2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

EEG-based Driving Fatigue Prediction System Using Functional-link-based Fuzzy Neural Network

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***Abstract*—This study presents a fuzzy prediction system for the forecasting and estimation of driving fatigue, which utilizes a functional-link-based fuzzy neural network (FLFNN) to predict the drowsiness (DS) level in car driving task. The cognitive state in car driving task is one of key issue in cognitive neuroscience because fatigue driving usually causes enormous losses nowadays. The damage can be extremely decreased by the assistant of various artificial systems. Many Electroencephalography (EEG)-based interfaces have been widely developed recently due to its convenient measurement and real-time response. However, the improvement of recognition accuracy is still confined to some specific problems (e.g., individual difference). In order to solve this issue, the proposed methodology in this paper utilizes a nonlinear fuzzy neural network structure to increase the adaptability in the real-world environment. Therefore, this study is further to analysis the brain activities in car driving, which is constructed in a simulated three-dimensional virtual-reality (VR) environment. Finally, through the development of brain cognitive model in car driving task, this system can predict the cognitive state effectively before drivers' action and then provide correct feedback to users. This study also compared the result with the-state-of-art systems, including Linear Regression (LR), Multi-Layer Perceptron Neural Network (MLPNN) and Support Vector Regression (SVR). Results of this study demonstrate the effectiveness of the proposed FLFNN model.**

Keywords*—Electroencephalography (EEG), Driving fatigue, functional link neural networks (FLNNs), fuzzy neural networks (FNNs)

I. Introduction

Accompany with the development of techniques, many artificial auxiliary systems have been designed to improve human's life[1]–[3]. Among these systems, brain monitoring system is an effective object type because it could evaluate cognitive states of human beings directly. There is a great deal of methodologies to measure brain activity [4] (e.g., Electroencephalography (EEG), Magnetoencephalography (MEG), Magnetic resonance imaging (MRI), etc.), and each of them has its own strength and weaknesses. As one of the most important methodologies, EEG has gradually attracted attention. A significant advantage of EEG over other extraction methodologies is that it provides abilities of convenient measurement and real-time response [5].

Although EEG has been widely utilized in brain monitor system, there are some basic problems which are not completely solved. Improvement of recognition rate is still a key issue. Because brain activities are dynamic and complex procedure, processing of EEG turns to be quite complicated nonlinear problem. Many authors have addressed this problem using different approaches [6]–[9], and the fuzzy neural network has been considered a flexible and rational manner because it combines the ability of bio-inspired learning and the mechanism of human thinking [10]–[14].

The proposed system in this paper is to introduce a functional-link-based neural fuzzy network (FLFNN) [15], [16], especially for [13], the authors have presented using Self-organizing Neural Fuzzy Inference Network (SONFIN) to evaluate the state of drowsiness in driving tsk. In this approach, to explicitly describe learning algorithms we divided two sections consisted of structure learning and parameter learning. For the structure learning algorithm, fuzzy partition of input variables is exploited to build fuzzy rules. In addition, through the parameter learning, which is based on the back propagation algorithm, all free parameters will be updated by patterns iteratively. In addition, in order to increase the flexibility of output layer, we utilize the functional-link expansion to the consequent layer. Further in this study, the system performances of FLFNN are compared with the benchmark systems including Linear Regression (LR), Multi-Layer Perceptron Neural Network (MLPNN), and Support Vector Regression (SVR) [17].

II. Experimental Setup

A. Experimental environment and paradigm

This study adopted an event-related lane-departure driving paradigm [18] using dynamic control platform [19] to evaluate brain dynamics associated with motion cues under different levels of task performance. The three-dimensional six-axis virtual reality (VR) scenario (Fig. 1(a)) provided nighttime driving environment which simulated participants

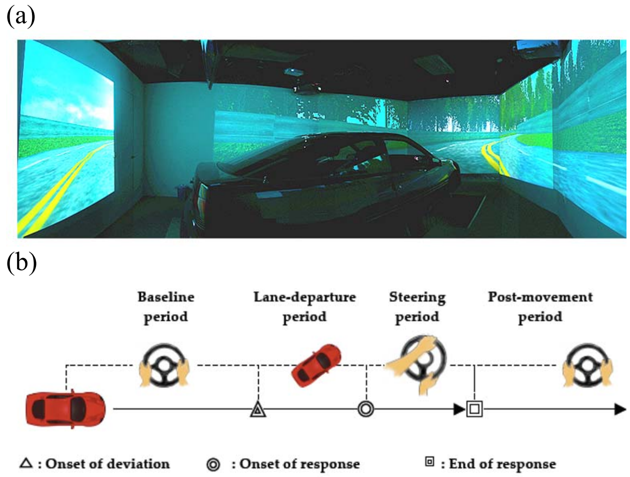

Fig. 1. (a) Three-dimensional-six-axis virtual reality (VR) scenario. (b) Schema for driving task in simulated scenario.

to drive on a four-lane divided highway at a constant speed of 100 km/hr. The VR experimental program (Fig. 1(b)) randomly introduced lane-perturbation events to cause the virtual vehicle to drift from the center of the cruising lane, and before the simulation start, participants had been instructed to steer the vehicle back to the cruising lane as fast as possible after becoming aware of the deviation. If the subjects did not respond to the lane-perturbation event, falling asleep, for example, and then the vehicle could hit the left and right curb of the roadside within 2.5s and 1.5s, respectively. The vehicle would then continue to move along the curb until it returned to the original lane. The inter-trial interval was set to 5~10 s. The experiment was begun in the early afternoon (13:00-14:00) after lunch and lasted for about 90min when the circadian rhythm of sleepiness was at its peak [20]. Participants' cognitive states and driving performance were monitored via a surveillance video camera and the vehicle trajectory throughout the experiment.

B. Participants

Ten right-handed healthy young adults took part in the behavioral experiment (mean age ± Standard Deviation; 24.2 ± 3.7 years old). All participants were recruited through online advertisement. No subject had a history of neurological, psychiatric, addictive disorders according to self-report, and no anti-psychotic treatments or other relevant psychoactive drugs within past two weeks. Before each section of experiment, the subjects needed to answer a questionnaire regarding their sleep patterns to make sure they were not sleep deprived or took any medication that might influence their cognitive states. Additionally, the subjects did not have imbibed alcohol and caffeinated drinks, or participated in strenuous exercise a day before the experiments. To evaluate accurately their driving performance, the participants attended a pre-test session to determine that none was afflicted with simulator sickness. The Institutional Review Board of the Veterans General Hospital, Taipei, Taiwan, approved the study. All participants were asked to read and sign an informed consent form before participating in the EEG experiments.

C. Independent EEG processes and category

Independent component analysis (ICA) [21] is an effective EEG signal processing technique which could find a source mapping matrix from original data which was blended with unrelated artificial noise. This method demonstrated one suitable solution to the problem of EEG source, and could decompose distinct brain activation. For each recorded datum, a maximum of 30 independent components (ICs) and their corresponding mixing matrix were decomposed. The ICs, obtained from 10 subjects, were grouped into distinct clusters with high intra-cluster similarity [21] based on commonalities of scalp topographies (2-D visualization maps of the columns of the mixing matrix), equivalent dipole source locations [22], and event-related spectral perturbations [21]. Based on suggestions in the literature [18], [19], [23], bilateral occipital was selected as the ICs of interest for further analysis. The continuous IC time series was then segmented into a set of epochs of varying lengths from 2 s before each deviation event to the occurrence of the following deviation event. The epoch datum was separated from artifacts using ICA algorithm which was implemented in EEGLAB toolbox to preserve real activated components. The response time (RT) to each lane-departure event (i.e., the time between the onset of the deviation and the onset of the response) was used as an objective behavioral measurement to characterize all EEG epochs as the level of drowsiness.

D. Event-related time-frequency estimation

To investigate brain dynamics following the lane-departure events and the subsequent motor responses, each epoch was separately transformed into the time-frequency representation using the event-related spectral perturbation routine [21]. For each component cluster and each driving session, the mean delta- (: 1-3 Hz), theta- (: 4-7 Hz), alpha- (: 8-12 Hz), and beta- (: 13-20 Hz) band powers high beta- (: 21-40 Hz)were collected according to the RT of the epoch.

III. PROPOSED METHOD

A. FLFNN

This section describes the model of FLFNN, which utilizes a nonlinear combination of input variables (FLNN). Each fuzzy rule corresponds to a sub-FLNN, comprising a functional link. The structure of FLFNN model is as illustrated in Fig. 2.

The operating principles of each layer are now described. In the following description, $u^{(l)}$ denotes the output of a node in the l_{th} layer.

No computation is done in layer-1. Each node in this layer, which corresponds to one input variable, only transmits input values to the next layer directly.

$$u_i^{(1)} = x_i \tag{1}$$

Next, layer-2 is membership function layer. Each node in this layer performs Gaussian membership function that corresponds to one linguistic label of the input variable in layer-1.The calculated membership value in layer-2 is

$$u_{ij}^{(2)} = \exp(-\frac{[u_i^{(1)} - m_{ij}]^2}{\sigma_{ij}^2}) \quad (2)$$

where m_{ij} and σ_{ij} are the mean and variance of the Gaussian membership function, respectively, of the j_{th} term of the i_{th} input variable x_i.

Nodes in layer-3 receive single-dimensional membership degrees based on the associated rule from the nodes of a set in layer-2.

Here, the product operator is adopted to perform the pre-condition part of fuzzy rules. As a result, the output function of each rule node can be denoted by

$$u_j^{(3)} = \Pi(u_{ij}^{(2)}) \quad (3)$$

where the $\Pi_i u_{ij}^{(2)}$ of a rule node represents the firing strength of its corresponding rule.

Nodes in layer-4 are called the consequent nodes. The input to each node in layer-4 is the output from layer-3, and the other inputs are calculated from the FLNN that has not used the function tanh(·), as shown in Fig. 2. Such a node

$$u_j^{(4)} = u_j^{(3)} \sum_{k=1}^{M} \omega_{kj} \phi_k \quad (4)$$

where ω_{ij} is the corresponding link weight of the FLNN and φk is the functional expansion of input variables. The functional expansion uses a trigonometric polynomial basis function, given by $[x_1 \sin(\pi x_1) \cos(\pi x_1)\ x_2 \sin(\pi x_2) \cos(\pi x_2)]$ for two-dimensional input variables. Therefore, M is the number of basis functions, $M = 3 \times N$, where N is the number of input variables. Moreover, the output nodes of the FLNN depend on the number of fuzzy rules of the FLFNN model. The output node in layer-5 integrates all of the actions recommended by layers-3 and layer-4 and acts as a fuzzy defuzzifier with

$$y = u_j^{(5)} = \frac{\sum_{j=1}^{R} u_j^{(4)}}{\sum_{j=1}^{R} u_j^{(3)}} = \frac{\sum_{j=1}^{R} u_j^{(3)} \left(\sum_{k=1}^{M} \omega_{kj} \phi_k \right)}{\sum_{j=1}^{R} u_j^{(3)}} = \frac{\sum_{j=1}^{R} u_j^{(3)} \hat{y}_j}{\sum_{j=1}^{R} u_j^{(3)}} \quad (5)$$

where R is the number of fuzzy rules and y is the output of the model of FLFNN.

B. *Proposed EEG-based driving perdition system*

The architecture of proposed system is shown in Fig. 3.The recorded EEG data sets are processed into two stages.

First section performs bio-signal preprocessing, including artifacts removal, independent component analysis. Following the event tag of recorded data, the data sets were divided into several epochs. By utilizing time-frequency analysis, adaptive features are selected and then transmitted into next stage.

Before entering data sets into the proposed prediction, we need to establish the format of our data sets. According to previous literatures, bilateral occipital was selected as the ICs of interest for further analysis. In addition, for the meaning of prediction, this study utilizes the data, which lengths from 2 s

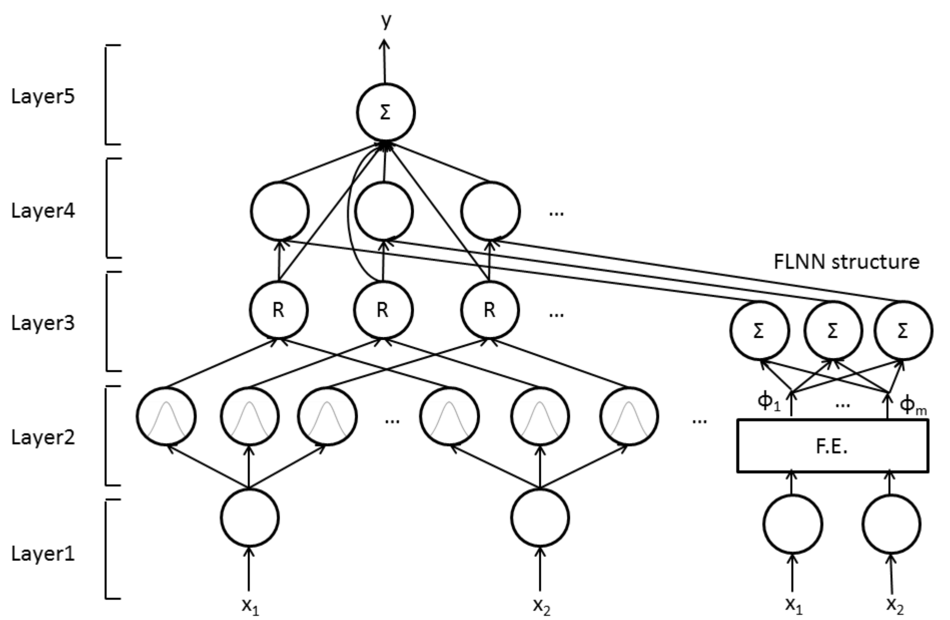

Fig. 2. Structure of functional-link-based fuzzy neural network (FLFNN), which comprises a five-layer neural network structure.

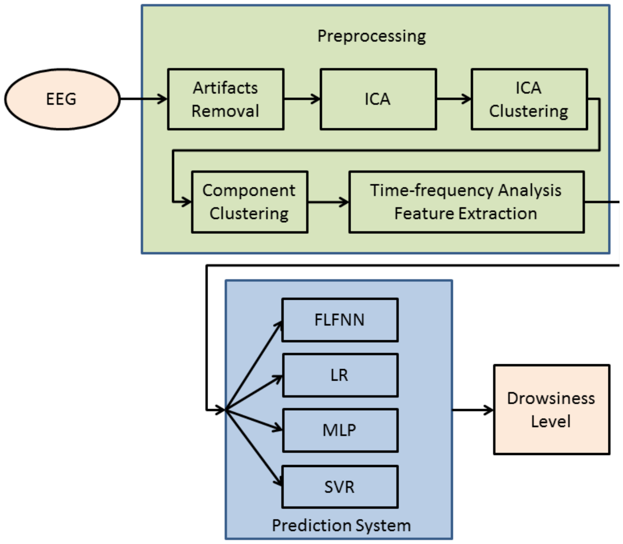

Fig. 3. EEG-based driving fatigue prediction system schematics. First section performs bio-signal preprocessing, including artifacts removal, independent component analysis. Following the event tag of recorded data, the data sets were divided into several epochs. Utilizing time-frequency analysis, adaptive features are selected into next station. Finally, processed data sets are transmitted to the model of FLFNN. The input data sets have been transformed from pattern phase into feature phase. Consequently, the FLFNN model predicts the cognitive state and is also trained simultaneously according to each input pattern.

before each deviation event, as target of prediction. Rather than adopting the signal coming after deviation event, although it would be more opportunities to have significant performance; however, it does not exist any rational and physical meanings.

Finally, the processed data sets are transmitted to the model of FLFNN. The input data sets have been transformed from pattern phase to feature phase. There are 944 patterns (total subjects) in that experiment and each pattern possesses 5 attributes (delta, theta, alpha, beta and high beta) as feature vector. Then the FLFNN model evaluate each data based on the principles introduced last sub-section. Consequently, the FLFNN model predicts the cognitive state and is also trained simultaneously according to piece of incoming pattern.

IV. Experimental Results and Discussion

In this section, we introduce FLFNN model to predict the level of drowsiness in car driving task. We evaluated this model by comparing with the state-of-the-art learning algorithms. We considered the following three well-known benchmark models: Linear Regression (LR), Multi-Layer Perceptron Neural Network (MLPNN), and Support Vector Regression (SVR).

The performance of this drowsiness-prediction procedure is revealed in this section. For each system in terms of executing 10 rounds along with ten-fold cross-validation, in which 90% of the trials were randomly selected as the training set and the reminding 10% of the trials as testing set. The averages of MSE between the actual and estimated RTs is shown in Tables I. The MSE of training and testing data obtained by FLFNN, LR, MLPNN and SVR are 0.009 s, 0.215 s, 0.008 s, 0.006 s and 0.067 s, 0.25 s, 0.112 s, 0.098 s. Fig. 4 depicts the boxplot of the MSE of drowsiness prediction with 10-fold cross-validation using FLFNN, LR, MLPNN and SVR. The proposed model of FLFNN produced the lowest MSE among all methodologies on the testing data in this experiment.

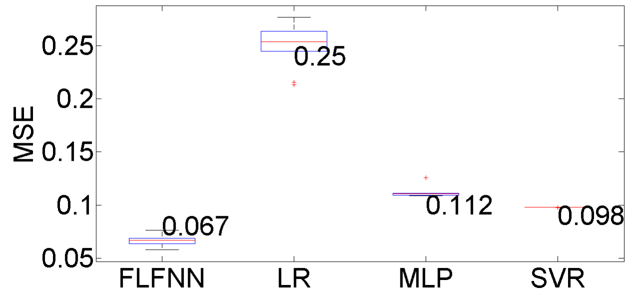

Fig. 4. Boxplot comparison of subject's drowsiness level testing evaluation for FLFNN model with LR, MLPNN, MLPNN and SVR. The boxes have three lines to present the values for lower quartile, median (red line), and upper quartile for each model. Two addition lines at both ends of the whisker indicate the maximum and minimum value of each model.

TABLE I
Mean Square Error (MSE) Comparisons for Various Model Prediction

MSE	FLFNN	LR	MLP	SVR	Average(s)
Training	0.009± 0.003	0.215± 0.009	0.008± 0.004	0.006± 0.001	0.060
Testing	0.067± 0.005	0.25± 0.021	0.112± 0.005	0.098± 0.001	0.132

V. Conclusion

A Characteristic of EEG signal is susceptible to uncertainties; therefore, its signal usually fluctuates extremely. This phenomenon comes from two major reasons, (1) the amplitude of EEG is relatively small comparing with the environments, and (2) brain activities are quite complicated originally. Therefore, it is an effective approach to increasing performance by augmenting nonlinear ability in most systems. The proposed model FLFNN employs the structure of FLNN in order to enforce the network's performance to achieve the generalization. Apparently by the experimental results, our proposed system demonstrates such effectiveness to process EEG signals and has remarkable performance in predicting car driving task.

Acknowledgment

This work was supported in part by the UST-UCSD International Center of Excellence in Advanced Bio-engineering sponsored by the Taiwan National Science Council I-RiCE Program under Grant Number: NSC 102-2911-I-009 -

101, in part by NSC-NSC102-2220-E-009-041,in part by the Aiming for the Top University Plan, under Contract 103W963.

The authors would like to thank Prof. Jyh-Yeong, Chang and all members at Brain Research Center, National Chiao Tung University, Taiwan.

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