Prediction of Driver's Stop-Go Decision at Signalized Intersection Based on EEG

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Abstract. Red light running (RLR) results in a large number of collisions and injuries of motor vehicles in the world. One of the main causes of RLR crashes is that drivers are unable to make the right decisions at intersections. In recent years, researchers have studied the influence of drivers' behavior on their stop-go decisions and used behavior to predict driver's decision-making. However, few studies used EEG to predict drivers' stop-go decisions. This study proposes a method based on BPNN to predict drivers' stop-go decisions using EEG data and provides a new research direction for the study of drivers' stop-go behavior.

1. Introduction
Red light running (RLR) at intersections is one of the most dangerous driving behavior which leads to a large number of traffic collisions and injuries. In the United States, it is estimated that the red light running causes 165,000 traffic accidents and 700-800 deaths every year [1]. Similarly, a survey from China between January and October 2012 showed that RLR violations at intersections resulted in 4227 casualties and 798 deaths [2]. Additionally, the report of the Federal Highway Administration in 2005 stated that more than $14 billion in economic losses were incurred due to the red light running [3]. The results of previous studies suggest that RLR has been a great threat to traffic safety at intersections, and how to reduce the occurrence of RLR is an urgent problem to be solved.

In general, one of the main reasons for RLR is that drivers cannot make the right stop-go decision at intersections, especially when the yellow light is on. The yellow light dilemma zone is widely known as an area where vehicles neither safely stop before the stop line nor proceed through the intersection during amber interval [4]. Previous researchers have found that once drivers were in a dilemma zone at intersections, they tended to make a wrong decision and consequently lead to RLR [5]. Hence, through predicting drivers' stop-go decision at intersections and help them make correct decisions is important for reducing the occurrence of RLR and improving traffic safety.

Previous studies have focused on identifying factors affecting drivers' stop-go decisions and RLR violations. Arash [6] utilized the approaching speed of vehicles, time to intersection, distance to intersection, etc. to predict drivers' RLR violations. Using video surveillance, Li [7] predicted stop-go decisions and RLR violations by vehicle type, yellow onset distance, vehicle speed and acceleration during the yellow interval and found that the yellow onset distance was an important predictor for both stop-go decisions and RLR violations. Elmitiny [8] used field data collected at a high-speed signalized intersection to predict RLR violations and identified the main factors (e.g. vehicle type, approach speed, distances from intersection, etc.) leading to RLR violations based on the classification tree.
With the development of driving psychology and physiology, Electroencephalogram (EEG) data are gradually introduced into the study of driving behavior, which is regarded as a reliable index of physical and psychological activities. Previous research suggested that EEG has been regarded as an effective non-invasive technology for monitoring and assisting real-world driving [9]. Kim [10] used EEG feature combination to detect braking intention in diverse situations. Brown [11] identified different periods of drowsy driving using EEG. Moreover, compared with traditional behavioral data, EEG data has a higher temporal resolution, allowing real-time classification based on EEG. On the other hand, in addition to kinematic vehicle index, EEG data can provide additional information e.g. physiological and emotional [10]. Although EEG data has many advantages, few researchers used drivers’ EEG data to predict drivers’ stop-go decisions at intersections.

Therefore, the objective of this paper is to propose a prediction method of driver’s stop-go decision considering EEG data. To fill the current research gaps, a driving simulator based experiment was conducted to obtain the data and back propagation neural network was applied for predicting. The findings of the study can provide some references to traffic management at signal intersections.

2. Methodology

2.1. Driving simulator experiment

2.1.1. Apparatus
The driving simulator used in this experiment is located in Beijing Jiaotong University. The simulator is composed of a full-size cabin, an operation interface, a vibration system, a digital video recording system, and control consoles (as seen in Figure 1(a)). The Simvista and Simcreator software were adopted for driving scenario design, virtual traffic environment simulation and virtual road modeling. The sampling frequency of the driving data was 60 Hz.

The equipment used to collect EEG data in this study was a Neuroscan system. The hardware of Neuroscan system consists of a Synamps2™ amplifier and an electrode cap. The electrode cap has 64 channels and its location follows the international 10–20 system.

2.1.2. Scenario Design
The test scenario designed in this study was a two-way, two lane straight road segment under an urban environment. The length of the road segment was about 12km with a width of 3.75m for each lane and the speed limit was 70km/h. There were 30 signalized intersections setting on the road and the distance between two adjacent intersections was 400m.

According to the recommendation of the Association of Transportation Engineers (1999), the length of yellow signal is set to 4.5s. When the yellow signal is on, the time required for the vehicle to intersection stop line at the current speed is defined as yellow-onset gap. In this research, six yellow-onset gaps were designed for the experimental intersections, ranging from 4.5s to 7s with a 0.5s increment. Yellow-onset gaps (YOGs) were randomly assigned to six test intersections to eliminate the influence of the temporal/spatial order effect. Additionally, to prevent participants from expecting signal
changes at each intersection, the other signalized intersections were also activated, which always displayed green light phases.

2.1.3. Participants and procedure
38 participants including 18 males and 20 females were recruited and they all finally completed the experiment. The participants’ age ranged from 20 to 40, with an average of 30.18. Each of them was required a valid driver’s license and had driven for more than 10,000 kilometers. During the experiment, all participants were asked to drive in accordance with their daily driving habits. After completing the experiment, each participant received 200 Chinese RMB.

2.2. EEG preprocessing
EEG signals are very weak and often mixed with artifacts. Before extracting features, raw EEG signals need to be preprocessed. In this study, Curry Neuroimaging Suite 7 is used for EEG preprocessing and Matlab 2016a for feature extraction. First, EEG data was downsampled to 256Hz for reducing memory consumption. Second, EEG data was re-referenced to average of M1 and M2. Then baseline correction was carried out and a band-pass FIR filter (0.5-30Hz) was performed to extract EEG data without noise. Artifacts were removed using recorded HEOG and VEOG. After preprocessing, EEG signals became smoother and cleaner.

2.3. Definitions of variables
**Dependent variable:** as the signal of intersection changes, we selected driver’s stop-go decision as dependent variable. Specifically, the stop-go decision was a binary variable (0 vs. 1) and equals 1 when the driver intended to carry out “go” strategy when they saw the yellow light at the intersection.

**Independent variables:** a fast Fourier transformation (FFT) was applied to extract 32 base EEG features (4 EEG bands × 4 Brain regions×2 Periods) from the preprocessed EEG measurements [12]. Four EEG bands are δ-band (0.5–3 Hz), θ-band (4–7 Hz), α-band (8–13 Hz), and β-band (14–30 Hz). 64 channels were divided into four brain regions including the frontal, parietal, occipital and temporal regions. EEG relative power was further extracted separately from these four brain regions. Additionally, in order to predict driver’s stop-go decision more accurately, the data before and after the yellow light was selected as 2 periods, and the time interval was 2 seconds.

2.4. Prediction model
2.4.1. Back Propagation Neural Network (BPNN)
BPNN training process is divided into two parts: a forward propagation of information and a backward propagation of error. Back propagation algorithm network adjusts the weight of each continuous layer to reduce the error of each level. In the layer link, the information transmission process is one-way transmission to the input layer, information in the input layer, hidden layer processing, and transmission to the output layer, the state of each layer can only be affected by the next layer. If there is no expected result in the output layer, it changes to reverse propagation, and the error between the result and the expected value returns along the origin path [13].

Then, according to the following steps, neural network training is developed: calculating the value of each layer; calculating the error of each layer; modifying the weight and value of each layer; and repeating the above steps according to the modified joint weight. The training parameters of the neural network, the prediction results of training samples and test samples, and the two-dimensional network are completed. This paper adopted the common five-layer network structures, including an input layer, three hidden layer and an output layer, as shown in Figure 2.
Figure 2. Network Architecture of Back Propagation Neural Network.

2.4.2. Confusion matrix
The confusion matrix is mainly used to compare the predicted classification results with the predicted real values. For a binary classification problem, it is shown in Table 1. TPR represents true positive rate, and TNR represents true negative rate. PPV represents positive predictive value, and NPV represents negative predictive value. Accuracy represents the overall accuracy rate. They are all important indicators for evaluating classification results. The formula for calculating were listed as (1)-(5).

| Observed | Predicted | true positive (TP) | false positive (FP) | false negative (FN) | true negative (TN) |
|----------|-----------|--------------------|---------------------|---------------------|--------------------|

\[ PPV = \frac{TP}{TP + FP} \] (1)

\[ NPV = \frac{TN}{TN + FN} \] (2)

\[ TPR = \frac{TP}{TP + FN} \] (3)

\[ TNR = \frac{TN}{TN + FP} \] (4)

\[ ACC = \frac{TP + TN}{(TP + FN + FP + TN)} \] (5)

3. Result and discussion

3.1. Basic description for stop-go decisions
Considering different yellow-onset gaps, basic descriptive statistics are summarized on the go-stop decisions. The results are shown in Table 6-2. In 222 intersection experiments, the number of times that drivers choose to go totals 60 times, accounting for 27.0%, and the number of times that drivers choose to stop totals 162 times, accounting for 73.0%. With the increase of yellow-onset gaps, the number of drivers choosing to go is decreasing, while the number of drivers choosing to stop is increasing. It shows that the farther the driver is from the intersection, the more people choose to stop, which is in line with the reality.
3.2. Results of Back Propagation Neural Network

EEG relative power before and after yellow light and stop-go decision were as input, and a 10-fold cross-validation was applied for evaluation. The summary of prediction accuracy and precision is presented in Table 3. The average accuracy was 91.44%, and precision parameter is acceptable.

Table 3. Summary of prediction accuracy and precision.

| YOG(s) | PPV   | NPV   | TPR   | TNR   | Accuracy |
|--------|-------|-------|-------|-------|----------|
| 4.5    | 87.50%| 76.92%| 87.50%| 76.92%| 83.78%   |
| 5      | 88.00%| 83.33%| 91.67%| 76.92%| 86.49%   |
| 5.5    | 83.33%| 76.92%| 86.96%| 71.43%| 81.08%   |
| 6      | 92.31%| 63.64%| 85.71%| 77.78%| 83.78%   |
| 6.5    | 86.67%| 57.14%| 89.66%| 50.00%| 81.08%   |
| 7      | 100.00%| 100.00%| 100.00%| 100.00%| 100.00% |
| Overall| 90.86%| 93.62%| 98.15%| 73.33%| 91.44%   |

3.3. Change Trends in predicted results

In this paper, PPV represents the proportion of decisions correctly predicted to stop to all decisions predicted to stop. NPV represents the proportion of decisions correctly predicted to go to all decisions predicted to go. TPR represents the proportion of decisions correctly predicted to go to all observed stop decisions. TNR represents the proportion of decisions correctly predicted to go to all observed go decisions. Prediction precision of BPNN model in different YOGs is shown in Figure 3.
Figure 3. Prediction precision of BPNN model in different YOGs

PPV and TPR are high in different YOGs, which indicates BPNN model has good prediction results for drivers' stop decisions. NPV and TNR are lower than PPV and TPR, which indicates the prediction results of drivers' go decisions is slightly worse than the prediction results of drivers' stop decisions. With the increase of YOGs, NPV and TNR showed a downward trend and reached the lowest level at 6.5s. The possible explanation is that with the increase of YOGs, driver's stop-go decision-making becomes more complex. In general, the prediction accuracy of the model is still very high and acceptable.

4. Conclusion

As an important factor affecting whether a driver runs a red light or not, scholars generally pay attention to the relationship between drivers' behavior and stop-go decisions. However, few studies use EEG to predict the driver's stop-go decisions. This study makes up for this gap. EEG, as the most important index reflecting physical and psychological activities, has high time resolution and can quickly judge the driver's state and decision-making. In addition, the traditional EEG acquisition system requires the contact of electrodes with human scalp, which is an obstacle to practical application. However, with the development of bio-potential signal acquisition technology, non-contact electroencephalogram sensors have emerged in the past decade. The main contribution of this paper is to establish a prediction model of driver's stop-and-go decision-making at intersections based on EEG relative power, and good prediction results have been obtained. After predicting the stop-go decisions of drivers after seeing yellow lights, we can develop a decision-making assistance system for drivers. For drivers who choose to go, it can remind them to slow down and help them stop. It also can help reduce RLR violations at intersections.

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