anger.

Results reveal significant associations between the different simulation scenarios, the participants' physiological state, and brain state. Compared with the control scenarios, the participants' BVP, SC, $\delta$%, and $\beta$% appear to have significant difference in the anger induced experiments. A similar pattern has also been demonstrated in the part of introduction, drivers' heart rate would be faster and the $\delta$%, $\beta$% would be significantly different when they were in a negative emotion [28, 29]. So the evidences from the participants' physiological and brain signals also indicate the scenarios of encountering the adjacent vehicle interfere, red light frequently, and traffic congestion easily lead to the driver becoming angry during driving.

It is particularly noteworthy that the participants' BVP, SC, $\delta$%, and $\beta$% have significant difference in different driving scenarios. However, previous research suggested that it would be different in real-world driving, and whether these four indexes could be regard as the features to develop an angry driving detection model is still an important project

which needs to be explored. Due to these reasons, the second experiment (an on-road experiment) was designed. In order to examine whether the characteristics of driver's physiological state and brain state would be different when they become angry during the real-world driving and simulation driving, it was accomplished by searching for a real-life experiment route which includes all of three types of anger induced scenes designed in experiment 1.

## 3. Experiment 2: Based on Real Road

The second experiment tried to explore the characteristics of driver's physiological state and brain state on angry driving and normal driving. Moreover, three forms of angry driving which the participants reported were considered in the real-world experiment: (a) encountering the adjacent vehicle interference; (b) encountering the red traffic light frequently and the red light lasting for a long time; and (c) encountering the traffic congestion. All of those three forms had already been described in experiment 1. It was hypothesized that the driver became angry when encountering these three types of traffic scenes and at that time they reported that they felt angry. The continuous values of physiological and brain state data with the length of 5s of before and after they report were recorded to evaluate driving anger. In addition, it was also hypothesized that a driver will keep normal driving when they could not report their emotional state.

*3.1. Participants.* In the on-road experiment, 22 volunteers (18 males and 4 females) were employed to complete driving experiment from a local taxi company. The ages of participants were between 20 and 60, and the average age of them was 42.27 years (SD=9.07). All of them possessed a full driver's license, and the average driving age was 13.5 years (SD=6.06). In addition, in order to simplify the process of response and reduce the difficulty of driving anger identification, the emotion feedback was classified as two levels (0: normal driving; 1: angry driving) during the on-road experiment. Each volunteer was paid 500 RMB for completing all experimental sessions.

*3.2. General Protocol.* A 53 km long urban road was chosen as the test route (shown in Figure 10) of this experiment in Wuhan, China. It includes 45 traffic lights, 2 bridges (B1 and B2 in Figure 10), 3 larger-scale business districts (A1, A2, and A3 in Figure 10) which easily caused traffic congestion, and about 10 km long expressway. All of the scenarios mentioned in experiment 1 would appear in this route. In addition, to examine the impact of the traffic congestion on angry driving, these experiments were conducted from 7 am to 9 am in the morning and 5 pm to 7 pm in the evening.

After arriving at the lab, the participants were asked to fill out some questionnaires such as the trait anger scale (TAS) to ensure whether they were suitable to take part in the experiment, and the individual characteristics (like the participants' age, sex, driving experience, and so on) were also collected. Then, the assistants gave a brief introduction about the procedure of this experiment to the participants and assisted them to wear the physiological devices. Next,

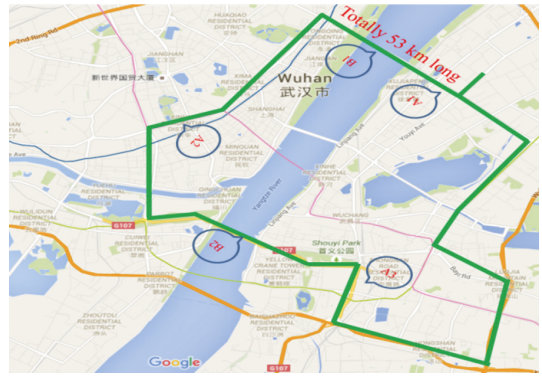



Figure 10: The test route.

Figure 11: The subject vehicle.

the participants were asked to carry out a driving practice by a subject vehicle (shown in Figure 11) so that they could be familiar with the subject vehicle and adapt themselves to driving with the devices. Finally, the participant was asked to start to drive normally following the test route; a simultaneous collection of drivers' physiological signals (including BVP and SC) and brain signals (including $\delta$ waves and $\beta$ waves) were conducted; similar equipment to that in experiment 1 was used to collect the signals data. The participants were asked to report their anger level when they felt angry during driving. In addition, to increase the effectiveness of the anger stimulation, a rule was established: all the participants were asked to complete the test within 2 hours, and 50 Yuan RMB would be deducted per 10 minutes if they could not finish the experiment on time. Any fine or deduction of license points was paid by them if they violated the traffic regulation.

*3.3. Results*

*3.3.1. Descriptive Statistics for Biosignals and Brain Signals.* From Table 3, we can see that the mean, standard deviation, minimum, maximum, range, kurtosis, and skewness of each signal seem to be different between the normal driving and angry driving. Compared with the normal driving, the mean of BVP and $\beta$% seems to increase in angry driving. The minimum of BVP, SC, $\delta$%, and $\beta$% also tends to increase

Table 3: The descriptive statistics of the biosignals and brain signals.

| Anger level | Normal driving | | | | Angry driving | | | |
|---|---|---|---|---|---|---|---|---|
| Index | BVP | SC | $\delta$% | $\beta$% | BVP | SC | $\delta$% | $\beta$% |
| Mean | 33.514 | 31.014 | 35.121 | 38.482 | 35.929 | 26.987 | 30.151 | 43.986 |
| STD | 1.632 | 9.080 | 9.221 | 9.777 | 1.712 | 7.775 | 7.248 | 6.712 |
| Min | 22.143 | 13.463 | 10.770 | 16.300 | 31.814 | 15.437 | 15.120 | 24.770 |
| Max | 37.026 | 38.332 | 51.650 | 63.730 | 39.453 | 38.332 | 48.270 | 57.600 |
| Range | 14.882 | 24.869 | 40.880 | 47.430 | 7.640 | 22.895 | 33.150 | 32.830 |
| Kurtosis | 13.806 | -.925 | -.761 | -.721 | .373 | -1.607 | -.483 | .053 |
| Skewness | -2.302 | -.913 | -.338 | .078 | .255 | -.034 | .237 | -.386 |

Table 4: T-test for the bio-signals and brain signals in angry driving and normal driving.

| | Test for Equality of Variances | | T-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | F | Sig | t | Df | Sig (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | | | | | | | Lower | Upper |
| BVP | .034 | .853 | -12.405 | 291.686 | **.000** | -2.405 | .194 | -2.787 | -2.023 |
| SC | 2.159 | .143 | 4.128 | 295.656 | **.000** | 4.026 | .975 | 2.107 | 5.946 |
| $\delta$% | 12.276 | **.001** | 5.202 | 290.377 | **.000** | 4.969 | .955 | 3.089 | 6.850 |
| $\beta$% | 30.242 | **.000** | -5.714 | 275.785 | **.000** | -5.504 | .963 | -7.400 | -3.608 |

Table 5: The correlations between bio-signals, brain signals and anger level.

| | Kendall's tau-b | | Spearman's rho | |
|---|---|---|---|---|
| | Sig. (2-tailed) | Correlation coefficient | Sig. (2-tailed) | Correlation coefficient |
| BVP | .000 | .534** | .000 | .653** |
| SC | .000 | -.232** | .000 | -.282** |
| $\delta$% | .000 | -.236* | .000 | -.289** |
| $\beta$% | .000 | .243** | .000 | .297** |

**Correlation is significant at the 0.01 level (2-tailed)

in angry driving. The maximum of BVP, the kurtosis of $\delta$% and $\beta$%, and the skewness of BVP, SC, and $\delta$% during angry driving are greater than that during normal driving. However, standard deviations of SC, $\delta$%, and $\beta$% during angry driving are smaller than during normal driving. The ranges of all four features during normal driving are larger than in normal driving, and the similar result appeared in the index of the kurtosis of BVP, SC, and $\delta$%. These indicate that the driver during angry driving keeps in a more active state than during normal driving.

*3.3.2. Independent Sample T-Test.* Levene's test for equality of variances shows that population variances of the power percentage of $\delta$ wave (F=12.276, P<0.05) and the power percentage of $\beta$ wave (F=30.242, P<0.05) are significantly different between normal driving and angry driving (see Table 4), using the significance level of alpha=0.05 respectively. The t-test for equality of means presents that means of blood volume pulse (t=-12.405, P<0.01), skin conductance (t=4.128, P<0.01), $\delta$% (t=5.202, P<0.01), and $\beta$% (t=-5.714, P<0.01) are not equal in different driving scenarios according to the significance level of alpha=0.01, respectively. In summary, the independent sample t-test indicates that the physiological state and brain state showed significant variation between normal and angry driving.

*3.3.3. The Correlation Test between Biosignals, Brain Signals, and Anger Level.* To examine the correlations between biosignals, brain signals, and different driving scenarios, the Spearman correlation test and Kendall's tau-b correlation test were adopted. As shown in Table 5, the Spearman correlation test presents that BVP (correlation coefficient=0.534, P<0.01), skin conductance (correlation coefficient=-0.232, P<0.01), $\delta$% (correlation coefficient=-0.236, P<0.01), and $\beta$%(correlation coefficient=0.243, P<0.01) are significantly correlated to the different driving scenarios, and the Kendall's tau-b correlation test obtains a similar result. Moreover, the correlation test also indicates that the relationship between BVP, $\beta$%, and anger level is significant positive correlation. A strong negative correlation existed between SC, $\delta$%, and driving anger levels.

*3.4. The Detection Model for Angry Driving.* The goal of angry driving detection is to classify the driver's state into two

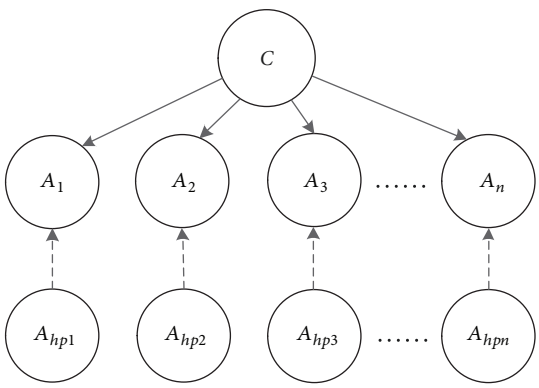



Figure 12: The structure of Hidden Naïve Bayes.

different classes: normal driving and angry driving. As shown in the above section, four features had been selected, and the detection model could be performed now. A Hidden Naïve Bayes (simply HNB) was employed in this study.

Hidden Naïve Bayes (HNB) includes three types of nodes: class nodes, attribute nodes, and hidden parent nodes. The structure of HNB is shown in Figure 12. In this figure, $C$ is the class node defined as the different driving state in the detection model, $A_n$ is the attribute node which is defined as four selected features, and each of $A_n$ has a hidden parent $A_{hpn}$ represented by a dashed circle. Compared with Naïve Bayes, the advantage of HNB is that the attribute dependencies are incorporated in the addition of hidden parent nodes. This model also can avoid the intractable computational complexity for learning and optimizing Bayesian network. The joint distribution represented by an HNB is defined as follows [30]:

$$P(A_1, \ldots, A_n, C) = P(C) \prod_{i=1}^{n} P(A_i \mid A_{hpi}, C) \tag{1}$$

where

$$P(A_i \mid A_{hpi}, C) = \sum_{j=1, j\neq i}^{n} W_{ij} \left(P(A_i \mid A_j, C)\right), \quad \sum_{j=1, j\neq i}^{n} W_{ij} = 1 \tag{2}$$

In formula (2), one-dependence estimators $P(A_i \mid A_j, C)$ are used to define hidden parents, and the influences from other attributes have been thought about in HNB. The approach to determine the weights $W_{ij}, i, j = 1, 2, \ldots, n$ is crucial for learning an HNB which is presented in (1) and (2). An approach based on directly computing the estimated values from data is employed in this study. The conditional mutual information between two attributes $A_i$ and $A_j$ is selected as the weight of $P(A_i \mid A_j, C)$ and $W_{ij}$ which is defined in

$$W_{ij} = \frac{I_p(A_i, A_j \mid C)}{\sum_{j=1, j\neq i}^{n} I_p(A_i, A_j \mid C)} \tag{3}$$

where $I_p(A_i, A_j \mid C)$ is the conditional mutual information defined in

$$I_p(A_i, A_j \mid C) = \sum_{a_i, a_j, c} P(a_i, a_j \mid c) \log \frac{P(a_i, a_j \mid c)}{P(a_i \mid c) P(a_j \mid c)} \tag{4}$$

Then, the classifier corresponding to an HNB on an example $E = (a_1, \ldots, a_n)$ which represents the driving state is defined as follows:

$$c(E) = \arg\max_{c \in C} P(c) \prod_{i=1}^{n} P(a_i \mid a_{hpi}, c) \tag{5}$$

where

$$P(a_i \mid a_{hpi}, c) = \sum_{j=1, j\neq i}^{n} W_{ij} * P(a_i \mid a_j, c) \tag{6}$$

The Hidden Naïve Bayes not only contains the characteristics of Naïve Bayes such as the high training speed and the simple structure, but also takes advantage of Bayesian network such as explaining the causal relationship between different variables [31]. Considering these reasons, the HNB was selected as the suitable algorithm to build the angry driving detection model.

*3.4.1. The Evaluation of Angry Driving Detection Model.* The method of percentage split validation was employed to estimate the accuracy of angry detection. In percentage split validation, the collected data was randomly partitioned into 2 sets: one set of data was performed as the training sample, and another set is used as the testing sample. The training set consisted of 80% groups of the whole data, and another 20% was regarded as the test samples. In addition, as well-known metrics of accuracy, the area under ROC curve (AUC) and many indexes such as (true positive) TP rate, FP (false positive) rate, precision, and F-measure were used to measure the performance of the detection model.

The training result presents the fact that the AUC of training set is 0.98, and the TP rate, precision, and F-measure are all close to 0.9 as shown in Figures 13 and 14. It indicates that the angry driving detection model owns a good training performance when using the HNB to classify the normal driving and angry driving.

The result of test set (see Figure 15) shows that although there still exists some error-prediction variables, the accuracy of the prediction model is close to 0.85 and the AUC reached 0.901 as shown in Figure 16; considering the uncertainty of emotional state, the detection model is encouraged to be regarded as an efficient discovery to identify the angry driving during the real-life driving.

*3.4.2. Comparing with the Other Classification Algorithms.* To reflect the prediction performance of the developed angry driving detection model, five common used classification algorithms were employed as comparisons, and ROCs for all of the algorithms were generated as shown in Figure 17,

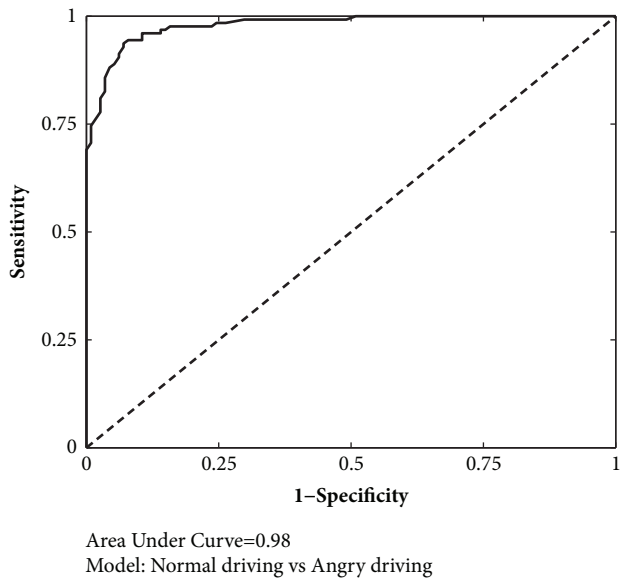



Figure 13: The ROC of training set.

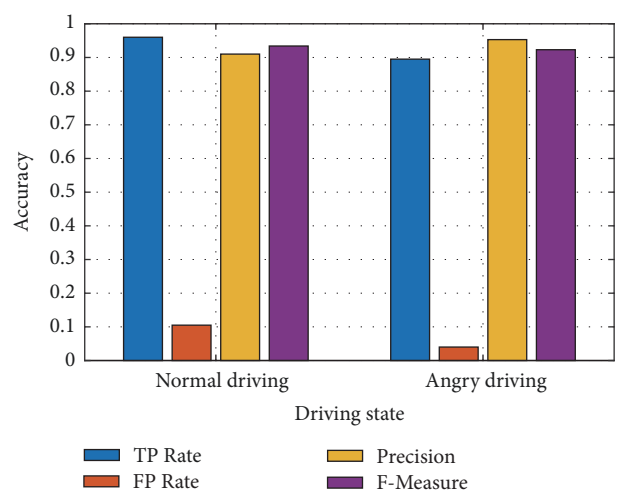



Figure 14: The accuracy of training.

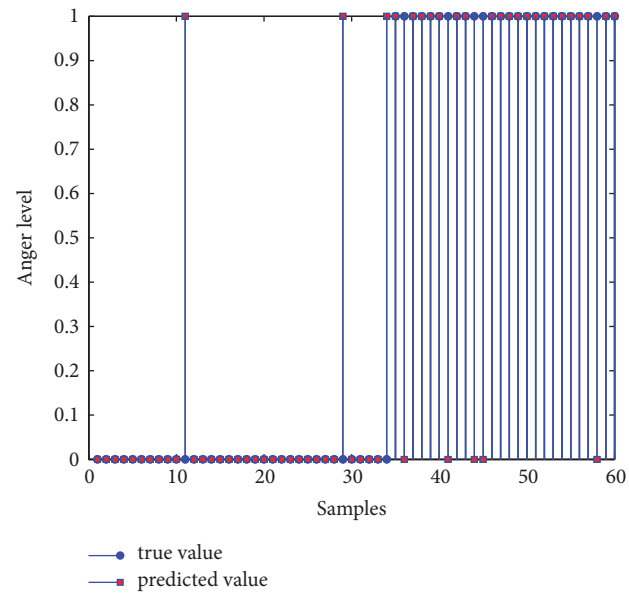



Figure 15: The prediction result of test sample.

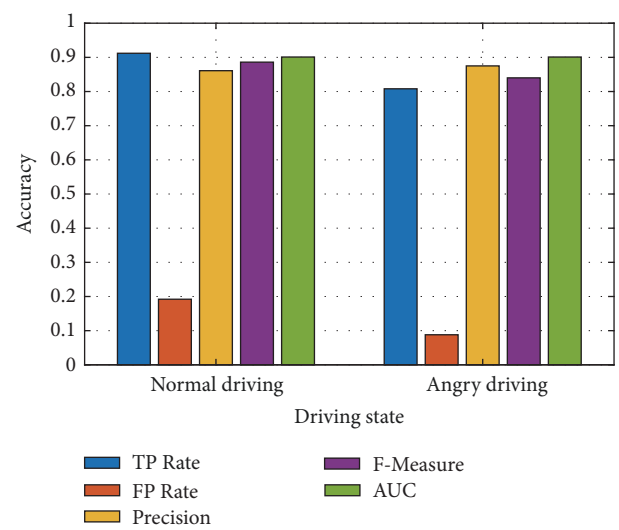
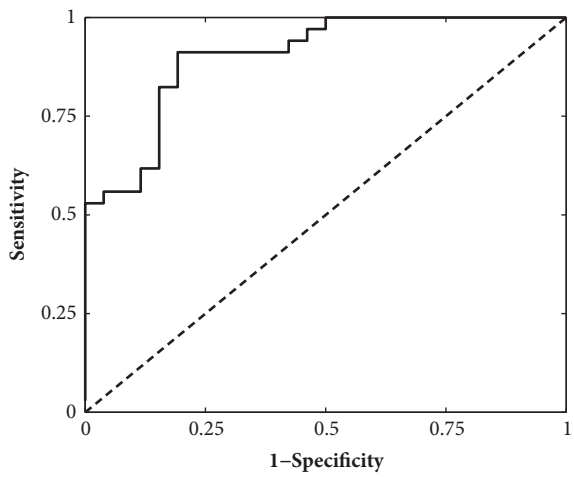



Figure 16: The accuracy of testing.

the solid bold lines are the ROC curves, and the straight diagonal dashed lines are the reference lines. From Figure 17, we can see that the AUC of HNB (Figure 17(a)) is larger than Naïve Bayes (NB) (Figure 17(b)), Bayesian network (BN) (Figure 17(c)), SVM (Figure 17(d)), ID3 (Figure 17(e)), and RBFNETWORK (Figure 17(f)). It indicates that the model we developed shows a higher predictive power than other classification algorithms.

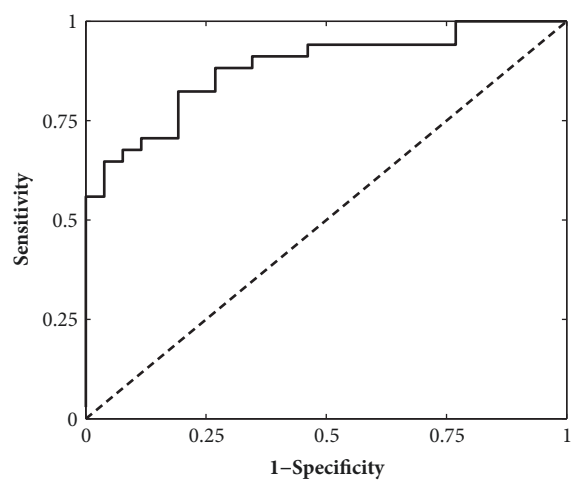
The results presented in Figure 18 show that the prediction accuracy of the HNB is the highest in six classification algorithms. The result of other three evaluation indexes (including kappa, the root means squared error (RMSE), and the root relative squared error (RRSE)) also indicates that the HNB is ranking best compared with other five algorithms. Although the value of kappa is the highest in ID3, the RMSE and RRSE in ID3 also are lowest compared with other five algorithms; it makes no sense as 7 unclassified instances exist in ID3.

*3.5. Discussion.* Road rage is easily occurring in our daily driving, especially when encountering the critical traffic events such as traffic jams, the adjacent vehicle interfere, and delay in red traffic light frequently. As a typical developing city in the Central China, Wuhan is a metropolitan area where the population is more than 10 million and the traffic pressure is really heavy which leads to the drivers easily experiencing traffic congestion and other unsafe traffic behaviors [32]. So angry driving is easily occurring in this city. The on-road driving experiment provides an opportunity to conduct a deep analysis about the causes and expression of angry driving.



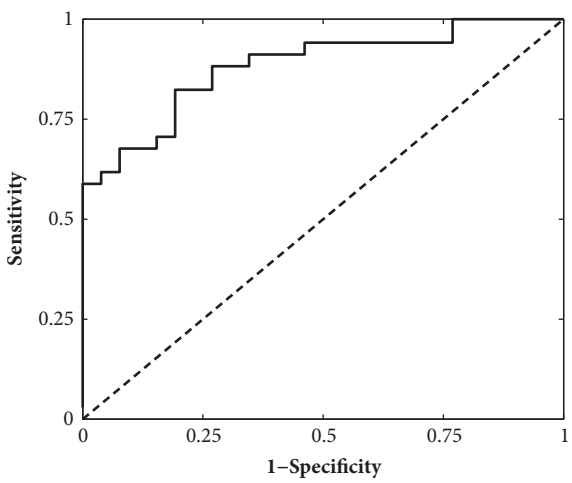

Area Under Curve=0.901
Model: Normal driving vs Angry driving

(a) The ROC of HNB



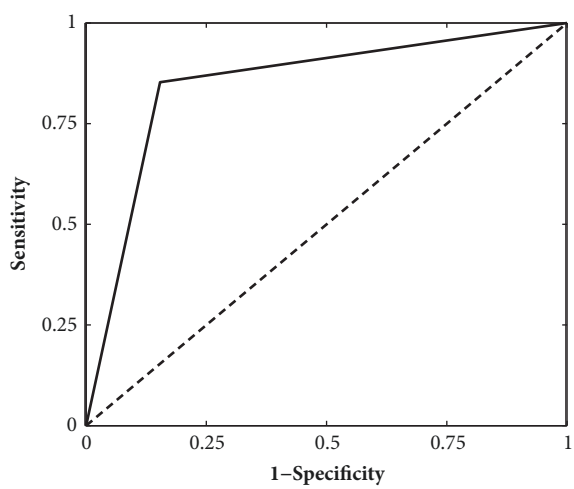

Area Under Curve=0.882
Model: Normal driving vs Angry driving

(b) The ROC of NB



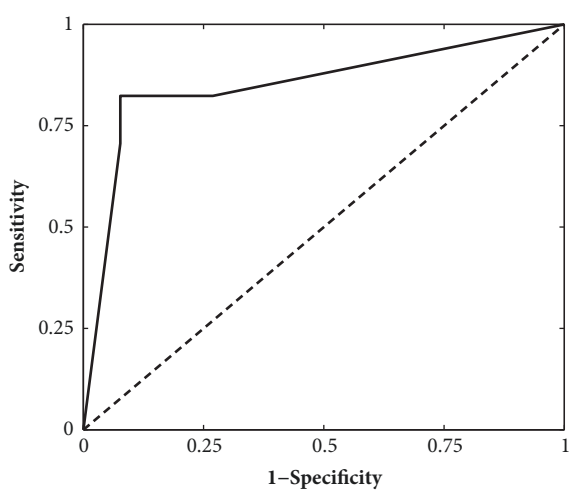

Area Under Curve=0.881
Model: Normal driving vs Angry driving

(c) The ROC of BN



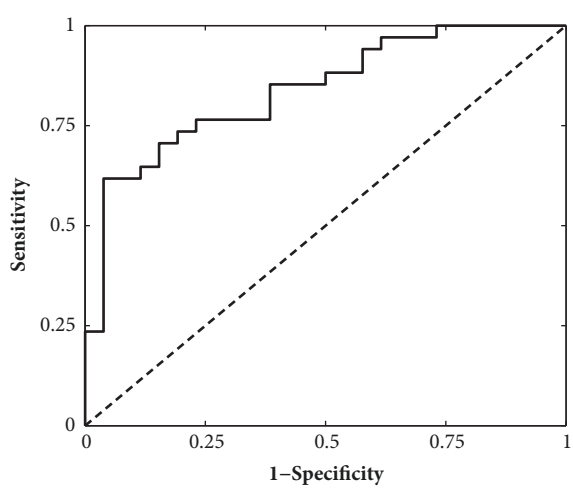

Area Under Curve=0.85
Model: Normal driving vs Angry driving

(d) The ROC of SVM




Area Under Curve=0.854
Model: Normal driving vs Angry driving

(e) The ROC of ID3




Area Under Curve=0.837
Model: Normal driving vs Angry driving

(f) The ROC of RBFNETWORK

Figure 17: ROC curves.

Table 6: The comparison between on-road test and driving simulation test.

| | Normal driving | | | | Angry driving | | | |
|---|---|---|---|---|---|---|---|---|
| | BVP | SC | $\delta$% | $\beta$% | BVP | SC | $\delta$% | $\beta$% |
| On-road test | 33.514 | 31.014 | 35.121 | 38.482 | 35.929 | 26.987 | 30.151 | 43.986 |
| Simulation test | 25.21 | 23.805 | 32.108 | 32.399 | 34.143 | 25.489 | 32.192 | 48.254 |

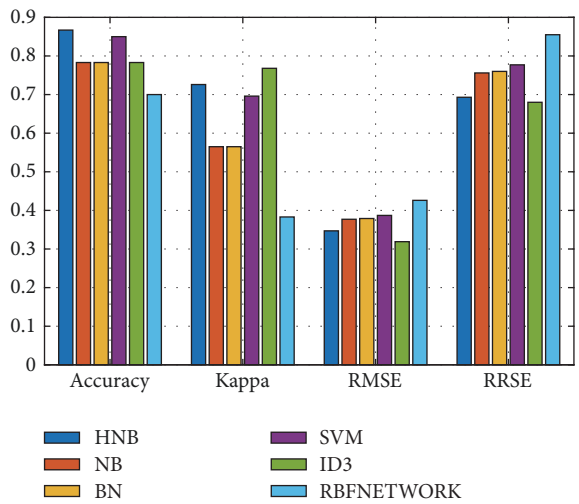



Figure 18: The statistical value of different algorithms.

One of the objectives for the on-road experiment is to evaluate the relationship between different driving scenarios and drivers' states in actual driving. Similar to experiment 1, study results suggest that a large variation among the physiological state and brain state appeared between angry driving and normal driving. It is surprising to observe that the mean of BVP, SC, $\delta$%, and $\beta$% presented significant differences between angry driving and normal driving (see Tables 3 and 4). The correlation test (see Table 5) indicated that the four selected features have strong correlations to the different driving emotional states.

A primary focus of this study is to develop a suitable model to predict the angry driving during real-life driving using the four selected features, which are strongly related to the drivers' physiological and brain states. An accuracy of 85% and the AUC of 0.901 were achieved using a HNB classifier in this study. It indicates that the detection model based on the HNB is accurate enough to identify the angry driving. The different statistical evaluation indexes resulted from comparisons between the HNB and other algorithms led to strong support for the hypothesis that the detection model based on the HNB is the most appropriate and usage of one to detect the angry driving.

## 4. General Discussions and Conclusions

Two typical experiments (driving simulation experiment and on-road experiment) were conducted to study the occurrence and expression of the driving anger in this study. One of the key purposes of the driving simulation experiment is to examine whether three driving anger induction scenarios could induce the angry emotion during the virtual reality environment. In addition, the simulation experiment also tried to provide an evidence rule to improve the identification accuracy of angry driving. In the on-road experiment, the ranking and causal relationship analysis of angry driving, driver's physiological state, and brain state were conducted. An angry driving detection model was developed based on biosignals and brain signals data.

In this study, four indicators (BVP, SC, $\delta$%, and $\beta$%) related to drivers' behavior were analyzed between normal driving and angry driving in two types of experiments. Previous study suggested that the angry driving leads to greater changes in physiological signals compared with in normal driving [24], and our findings were consistent with this fact. Drivers' BVP and $\beta$% have a significant increase when they felt angry in both driving simulation and on-road experiment. However, the indicators of SC and $\delta$% did not present a similar result in different experiments. These two indicators showed a slight fall when the driver felt angry in on-road experiment, but the similar result did not appear in three driving anger induced scenarios in driving simulation experiment. It is interesting that when comparing two types of experiment (see Table 6), the mean of drivers' biosignals (including BVP and SC) is higher in on-road experiment than in simulation experiment in both normal driving and angry driving. However, similar regular differences could not appear in the indicators of brain signals. It should also be noted that the different induced scenarios caused the different levels of driving anger; considering the incompletion of the collected data, only two levels (normal driving and angry driving) being classified may also be a reason to cause the differences.

Three typical scenarios which could induce driving anger based on the virtual scene are designed in this study. Meanwhile, the self-reported data indicated that the induction method could effectively induce the target mood. Due to the uncontrollability of the anger emotion, it has ethical concerns and would be more dangerous to study the driving behaviors using the on-road experiment when the driver is angry. Therefore the development of driving anger induced method on the laboratory setting has a realistic significance to explore the trigger mechanism of driving anger and the relevant measures to prevent angry driving.

An angry driving detection model based on four selected features (namely, BVP, SC, $\delta$%, and $\beta$%) is proposed in this study. Unlike the traditional evaluation methods, the proposed model could identify angry driving automatically and avoid the influence from the driver's subjective emotions. It is also proved that the proposed angry driving detection

model has a precision high enough to differentiate the angry driving from the normal driving.

*4.1. Limitations.* The reported studies have several strengths. An angry driving induction method was firstly reported to induce the angry emotion based on three typical developed traffic scenarios. Meanwhile, an angry detection model based on four driver related features was developed to identify angry driving efficiently. However, no study is without limitations. In order to enhance the effectiveness of the occurrence and expression of driving anger, 15 participants (13 males and 2 females) in simulation experiment and 22 volunteers (18 males and 4 females) in on-road experiment were recruited as the participants to conduct the two different types of experiment. A gender difference had been found as an important factor to influence the occurring of the driving anger. So larger samples especially female drivers recruited to conduct the similar experiment are encouraged in the future. In addition, the on-road experiments were only conducted in Wuhan; the samples from other geographic regions should also be added when considering the bias towards social desirability. There are many traffic scenarios that could induce driving anger during driving. However, this study only focuses on the angry driving detection under three specific angry driving induction scenarios (A∗, B∗, and C∗) mentioned in experiment 1. Future study should focus on how to expand the scope and identification accuracy of the detection model. Finally, there is an assistant in the vehicle to record the data during each experiment. However, it is unknown whether the presence of a passenger in the vehicle influences the driving anger level and physiological states of the participants [33].

*4.2. Practical Implications and Direction for Further Research.* The results in this study provided an important step to explore the induction of driving anger under the laboratory environment. The development of driving anger induced scenarios not only helps us to find the reasons of road rage, but also is useful in exploring the relationship between the traffic accident, unsafe driving behavior, and angry driving. The detection model of angry driving provided a new approach which may inform intelligent system practitioner to develop the related warning system based on the biosignals and brain signals to prevent the injury from angry driving.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Disclosure

The manuscript is an extended version of the conference article (TRB2015).

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## Acknowledgments

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## References

[1] J. E. W. Roseborough and D. L. Wiesenthal, "Roadway justice - Making angry drivers, happy drivers," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 24, pp. 1–7, 2014.

[2] G. Underwood, P. Chapman, S. Wright, and D. Crundall, "Anger while driving," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 2, no. 1, pp. 55–68, 1999.

[3] E. R. Dahlen and K. M. Ragan, "Validation of the propensity for angry driving scale," *Journal of Safety Research*, vol. 35, no. 5, pp. 557–563, 2004.

[4] S. A. Bone and J. C. Mowen, "Identifying the traits of aggressive and distracted drivers: a hierarchical trait model approach," *Journal of Consumer Behaviour*, vol. 5, no. 5, pp. 454–464, 2006.

[5] R. Abdu, D. Shinar, and N. Meiran, "Situational (state) anger and driving," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 15, no. 5, pp. 575–580, 2012.

[6] J. L. Deffenbacher, E. R. Oetting, and R. S. Lynch, "Development of a driving anger scale.," *Psychological Reports*, vol. 74, no. 1, pp. 83–91, 1994.

[7] J. L. Deffenbacher, E. R. Oetting, and R. A. DiGiuseppe, "Principles of empirically supported interventions applied to anger management," *The Counseling Psychologist*, vol. 30, no. 2, pp. 262–280, 2002.

[8] J. L. Deffenbacher, D. M. Deffenbacher, R. S. Lynch, and E. R. Oetting, "Further evidence of reliability and validity for the driving anger expression inventory," *Psychological Reports*, vol. 89, no. 3, pp. 535–540, 2001.

[9] B. González-Iglesias, J. A. Gómez-Fraguela, and M. Á. Luengo-Martín, "Driving anger and traffic violations: Gender differences," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 15, no. 4, pp. 404–412, 2012.

[10] J. L. Deffenbacher, R. S. Lynch, E. R. Oetting, and R. C. Swaim, "The Driving Anger Expression Inventory: A measure of how people express their anger on the road," *Behaviour Research and Therapy*, vol. 40, no. 6, pp. 717–737, 2002.

[11] B. Eşiyok, Y. Yasak, and I. Korkusuz, "Anger expression on the road: Validity and reliability of the driving anger expression inventory," *Türk Psikiyatri Dergisi*, vol. 18, no. 3, 2007.

[12] D. Parker, T. Lajunen, and H. Summala, "Anger and aggression among drivers in three European countries," *Accident Analysis & Prevention*, vol. 34, no. 2, pp. 229–235, 2002.

[13] J. P. Maxwell, S. Grant, and S. Lipkin, "Further validation of the propensity for angry driving scale in British drivers," *Personality and Individual Differences*, vol. 38, no. 1, pp. 213–224, 2005.

[14] A. N. Stephens and J. A. Groeger, "Situational specificity of trait influences on drivers' evaluations and driving behaviour," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 12, no. 1, pp. 29–39, 2009.

[15] S. S. McLinton and M. F. Dollard, "Work stress and driving anger in Japan," *Accident Analysis & Prevention*, vol. 42, no. 1, pp. 174–181, 2010.

[16] F. Li, X. Yao, L. Jiang, and Y. Li, "Driving anger in China: Psychometric properties of the Driving Anger Scale (DAS) and its relationship with aggressive driving," *Personality and Individual Differences*, vol. 68, pp. 130–135, 2014.

[17] R. G. Smart, G. Stoduto, R. E. Mann, and E. M. Adlaf, "Road rage experience and behavior: Vehicle, exposure, and driver factors," *Traffic Injury Prevention*, vol. 5, no. 4, pp. 343–348, 2004.

[18] D. Shinar, "Aggressive driving: The contribution of the drivers and the situation," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 1, no. 2, pp. 137–160, 1998.

[19] M. Martin, "On the induction of mood," *Clinical Psychology Review*, vol. 10, no. 6, pp. 669–697, 1990.

[20] E. C. Suarez and R. B. Williams Jr., "Situational determinants of cardiovascular and emotional reactivity in high and low hostile men," *Psychosomatic Medicine*, vol. 51, no. 4, pp. 404–418, 1989.

[21] P. N. Juslin and J. A. Sloboda, *Handbook of Music and Emotion: Theory, Research, Applications*, 2010.

[22] K. Schaaff and T. Schultz, "Towards emotion recognition from electroencephalographic signals," in *Proceedings of the 2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, ACII 2009*, Netherlands, September 2009.

[23] C. D. Katsis, N. Katertsidis, G. Ganiatsas, and D. I. Fotiadis, "Toward emotion recognition in car-racing drivers: A biosignal processing approach," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 38, no. 3, pp. 502–512, 2008.

[24] H. Lei, X. Yan, C. Wu, and M. Zhong, "A Study of Chinese Motorists Physiological Characteristics Under Angry Driving Hu," *In Transportation Research Board 92nd Annual Meeting*, pp. 13–27, 2013.

[25] L. Yan, D. Zhu, C. Wu, M. Zhong, and K. Zheng, "Ranking and causal relationship analysis of incentive factors of driving anger: A case study from an on-road experiment in China," in *Proceedings of the 14th COTA International Conference of Transportation Professionals: Safe, Smart, and Sustainable Multimodal Transportation Systems, CICTP 2014*, pp. 2534–2547, China, July 2014.

[26] J. Kagan, "A Trio of Concerns," *Perspectives on Psychological Science*, vol. 2, no. 4, pp. 361–376, 2007.

[27] P. Wan, C. Wu, Y. Lin, X. Ma, and Z. Huang, "A Recognition Model of Driving Anger Based on Belief Rule Base," *J. Transp. Syst. Eng. Infomation*, vol. 15, pp. 96–102, 2015.

[28] H. Leng, Y. Lin, and L. A. Zanzi, "An Experimental Study on Physiological Parameters Toward Driver Emotion Recognition," *Ergon. Heal. Asp. Work with Comput*, vol. 4566, pp. 237–246, 2007.

[29] Y.-P. Lin, C.-H. Wang, T.-P. Jung et al., "EEG-based emotion recognition in music listening," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 7, pp. 1798–1806, 2010.

[30] L. Jiang, H. Zhang, and Z. Cai, "A novel bayes model: hidden naive bayes," *IEEE Transactions on Knowledge and Data Engineering*, vol. 21, no. 10, pp. 1361–1371, 2009.

[31] Y. Ji, S. Yu, and Y. Zhang, "A novel Naive Bayes model: Packaged Hidden Naive Bayes," in *Proceedings of the 2011 6th IEEE Joint International Information Technology and Artificial Intelligence Conference, ITAIC 2011*, pp. 484–487, China, August 2011.

[32] Y. He, X. Yan, C. Wu et al., "Evaluation of the effectiveness of auditory speeding warnings for commercial passenger vehicles - A field study in Wuhan, China," *IET Intelligent Transport Systems*, vol. 9, no. 4, pp. 467–476, 2015.

[33] H. Li, X. Li, X. Xu, J. Liu, and B. Ran, "Modeling departure time choice of metro passengers with a smart corrected mixed logit model - A case study in Beijing," *Transport Policy*, vol. 69, pp. 106–121, 2018.