Classification of Driver's Cognitive Responses Using Nonparametric Single-trial EEG Analysis

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***Abstract*—Accidents caused by errors and failures in human performance among traffic fatalities have a high rate causing death and become an important issue in public security. The key problem causing these car accidents is mainly because that the drivers failed to perceive the changes of the traffic lights or the unexpected conditions happening accidentally on the roads. In this paper, we devised a quantitative analysis for ongoing assessment of driver's cognitive responses by investigating the neurobiological information underlying electroencephalographic (EEG) brain dynamics in traffic-light experiments in a virtual-reality (VR) dynamic driving environment. Three different feature extraction methods including Nonparametric Weighted Feature Extraction (NWFE), Principlal Component Analysis (PCA), Discriminant Analysis Feature Extraction (DAFE) are applied to reduce the feature dimension and project the measured EEG signals to a feature space spanned by their eigen-vectors. After that, the mapped data can be classified with fewer features and their classification results are compared by utilizing three different classifiers including Gaussian classifier (GC), *k* Nearest neighbor classification (KNNC), and Naive Bayes Classifier (NBC). Experimental results show that the successful rate of Nonparametric Weighted Feature Extraction combined with Gaussian classifier is higher more than 10% compared with other combinations. It also demonstrates the feasibility of detecting and analyzing single-trail ERP signals that represent operators' cognitive states and responses to task events.**

Keywords: Electroencephalographic, Nonparametric Weighted Feature Extraction, Principlal Component Analysis, Discriminant Analysis Feature Extraction, Gaussian classifier, *k* Nearest neighbor classification, Naive Bayes Classifier

I. INTRODUCTION

During the past years, driving safety has received increasing attention due to the growing number of traffic fatalities. Among these fatalities, the most frequent accidents are caused by drunk driving, speeding, and red light running. Preventing such accidents is thus a major focus of efforts in the field of active safety research in vehicle safety-driving systems. In recent studies [1-3], many researchers had proposed to develop quantitative techniques for ongoing assessment of cognitive effort, engagement and workload, by investigating the neurobiological mechanisms underlying electroencephalographic (EEG) brain dynamics.

A way to determine the relationship between different stimuli and human cognitive responses accompanying correct, incorrect and absent motor responses is the use of event-related brain potential (ERP) signals. An ERP signal can be observed with some latency (e.g., P300) as the stimulus event is given or removed to a subject. The recent brain computer interface (BCI) works [4-6] have focused on the feasibility studies of on-line averaging and biofeedback methods in order to choose characters or move a cursor on a computer screen. Jessica D. Bayliss, et al. [7, 8] designed an experiment to recognize the existence of P300 ERP epochs at red stoplights and the absence of this signal at yellow stoplights in a virtual driving environment. They have shown that building a brain computer interface using the P300 ERP would prove feasible.

The main purpose of this paper is to analyze recorded single-trial EEGs, extracting and combining the multidimensional information obtained from the scalp EEGs by utilizing various feature extraction methods combined with different classifiers, and to model the dynamics of underlying brain networks in the dynamic VR environment.

II. SYSTEM ARCHITECTURE

A. *Virtual Reality (VR)-based Dynamic Driving Simulator*

To explore brain activities in the safety-driving system, we design this experiment to detect and analyze the Event Related Potential (ERP) signals of brain activities related to the traffic-light events (Red-Green-Yellow) since they are the most

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frequently happened events when driving on the roads and have a high fatality rate when drivers run and ignore the stoplight. The overall dynamic VR-based safety-driving experimental environment includes four major parts as shown in Fig. 1: (1) the virtual driving environment based on dynamic virtual reality technology, (2) the driving motion simulator based on a 6-DOF Stewart platform, (3) EEG measurement system with 36-channel EEG head mounted sensors, and (4) spatial and temporal signal processing technologies based on several kinds of feature extraction and classification methods.

B. Subjects and EEG Data Collection

Three subjects (ages from 20 to 40 years) participated in the VR-based traffic-light driving experiments where EEG signals were simultaneously recorded. The subject is asked to decelerate/stop the car by pressing the right button of a joystick using right hand when he/she detected a red light, to accelerate the car by pressing the left button using left hand when he/she saw a yellow light, and do nothing (keep constant speed) when he/she saw the green light. Thirty-six EEG/EOG channels (using sintered Ag/AgCl electrodes with a unipolar reference at right earlobe), 2 ECG channels (bipolar connection) are simultaneously recorded by the Scan NuAmps Express system (Compumedics Ltd., VIC, Australia). All the EEG/EOG sensors were placed based on a modified International 10-20 system. Before data acquisition, the contact impedance between EEG electrodes and scalp was calibrated to be less than 5kΩ. The EEG data were recorded with 16-bit quantization level at a sampling rate up to 1 KHz. Then EEG data were preprocessed using a simple low-pass filter with a cut-off frequency of 50 Hz to remove the line noise (60 Hz and its harmonic) and other high-frequency noise for further analysis.

III. ANALYSIS OF EEG SIGNALS

Fig. 2 shows the system flowchart for processing the ERP signals. The Pz-channel EEG signals are processed through one of three different feature extraction methods, and fed into one of three different classifiers for comparison of classification accuracy. Each analysis method is described briefly in this section.

A. Nonparametric Weighted Feature Extraction

NWFE is a nonparametric feature extraction [9]. The main ideas of NWFE are putting different weights on every sample to compute the "local means" and defining new nonparametric between-class and within-class scatter matrices to get more features. In NWFE, the nonparametric between-class scatter matrix is defined as

$$S_b^{NW} = \sum_{i=1}^{L} P_i \sum_{\substack{j=1 \\ j\neq i}}^{L} \sum_{k=1}^{N_i} \frac{\lambda_k^{(i,j)}}{n_i} \left(x_k^{(i)} - M_j\left(x_k^{(i)}\right)\right)\left(x_k^{(i)} - M_j\left(x_k^{(i)}\right)\right)^T \tag{1}$$

The nonparametric within-class scatter matrix is defined as

$$S_w^{NW} = \sum_{i=1}^{L} P_i \sum_{k=1}^{N_i} \frac{\lambda_k^{(i,j)}}{n_i} \left(x_k^{(i)} - M_i\left(x_k^{(i)}\right)\right)\left(x_k^{(i)} - M_i\left(x_k^{(i)}\right)\right)^T \tag{2}$$

where $x_k^{(i)}$, L and P_i refer to the k-th sample from class i, the number of classes, the prior probability of class i, respectively. The scatter matrix weight $\lambda_k^{(i,j)}$ is defined as:

$$\lambda_k^{(i,j)} = \frac{dist(x_k^{(i)}, M_j(x_k^{(i)}))^{-1}}{\sum_{l=1}^{n_j} dist(x_l^{(i)}, M_j(x_l^{(i)}))^{-1}} \tag{3}$$

where $dist(a,b)$ means the distance from a to b and $M_j(x_k^{(i)})$ is the local mean of $x_k^{(i)}$ in the class j and defined as:

$$M_j(x_k^{(i)}) = \sum_{l=1}^{N_i} w_l^{(i,j)} x_l^{(j)} \tag{4}$$

where

$$w_l^{(i,j)} = \frac{dist(x_k^{(i)}, x_l^{(j)})^{-1}}{\sum_{l=1}^{N_j} dist(x_k^{(i)}, x_l^{(j)})^{-1}} \tag{5}$$

The optimal features are determined by optimizing the criteria given by

$$J_{NWFE}(p) = tr[(S_w^{NW})^{-1} S_b^{NW}] \tag{6}$$

B. Principlal Component Analysis(PCA)

PCA is defined by the transformation:

$$Y = A^T X \tag{7}$$

where $X \subseteq R^n$, A is a p-dimensional transformation matrix whose columns are the eigenvectors related to the eigenvalues computed according to the formula:

$$\lambda e = Se \tag{8}$$

$$S = \frac{1}{N-1}(X-M)(X-M)^T,\ M = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{9}$$

where S is the scatter matrix (i.e., the covariance matrix), $x_i \in X$, i=1,…, N, M is the mean vector of X, N is the number of samples.

This transformation A is called Karuhnen-Loeve transform. It defines the p-dimensional space in which the covariance among the components is zero. In this way, it is possible to consider a small number of "principal" components exhibiting the highest variance (the most expressive features).

C. Discriminant Analysis Feature Extraction (DAFE)

DAFE also known as Linear Discriminant Analysis is often used for dimension reduction in classification problems. It is also called the parametric feature extraction method in [10] since DAFE uses the mean vector and covariance matrix of each class. In DAFE statistics, within-class and between-class scatter matrices are used to formulate criteria of class separability. For using DAFE, the size of all training samples must be greater than the dimensionality. But if the training sample size is very small or the within-class scatter matrix is singular or nearly singular, the performances of DAFE will be poor.

D. Classifiers

In this study, three types of classifiers are used.

- Gaussian classifier (GC) belongs to parametric classifier which was made up of mean vector and covariance matrix for a normal distribution. The definition is introduced as in [10].
- k Nearest neighbor classification (kNNC) is a simple and appealing approach in pattern recognition. k nearest neighbor classifier find the set of k nearest neighbors in the training set to a testing sample, x, and then classify x as the most frequent class among the k neighbors. Nearest neighbors is a flexible classification scheme, and does not involve any preprocessing or fitting of the training data. Hence, k nearest neighbor classifier belongs to nonparametric classifier. The definition of nearest neighbor classification is described as in [10]. In this paper, the parameter k is set to 1 or 3 and the classifiers are denoted as KNN1 or KNN3 in the following paragraphs.
- Naive Bayes Classifier (NBC): Let C be the set of class label $C = \{c_1, c_2, \ldots, c_m\}$, each data object has a set of attribute values $X = \{a_1, a_2, \ldots, a_n\}$. NBC classifies a new data object X to a class c_i that has the highest posterior probability $P(c_i|X)$. According to Bayes theorem $P(H|X) = P(X|H) * P(H)/P(X)$, the posterior probability $P(c_i|X)$ is equivalent to $P(c_i)P(X|c_i)/P(X)$

IV. Experiment Results

In our experiment, a subject was driving a car in the VR-based ERP experimental system described in Section II. The continuous EEG signals measured from EEG sensors are firstly separated into several epochs/trials where Pz-channel data are used for classification. An epoch or a trial contains the sampled data from –200 ms to 1000 ms when a light event was given at 0 ms. The objective of this experiment is to detect and analyze cognitive responses of the driver to traffic-light events by analyzing the measured EEG signals.

Fig. 3 shows the classification results of the 3 subjects using the different feature extraction methods and different classifiers. Each EEG trial is down-sampled and picked up 400-point signal to form the dataset. Each dataset for one subject is shuffled and randomly divided to 4 sub-datasets to do 4-fold cross-validation. Such process is repeated 10 times to get the average accuracy and standard deviation to decrease possible bias caused by any specific selected dataset. Besides, feature numbers ranging from 1 to 50 are chosen for classification when doing feature extraction, and it can reduce the feature dimension from original hundred of features down to less than 50 features. Testing all the above-mentioned cases, the maximum averaged accuracy and standard deviation are plotted in Fig. 3

As shown in Fig. 3, the NWFE+GC gives better classification accuracy than others among these 3 subjects and the improvement of classification accuracy is 10%~24% higher than DAFE+NBC. It shows that the choice of feature extraction methods and classifiers makes a big difference. Also, NWFE effectively reduces the feature number from 400 down to 2 and gives the best accuracy among these test cases. To graphically visualize the difference of projected data spread in the reduced feature space, training and testing data are projected to 2-dimention feature space. Three scatter-plots are shown in Fig. 4 through Fig. 6, where the left-hand side is the training data projection and the right-hand side is the test data projection. From the figures, NWFE and DAFE both separate projected training data better than PCA, while NWFE also performs better than DAFE for projected test data separation. That gives a visual interpretation for the classification results.

V. Conclusion

In this paper, we developed a quantitative analysis technique for ongoing assessment of drivers' cognitive responses by investigating the neurobiological information underlying EEG brain dynamics in traffic-light motion simulation experiments. It consists of a virtual-reality (VR) motion-simulation driving platform and an EEG signal detection and analysis system. Three different feature extraction methods combined with three different types of classifiers are utilized to analyze the single-trial EEG signal for classification of driver's cognitive responses to traffic light events. The experimental results show that we can analyze ERP signals in single trials correctly without using traditional time-domain overlap-added method. The successful rate of Nonparametric Weighted Feature Extraction combined with Gaussian classifier is higher more than 10% compared with other combinations under 10 x 4 cross-validations on the 3 subjects. The feasibility of detecting and analyzing single-trail ERP signals that represent operators' cognitive states and responses to task events is also demonstrated.

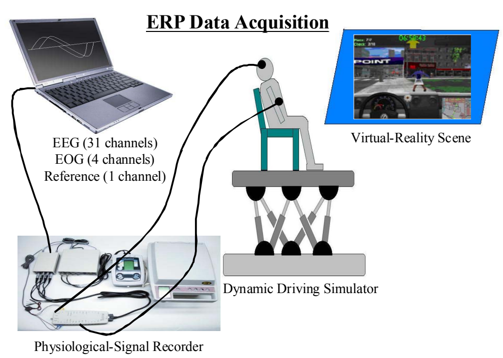

Figure 1. Physiological signal measurement system with kinesthetic/visual/auditory stimuli in the 3D dynamic VR-based traffic-light motion simulation experiments.

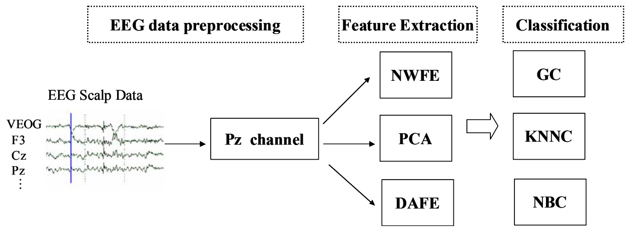

Figure 2. System flowchart for processing the ERP signals.

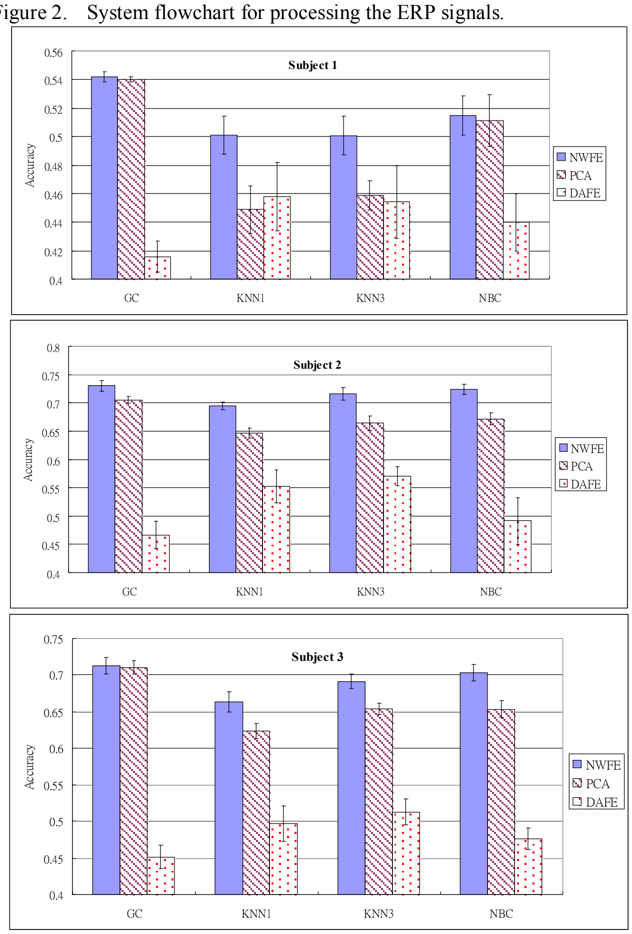

Figure 3. Classification results for three different subjects.

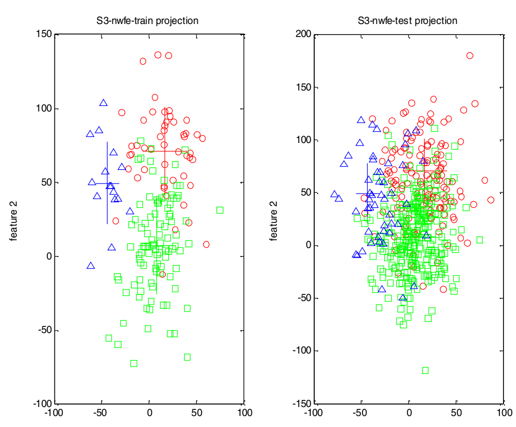

Figure 4. Scatter-plot for subject 3 in NWFE-mapped feature space.

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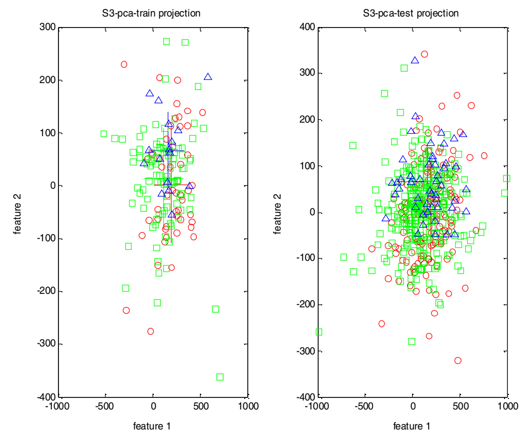

Figure 5. Scatter-plot for subject 3 in PCA-mapped feature space.

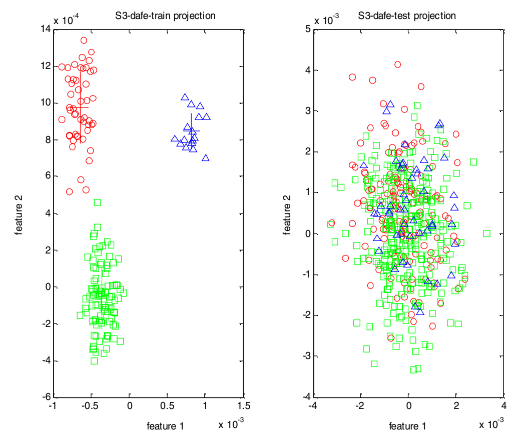

Figure 6. Scatter-plot for subject 3 in DAFE-mapped feature space.

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