A Recognition Model of Driving Anger Based on Physiological Features by ROC Curve Analysis

Ping Wan¹,², Ph.D. Candidate,
¹Intelligent Transport Systems Research Center & Engineering Research Center of Transportation
Safety, Ministry of Education
Wuhan University of Technology
Heping Avenue #1040, Wuhan, 430063, P.R. China
Tel: + 86-15902764894
Email: pingw04@whut.edu.cn

²Intelligent Human-Machine Systems Laboratory,
Department of Mechanical and Industrial Engineering,
Northeastern University
334 Snell Engineering Ctr., 360 Huntington Ave. Boston, MA, 02115, USA
Tel: 857.234.3769.
Email: wulinwan2007@gmail.com

Chaozhong Wu, Professor
Intelligent Transport Systems Research Center & Engineering Research Center of Transportation
Safety, Ministry of Education
Wuhan University of Technology
Heping Avenue #1040, Wuhan, 430063, P.R. China
Tel: + 86-1334987361
Email: wucz@whut.edu.cn

Yingzi Lin, Associate Professor
Intelligent Human-Machine Systems Laboratory,
Department of Mechanical and Industrial Engineering,
Northeastern University
334 Snell Engineering Ctr., 360 Huntington Ave. Boston, MA, 02115, USA
Tel: 617.373.8610.
yilin@coe.neu.edu

Xiaofeng Ma*, Associate Researcher
Intelligent Transport Systems Research Center & Engineering Research Center of Transportation
Safety, Ministry of Education
Wuhan University of Technology
Heping Avenue #1040, Wuhan, 430063, P.R. China
Tel: + 86-13349885778
Email: maxiaofeng@whut.edu.cn

*Corresponding author
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Abstract:

“Road rage” has become increasingly common nowadays, and driving anger has been a concern to traffic safety and management authorities. So a recognition method to differentiate driving anger from neutral is necessary for detection of driving anger and then improves driving safety. Twenty-six drivers were recruited for conducting on-road experiments within limited time (110 minutes) on busy road sections in Wuhan, China. In the experimental route, drivers’ anger could be elicited by various stimulation events, e.g., weaving/cutting in line, jaywalking, traffic congestion and long-time red light waiting. During the experiments the drivers’ self-reported anger level was recorded every two minutes while physiological (Blood Volume Pulse (BVP), Skin Conductance (SC), Finger Temperature (FT), and Respiration Amplitude (RA)) and Electroencephalogram (EEG) signals were also acquired by using Biograph Infiniti System and Neural Scan System respectively. The study results indicate that five physiological features including the mean of SC, the SDs of BVP and RA and the relative energy spectrums of $\beta$ band and $\theta$ band of EEG signals can be used as recognition indicators for driving anger because they are significantly different between driving anger and neutral. Then, a method of receiver operating characteristic (ROC) curve analysis was introduced to determine the discriminating thresholds of the five indicators for driving anger. Finally, according to the thresholds and the relative weights of the five indicators, a comprehensive recognition model of driving anger based on ROC curve analysis was proposed. The model’s accuracy is 85.26%, increasing 8.16% and 6.24% when compared with the models of BP neural network (BPNN) and support vector machine (SVM) respectively. The results can provide theoretical foundation for developing physiological and EEG signals-based driving anger recognition and warning devices.

Key words: driving anger; physiological features; EEG signal; ROC curve; discriminant threshold
INTRODUCTION

Driving anger, which is also called “road rage” in psychology, is a special emotion caused by driving pressure or frustration in a bad or unfriendly traffic situation including traffic congestion and other drivers’ discourtesy behaviors (1). Road rage has been becoming more and more common all over the world. For example, a possible “road rage” shooting left one dead, one injured in Southwest of Washington D.C, US on May 28th 2015 (2). Five people were killed in an accident in Fangshan District of Beijing, China by the driver’s aggressive behaviors because of road rage in July 2nd 2015 (3). According to a report from American Automobile Association in 2009, 5%-7% of 9282 surveyed drivers were the perpetrators of road rage, and the percentage of professional drivers such as truck and bus drivers reached 30% (4). Meanwhile, a survey of 9,620 people from China in 2008 showed that about 60.72% drivers had “road rage” experiences (5). As anger emotion can affect whole PIDV (perception, identification, decision and volition) process during driving, driving performances will be severely degraded (6). Then, a driver is inclined to have more violations or more liable to be involved in a traffic accident when he or she becomes angry during driving by some irritating or frustrating events (7-8). Therefore, road rage/driving anger has become a serious psychological issue affecting traffic safety.

LITERATURE REVIEW

Some emotion detection and warning device can be installed in vehicles to interfere driving anger before it generates bad impact on traffic safety. Nonetheless, emotion recognition is premise of the effective interference. The main aim of this study is to research physiological features of driving anger and explore a method to recognize it further. For the research like this, emotion elicitation and emotion recognition is two most important components analyzed in a literature review.

Emotion Elicitation

Emotion elicitation is precondition for the research on emotion recognition, and kinds of emotions have been induced under laboratory conditions. Suarez et al firstly put forward a deception-based method to elicit anger emotion in laboratory (9). However, the deception method made the researchers involve in elaborate choreography to hide real aim of the experiments, which led to ethical concerns. Kessous et al. (10) elicited eight different emotions including amusement, sadness, anger, fear, surprise and disgust based on speech-based interaction, in which, participants interacted with an agent by pronouncing a sentence in a special scenario. Lei et al. (11) adopt video clips chosen from famous films such as “The Rape of Nanking” and “Fist of Fury” to induce anger for the research on Chinese motorist’s vehicle speed characteristics under driving anger. Abdu et al (12). studied a driver’s skilled driving behavior and risk taking behavior when the driver’s anger was induced by recalling angry events. Juslin et al. (13) proposed a music-based anger elicitation method, which is based on different combinations of high/low energy and positive/negative valences of music and his results showed that the negative music with high energy could elicit the highest-level anger. Cai et al. (14) elicited three types of emotion including anger, neutral and excitation by driver-to-driver interactions using multiple networked driving simulators. However, the emotion elicitation methods mentioned above have their own deficiencies respectively. For example, the elicitation effect of the methods based on speech, video, music, and pictures may depends on individual cultural background or hobby preference, then the generalizability of those methods is limited. Moreover, the arousal and strength of those induced emotions may be not strong enough for running through subsequent experiments. For the elicitation methods based on emotion-related events recalling or interactive behaviors in virtual
environment, the elicited anger is less likely to be valid as those elicited in real traffic environment because of some demand characteristics and social desirability.

**Emotion Recognition**

Currently, the research about emotion recognition were mainly based on facial expression, voice, posture (or behavior) and physiology. As physiological signals are spontaneous and hard to be controlled by human factors, they reflect human’s emotion state or mental workload more objectively (15, 16). Hence, the studies about emotion recognition based on physiological signals have gradually become research hotspot. Flidlund et al. (17) firstly recognized four different emotions such as pleasure, anger, sadness and fear based on electromyography (EMG) features of facial expressions by the method of linear discriminants, with a recognition rate of 38%-51%. Wang et al. (18) proposed an auxiliary dimension model and a factorization model to identify driver’s multiple emotional states by using physiological signals such as blood volume pulse (BVP), skin conductance (SC), Respiration Amplitude (RA) and finger temperature (FT). Katsis et al. (19) utilized the features of facial EMG, electrocardiogram(ECG), respiration, and electrodermal activity in simulated racing environment, to classify car-racing drivers’ emotion states, which included high stress, low stress, disappointment, and euphoria, the classification was based on the methods of SVM and adaptive neural-fuzzy inference system with a recognition rate of 79.3% and 76.7% respectively. Schaaff et al. (20) recognized three different emotions including pleasant, neutral, and unpleasant by using EEG characteristics based on SVM, with an average recognition rate of 66.7%. Fan et al. (21) proposed a recognition model of driver’s emotion based on Bayesian Network with EEG characteristics, which had taken driver personality and traffic situation into consideration. Cai et al. (22) established a quantification model to depict the relationship between the arousal and valence of emotion and task performances by collecting data of visual attention, traffic violations number and lane deviation in virtual driving environment based on driver-to-driver interactions.

All in all, the most research mentioned above mainly focused on recognition of a variety of human emotions. However, little systematic and deep research for studying driving anger’s physiological features (especially combined with EEG) has been carried out. Moreover, no special study for determining threshold of driving emotion especially driving anger based on those physiological features. Receiver Operating Characteristic (ROC) curve originated from electrical signal detection theory and now has been widely used in fields of medical diagnosis, human decision-making, industrial quality control, military monitoring and so on(23). It is a quantitative approach for accurate decision or judgment for two confused state by determining the best discriminant threshold, which can be used for driving emotion recognition.

In order to overcome the deficiencies of driving emotion elicitation under laboratory conditions and make an accurate recognition of driving anger based on systematic study of physiological characteristics, a high-arousal anger elicitation method is conducted by the stimulation of specific road events (e.g., weaving/cutting in line, jaywalking, traffic congestion) happening in real traffic environments. Then, a comprehensive recognition method of driving anger based on the discrimination thresholds of physiological features calculated by ROC curve analysis is proposed in this study for developing physiological and EEG signals-based driving anger detection devices.
EXPERIMENTAL DESIGNS

Participants
Twenty-six private car drivers were recruited as volunteers from Wuhan, China to complete on-road experiments. Males are generally more likely to be involved in angry driving than females (24). To maximize the statistical power, we only chose male drivers to carry out the experiments. The subjects had an average age of 39.8 years with a standard deviation of 5.1 years. And they had an average driving experience of 9.2 years with a standard deviation of 4.5 years. All subjects were medically checked to be in good physical condition, which was important for our study on their physiological features. The subjects were paid for 200 RMB if they completed their experiment task on time. Additionally, an observer with rich driving experience was recruited to be seated in co-pilot position to record self-report about emotion state of subjects, and assure the safety during whole experiments.

Apparatus
An automatic transmission car was used as a test vehicle for on-road experiments shown in Figure 1(a). NeuroScan4.5 acquisition system was adopted to collect the subjects’ EEG. It consisted of a 32-channel-electrode cap, an amplifier of NuAmp and acquisition software, shown in Figure 1(b). BioGraph Infiniti System consisted of ProComp Infiniti system and BioGraph software, shown in Figure 1 (c). The system was used to collect the subjects’ physiological signals such as BVP, SC, FT, and RA by sensors taped on their fingers and stomach respectively. Additionally, three HD cameras equipped on the front windshield of the test vehicle were used to record traffic environment ahead, the subjects’ facial expression and their operating behaviors respectively, shown in Figure1 (d), which could be used as auxiliary evidences for emotion discrimination when the self-reports gravely deviated from the true ones. Finally, a five-point emotion level scale from 1(not at all) to 5(very much) was used for recording intensity levels of five possible and common emotion (anger, happiness, sadness, fear and calmness) during driving, which was an very important evidence to discriminate anger from the other four emotions.

Figure 1 The Apparatus of On-Road Experimental System
Experimental Design

Based on an investigation about driving anger from car drivers in Wuhan, China, some specific road events such as weaving/cutting in line, jaywalking/cyclist crossing, traffic congestion and waiting red lights were found to be the top four anger elicitation events (25). Therefore, in order to induce anger as much as possible, a special route of urban road including busy parts across Hankou and Wuchang District of Wuhan, was selected as test route for the on-road experiments, shown in Figure 2(a). The test route with 53 kilometers consisted of 45 signalized intersections, two tunnels, two expressways, three large-scale business districts and 59 pedestrian crosswalks. In the test route, the subjects would often meet those anger elicitation events which naturally occurred, especially in morning or afternoon peak hours, shown in Figure 2(b). Hence, twenty-six subjects were randomly divided into morning or afternoon group. The subjects in the morning peak group were required to depart at approximately 8:00 a.m., while 17:30 p.m. for the afternoon group. No matter which group the subjects were divided into, data processes were only based on the anger elicitation events without considering the effect of time-of-day on physiological signals. In order to enhance the induction effect, the subjects will get extra paid with 15RMB/min if they complete the whole experiment ahead of required time (110 minutes), which is proved to have a little pressure for accomplishment after several field pretests when choosing the test route.

![The test route (shown as blue line) and Traffic environment](image)

Figure 2 The test route and traffic environment of on-road experimental system

Experiment Procedure

Experiment preparation

Firstly, an informed consent agreement based on experiment requirements was signed by the subjects. It is noted that the subjects were forbidden to violate any traffic rule, especially over speed driving (speed limit is 60 Km/h). Secondly, after NeuroScan4.5 acquisition system and ProComp Infiniti system were wore and configured adequately, the subjects conducted ten minutes’ driving practice to get used to the physiological equipment as well as the test vehicle.

Formal on-road test

Every 2 minutes during the normal driving or the anger elicitation events happened in the test route, the subject was surveyed by the observer through a simple question,“How do you feel in the last 2 minutes” or “How do you feel just now?” and they had to respond to evaluate their emotion level objectively based on the five-point scale. Besides the drivers’ self-response, the physiological features such as BVP, SC, RA, FT and EEG were also recorded to assess emotion state. In this study, the ambient temperature and noise were controlled to be 18±2°C and 60±5dB respectively, so as to eliminate the influences of these parameters on the physiological signals. It is
noted that the experiments on the subjects complied with Chinese law about scientific research.

STUDY DATA AND METHODOLOGY

Emotion Elicitation Effect Check

As the subjects may experience different emotions in the test route, it’s needed to evaluate whether the self-reported emotions match well with target emotion (i.e. anger). In this study, occurrence rate of anger was used as an indicator to evaluate emotional differentiation degree. As a subject had to report his emotion level every two minutes during the whole experiment, the average number of self-reports from all subjects was 55 and 20 of them were about the elicitation events.

Table 1 shows the average number of all emotions elicited during the whole experiments based on all subjects’ self-reports. Under the stimulation of anger elicitation events, the occurrence rate of anger emotion reaches 85%, which is significantly higher than that (11%) under no anger elicitation events. Further, we find that the average of anger level (i.e. 3.6) caused by the elicitation events is also significantly higher than that (i.e. 1.4) without the elicitation events. Hence, those anger elicitation events such as weaving/ cutting in line, jaywalking/cyclist crossing, traffic congestion, waiting red lights can effectively induce the subjects’ anger.

Table 1 The occurrence number of five emotions with and without stimulation of the anger elicitation events

<table>
<thead>
<tr>
<th>Elicitation type</th>
<th>fear</th>
<th>happy</th>
<th>anger</th>
<th>Sad</th>
<th>calm</th>
<th>Total</th>
<th>Occurrence rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>No anger events</td>
<td>2</td>
<td>9</td>
<td>4</td>
<td>1</td>
<td>19</td>
<td>35</td>
<td>11%</td>
</tr>
<tr>
<td>Anger events</td>
<td>4</td>
<td>0</td>
<td>17</td>
<td>1</td>
<td>0</td>
<td>20</td>
<td>85%</td>
</tr>
</tbody>
</table>

Physiological Features

Analysis of indicators of BVP, SC, FT and RA

In this study, the subjects’ self-reported anger state when the elicitation events happened were selected as driving anger state, while the calm state without the elicitation events were selected as driving neutral state. Then, the averages and standard deviations (SD) of BVP, SC, FT, and RA were statistically analyzed, shown in Table 2. Moreover, the paired t-tests of these features of the indicators between anger and neutral were also proposed. From Table 2 we can see that the average of BVP in anger is not significantly different from that in neutral, while the SD of BVP in anger is significantly bigger than that in neutral. Similarly, the average of RA in anger is nearly the same with that in neutral, but with a significantly bigger SD. Here, the effect of hand movements on SDs of those physiological indicators are reduced to its minimum because the hands of every subject are required to move steering wheel and gear lever only without any other movements during driving. Meanwhile, we find only the average value of SC in anger is significantly bigger than that in neutral. However, we don’t find any significant differences in both average and SD of FT between anger and neutral. Therefore, the SDs of BVP and RA and the average of SC are suitable to be used as effective physiological features to discriminate anger from neutral.

Table 2 Descriptive statistics of four physiological indicators between anger and neutral

<table>
<thead>
<tr>
<th></th>
<th>BVP</th>
<th>SC</th>
<th>FT</th>
<th>RA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Anger</td>
<td>36.643</td>
<td>6.495</td>
<td>10.275</td>
<td>3.275</td>
</tr>
<tr>
<td>Neutral</td>
<td>36.482</td>
<td>4.554</td>
<td>5.397</td>
<td>3.037</td>
</tr>
<tr>
<td>P value(95% confidence)</td>
<td>0.085</td>
<td>0.021*</td>
<td>0.026*</td>
<td>0.356</td>
</tr>
</tbody>
</table>
Analysis of EEG

As EEG has a close relationship with physical and mental actives, it is widely used as the most significant and reliable indicator for mental state detection (26). Because the designed experiments were conducted in real traffic environment, the raw EEG data were mixed with numerous noises, among which, the high frequency noise is due to atmospheric thermal noise while the low frequency noise is mainly due to eye movements, respiration and heart beats. As the frequency of EEG concentrates 35Hz below, the high and low frequency noise can be filtered through band pass filter with cutoff frequencies of 0.5 Hz and 35 Hz. After noise elimination of EEG signals, EEG signal is processed through Fast Fourier Transform to get its relative energy spectrum (content percentage in frequency domain) of four different bands of wave, including δ band(0.5-4Hz), θ band (4-8Hz), α band (8-14Hz) and β band (14-35Hz) (the total relative energy spectrum of these four band is 100%).

Figure 3 is the spectrum maps of four different bands of EEG signal between neutral and anger from one subject. We can see that the relative energy spectrum of θ band reduced significantly from 25.07% in neutral to 15.57% in anger. Meanwhile, the relative energy spectrum of β band increased greatly from 26.86% in neutral to 37.68 % in anger. Nonetheless, no great changes of the relative energy spectrums of δ band and α band have been found between anger and neutral. Further, the relative energy spectrums of the four bands from all subjects were statistically analyzed, shown in Figure 4. Moreover, the paired t-tests show that the relative energy spectrums of β band in anger is significantly bigger (p=0.032<0.05) than that in neutral, whereas, the relative energy spectrums of θ band in anger is significantly smaller (p=0.025<0.05) than that in neutral. Hence, the relative energy spectrums of θ band and β band can be used as two features of EEG to discriminate anger from neutral.
Recognition Method of Driving Anger Based on ROC Curve Analysis

Method of ROC curve analysis

Based on the usages of ROC curve analysis in the researches on prevention medicine and radar techniques (23,27), three important principles of the method of ROC curve analysis are listed as follows.

(1) Generation of ROC curve. For a diagnostic test, a specific threshold of an indicator to discriminate positive samples from negative ones is called cut-off point, shown in Figure 5(a). Sensitivity, namely true positive rate (TPR) is the probability at which positive samples are correctly diagnosed as positive ones based on the cut-off point. Specificity, namely true negative rate (TNR), is the probability at which the negative samples are correctly diagnosed as negative ones. Additionally, false positive rate (FPR), namely 1-TNR, is the probability at which negative samples are falsely diagnosed as positive ones, while false negative rate (FNR) is the probability at which the positive samples are falsely diagnosed as negative ones. Here, it is assumed that vertical and horizontal ordinate of the cut-off point are represented by TPR and FPR respectively. If different cut-off points are used to find the highest recognition accuracy of the diagnose test, the ROC curve will be generated by connecting those cut-off points with line in coordinate system, shown in Figure 5(b). For the diagnose test, the aim is to find the best cut-off point (i.e. the optimal discrimination threshold) with the minimum of the sum of FPR and FNR, shown in Figure 5(a).

(2) Discrimination accuracy by ROC curve. The recognition capacity of detection method (i.e. based on a certain discrimination indicator) is determined by position and shape of its ROC curve in coordinate system, shown in Figure 5(b). If the cut-off point lies on line AB (reference line), it means the sensitivity and specificity of the cut-off point are both 50%, which has no practical significance (28). If the cut-off point lies on line AC or CB, it means the sensitivity or specificity of the cut-off point is 100%, which means the discrimination accuracy under these two cases can get its maximum because FPR=0 or FNR=0. If the cut-off point lies on arc FD, it represents that there are overlap regions between negative and positive samples, which makes FPR and FNR generate during the diagnose test. The discrimination accuracy of the cut-off point will become higher if it locates closer to the upper left corner (i.e. point C) of the ROC curve. For any detection

Figure 4 The relative energy spectrums of four bands of EEG between neutral and anger from 26 subjects

Figure 5 Schematic of ROC curve
algorithm, its sensitivity and specificity cannot be improved at the same time, but, the area under the curve (AUC) of ROC can be used as an intuitionistic index to comprehensively evaluate the accuracy of the detection algorithm, shown in Figure 5 (b). The greater of AUC, the higher accuracy of the detection algorithm using the specific indicator. Here, the AUC can be computed through trapezoidal integration.

(3) Determination of the optimal threshold.

The best cut-off point can be calculated based on the principles of ROC listed above, which is one of the most important potentials for ROC curve. The closer the cut-off points lies to the upper left of the ROC curve, the higher discrimination accuracy it will obtain. Then, in the process of determining the best cut-off point, a special variable called Youden index is used. Here, Youden index = Sensitivity + Specificity - 1, if the Youden index of a cut-off point gets its maximum when it locates near to the upper left corner of the ROC curve, then, the cut-off point is considered to be the best one with the optimal threshold to do the discrimination test because the sum of FPR and FNR gets its minimum at this moment.

Determining the optimal thresholds of physiological features of driving anger

Five physiological features including the averages of SC and relative energy spectrums of θ band and β band and the SDs of BVP and RA are chosen to discriminate driving anger from neutral. According to the principles of the analytic method of ROC curve above, the following steps are needed for determining optimal thresholds of those physiological features. First, all possible cut-off points (i.e. thresholds) of the five features are prepared for recognizing driving anger. Second, the corresponding TPR and FPR of each cut-off point are calculated. Then the ROC curve can be drawn based on these two steps and the best cut-off point from the ROC curve will be determined further. Take BVP for example, the SD of BVP in anger belongs to the range of [5.126, 7.452], while the SD of BVP in neutral belongs to the range of [3.674, 5.386]. Then 0.002 is selected as the interval of the discrimination thresholds based on the mixed range [3.674, 7.452] of the SDs of BVP in anger and neutral. The detailed drawing process of ROC curve for the SD of BVP is show in Figure 6.

According to the drawing process, the ROC curve of the SD of BVP is shown in Figure 7. The vertical axis (sensitivity) represents the probability of driving anger samples correctly identified while the horizontal axis (1 - specificity) represents the probability of driving neutral samples identified as driving anger ones. Based on the principle about optimal discrimination threshold, point H is considered to be the best cut-off point, which is corresponding to the optimal threshold of 5.336, with TPR of 80.13% and FPR of 16.70%. Meanwhile, the AUC of the ROC is 0.8562, which means the driving emotion can be considered to be anger with an identification rate of 85.62% when the driver’s SD of BVP is bigger than 5.336. It is notable that there are two turning points G(0, 0.3225) and J (0.5952, 1) in Figure 7. The specificity of point G is 100%, but the sensitivity is only 32.25%, indicating that 67.75% driving anger samples are not correctly identified. The sensitivity of point J is 100%, with the specificity of 40.48%, indicating that 40.48% of driving neutral samples are correctly identified. Therefore, if the cut-off point locates between point G and J, then its threshold is corresponding to the range of 4.986 to 6.618, which means that the driver’s anger state is not easy to be discriminated. Moreover, the driver is very likely to be considered to be in a transitional state of driving anger when his or her SD of BVP locates in that range, which indicates that some intervening measures are needed to prevent the driver from possible road rage.
Similarly, the optimal discrimination thresholds of the other four physiological features for driving anger are calculated respectively by ROC curve analysis, shown in Table 3. Meanwhile, the AUCs of ROC curves of the four physiological features are also computed to show the effectiveness of different detection methods based on the related physiological features.

Table 3 The thresholds and effectiveness of physiological features to discriminate driving anger based on ROC curves analysis

<table>
<thead>
<tr>
<th>Physiological features</th>
<th>Discrimination thresholds and its effectiveness</th>
<th>AUC</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD of BVP</td>
<td>5.336</td>
<td>0.8662</td>
<td>81.72%</td>
</tr>
<tr>
<td>SC</td>
<td>9.485</td>
<td>0.8168</td>
<td>76.89%</td>
</tr>
<tr>
<td>SD of RR</td>
<td>8.696</td>
<td>0.8548</td>
<td>81.06%</td>
</tr>
<tr>
<td>θ%</td>
<td>0.1938</td>
<td>0.8276</td>
<td>77.67%</td>
</tr>
<tr>
<td>β%</td>
<td>0.2704</td>
<td>0.8774</td>
<td>83.86%</td>
</tr>
</tbody>
</table>

Remarks
- P: Positive samples of SD of BVP of driving anger
- N: Negative samples of SD of BVP of driving neutral
- Aa(Len): Sample size of positive samples (i.e., 26)
- Bb(Len): Sample size of negative samples (i.e., 26)

The two steps left are used to compute the number of positive samples correctly diagnosed as positive ones and the number of negative samples falsely diagnosed as positive ones, according to the actual positive samples and the inferred "positive" or "negative" samples based on the discrimination threshold.

Figure 6 Drawing processes of ROC curve and determining optimal threshold for discriminating driving anger from neutral based on the SDs of BVP
A comprehensive recognition model of driving anger is proposed based on the thresholds of physiological features which are calculated by ROC curve. Based on the principles of ROC curve, the number of true positive samples (i.e. TP) and the number of true negative samples (i.e. TN) can be calculated corresponding to each threshold, so the discrimination accuracy (denoted as B) of the threshold can be calculated as follows:

\[ B = \frac{TP + TN}{P + N} \]  

Then, the discrimination accuracy (i.e. B) of the thresholds of those five physiological features can be calculated, shown in Table 3. As AUC can be used to quantify the effectiveness of the specific physiological feature, the comprehensive discrimination accuracy (denoted as C) of the threshold of the specific physiological feature can be calculated according to equation (2):

\[ C = AUC \ast B \]  

Moreover, it is noted that the relative weight of every physiological feature is linearly matched to their comprehensive discrimination accuracy (28), so the relative weight of a physiological feature can be obtained based on equation (3)– (5).

\[ \frac{C_i}{C_j} = \frac{w_i}{w_j} \quad i, j = 1,2,...,5 \]  

\[ C_i = AUC_i \ast B_i \quad i, j = 1,2,...,5 \]

Subject to \[ \sum_{i=1}^{5} w_i = 1 \]  

Therefore, in practical application, the comprehensive discriminant value of driving anger can be defined through combining the five features’ actual value and their discriminant thresholds calculated by ROC curve analysis. Firstly, the ration of the actual value and its discriminant threshold of a physiological feature, denoted as \( D_j \), can be calculated as follows:
\[
D_i = \begin{cases} 
\frac{X_i}{T_i} & i \neq 4 \\
\frac{T_i}{X_i} & i = 4 
\end{cases}
\]

(6)

where \(X_i\) is the actual value of a physiological feature; \(T_i\) is the discriminant threshold of the physiological feature, and it is assumed that the relative energy spectrum of band \(\theta\) is the 4\textsuperscript{th} feature of those five features. As the relative energy spectrum of band \(\theta\) in anger is smaller than that in neutral, which takes an opposite changing trend from neutral to anger when compared with the other four physiological features, \(D_i\) is then separated into two parts to reflect the different changing trends.

Secondly, the comprehensive discriminant value (denoted as \(E\)) of driving anger based on the five physiological features, and the discriminant evidence for recognizing driving emotion are indicated by equation (7) and (8) respectively.

\[
E = \sum_{i=1}^{5} w_i D_i
\]

(7)

\[
\text{Driving_emotion} = \begin{cases} \text{anger} & E > 1 \\ \text{neutral} & E \leq 1 \end{cases}
\]

(8)

Validation

In order to test the effectiveness of the comprehensive recognition model, 750 emotion samples from 15 subjects were used as the test samples. Further, the accuracy of the recognition model proposed in this study was compared with the models of BPNN and SVM, shown in Table 4. From Table 4, we can calculate that average recognition accuracy of the proposed model based on ROC curve is 85.26\%, while 77.10\% and 79.02\% for the model of BPNN and SVM respectively. Namely, the average recognition accuracy of the proposed model is 8.16\% and 6.24\% higher than that of the model of BPNN and SVM respectively. Further, the recognition accuracy of driving anger for the younger subjects are higher than that of the older ones, and the reason for that may be that the younger ones are inclined to become angry along with a bigger fluctuation of physiological features when meeting those anger elicitation events in the driving test route.

<table>
<thead>
<tr>
<th>ID</th>
<th>Age</th>
<th>ROC (%)</th>
<th>BPNN (%)</th>
<th>SVM (%)</th>
<th>ID</th>
<th>Age</th>
<th>ROC (%)</th>
<th>BPNN (%)</th>
<th>SVM (%)</th>
</tr>
</thead>
<tbody>
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DISCUSSIONS AND CONCLUSIONS

As the physiological features are most effective and reliable measures for recognizing emotion
when compared with facial expression, voice, gesture and behaviors, the main objective of this paper is to study the physiological features in driving anger and neutral and further recognize driving anger based on the physiological features.

Firstly, a special busy route was chosen for the on-road experiments, on which the elicitation events such as weaving/cutting in line, jaywalking/cyclist crossing, traffic congestion and waiting red lights are frequent in morning or afternoon peak. The emotion elicitation effect check based on the drivers’ self-reports showed that the occurrence rate of anger under stimulation of the elicitation events can reach 85%, much higher than without stimulation of the elicitation events, which indicates that the driving anger elicitation method is feasible by the stimulating events in real traffic environment within the limited task time.

Secondly, physiological indicators such as BVP, SC, RA and FT as well as EEG signals were analyzed between anger and neutral. The results show that the SDs of BVP and RA and the average of SC in anger are significantly bigger than that in neutral, which is consistent with the results in literature (14). Additionally, we found that the relative energy spectrum of β band in anger is significantly higher than that in neutral, while the relative energy spectrum of θ band in anger is significantly smaller than that in neutral. And in literature (29), the power of β band in negative emotion (e.g. sadness, anger) was also found to be significantly bigger than that in calmness. Therefore, the five physiological features including the SDs of BVP and RA, the average of SC, and the relative energy spectrums of θ band and β band are suitable to be used as indicators for discriminating anger from neutral.

Thirdly, the optimal thresholds of the five physiological features for discriminating anger from neutral emotion were calculated by ROC curve analysis. For example, the optimal threshold of SD of BVP is 5.336 with a discrimination accuracy of 81.72%. Moreover, the special range of a certain physiological feature for the transitional state of driving anger can be calculated by the turning points in the ROC curve. Compared with the other pattern recognition method, the recognition method based on ROC curve analysis can calculate the specific discrimination threshold, which is helpful for soft interference (e.g. releasing relaxed music when anger emotion is detected) in advance for human-computer interaction by multimodal affective car interface in future.

Finally, a comprehensive recognition method of driving anger based on physiological features fusion and ROC curves analysis was proposed. However in literature (28), the identification effectiveness of the model of ROC curves is not analyzed by comparing with any other recognition method. In this study, the identification rate of the proposed model was compared with that of BPNN and SVM model. It is verified that recognition accuracy of the proposed model can reach 85.26% which is 8.16% and 6.26% higher than that of BPNN and SVM model respectively. Therefore, the recognition model based on ROC curve analysis has more privilege than the other two models when applied in anger detection for human-machine system.

However, there are three notable limitations in this study. First, the instruments collecting driver’s physiological signals were directly attached the subjects’ body, which might interfere the subjects’ regular operation. Then some non-invasive wearable instruments should be applied for physiological signals collection in future. Second, some indirect indicators such as driving behaviors and vehicle motions can be combined with the physiological indicators proposed in this study to improve recognition accuracy of driving anger. Third, as only male drivers were recruited because of statistic power, female drivers should be added to improve the generalizability of the
ACKNOWLEDGEMENT

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