



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

# IJRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 13, April 2023

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

9940 572 462

6381 907 438

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# Non Linear EEG Signal for Anti Accident Vehicle System

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**ABSTRACT:** In this paper, a new approach to Principal Component Analysis (PCA), Adaptive Neuro Fuzzy Interference System (ANFIS) and automatic Pattern recognition are carried out using Fuzzy Clustering non-Stationary bio signals. A wireless embedded system with real-time bio signals processing ability to remove effective noise in bio-signals by means of Discrete Walsh Hadamard transform (DWHT) with help of fuzzy logic system is proposed in this paper. The EEG signal was first acquired by signal-acquisition and amplification unit, and then, transmitted from wireless data transmitter to wireless data receiver. Using Ag/AgCl EEG/ECG signals were gathered and processed with the help of DWHT to remove excessive noise in bio-signals, and then processed results were further transmitted to the sensing system for data storage. As a result, noise is removed completely with the help of the proposed system. Adaptive Neuro Fuzzy inference system, integration of fuzzy logic and neural networks and have the potential to capture the benefits of both these fields in a single framework.

**KEYWORDS:** Alertness estimation, Electroencephalogram (EEG), Principal Component Analysis (PCA), model-based self-constructing fuzzy neural, Adaptive Neuro Fuzzy Interference System (ANFIS)

## I. INTRODUCTION

The development of the drowsiness monitoring technology for preventing accidents behind the steering wheel has become a major interest in the field of safety driving since drivers' fatigue is a causal factor in many accidents because of the marked decline in the drivers' abilities of perception, recognition and vehicle control abilities while sleepy.

Thus, developing accurate and non-invasive real-time driver drowsiness monitoring system would be highly desirable, particularly if this system can be further integrated into an automatic warning system.

It is well known that there is an abundant information on physiological changes such as eye activity measures, heart rate variability (HRV) and electroencephalogram (EEG) activities. Previous studies shown that the eye blink duration and the blink rate typically increases while blink amplitude decreases as function of the cumulative time, and the saccade frequencies and velocities of electroculogram (EOG) decline when people get drowsy.

Although approaches based on EOG signals showed that eye-activity variations were highly correlated with the human fatigue and can estimate alertness levels accurately and quantitatively.

The step size (temporal resolution) of those eye-activity based methods is relatively long (about 10 sec) to track slow changes in vigilance. Contrarily, the step size of the EEG-based methods can be reduced to about 2 sec. to track second-to-second fluctuations in the subject's performance. Since the computer power becomes faster and faster, it is practicable and appealing to know what information about human cognitive state and behavior are available through analyzing complex EEG signals. Here a Virtual-Reality (VR) based highway-driving environment is proposed to study drivers' cognitive changes during a long-term driving. A lane-keeping driving experiment is designed to indirectly quantify the driver's drowsiness level and a drowsiness estimation system combining the EEG power spectrum analysis, the Principal Component Analysis (PCA) and the linear regression model is also developed. Independent Component Analysis (ICA) is also used in to locate the optimal electrode placements for each individual.

A total of ten frequency bands in two ICA components are selected and fed to the linear regression models to estimate driver's performance.

For the propose of an on-line alertness estimation system and its improved performance, a novel Adaptive Feature Selection Mechanism (AFSM) is developed based on the correlation analysis between the subjects' driving errors and power spectra of the ICA components to automatically select effective features in this paper. In addition, the ICA-Mixture-Model-Based Fuzzy Neural Networks is also (ICAFNN) developed and employed as the drowsiness estimator to improve the prediction performance.

## II. BRAIN SENSORS AND SIGNALS

A variety of sensors for monitoring brain activity exists and could in principle provide the basis for a BCI.

These include, besides EEG and more invasive electrophysiological methods such as Electrocardiography (ECG) and recordings from individual neurons within the brain, magneto Encephalography (MEG),

Positron Emission Tomography (PET), Functional Magnetic Resonance Imaging (fMRI), and optical imaging (i.e., Functional Near Infrared (fNIR)).

However, MEG, PET, fMRI, and fNIR are still technically demanding and expensive, which impedes widespread use. Despite these impediments, several studies have recently explored the value of these modalities for BCI research.

At present, non-invasive and invasive electrophysiological methods (i.e., EEG, ECG, and single-neuron recordings, see illustration in Figure) are the only methods that use relatively simple and inexpensive equipment and have high temporal resolution.

Thus, these three alternatives are at present the only methods that can offer the possibility of a new non-muscular communication and control channel a practical brain computer interface.

## III. VIRTUAL-REALITY (VR)-BASED DRIVING ENVIRONMENT

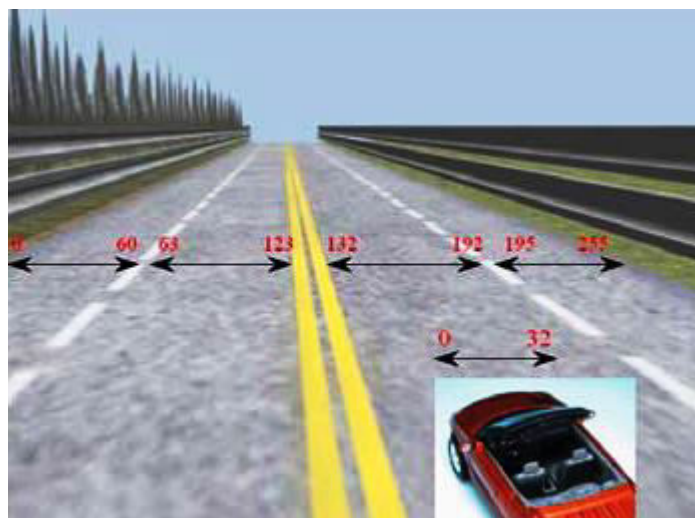


Figure 1 VR Based Driving Performance

Virtual-Reality (VR) based highway-driving environment that was developed in our previous studies to investigate driver's cognitive changes during a long-term driving was also used in this paper. It includes 3-D surround scenes by seven Papers and a real car mounted on a 6-degree-of-freedom Stewart platform. During the driving experiment, all scenes are moving according to the displacement of the car and the subject's wheel handling. The driving speed is fixed as 100 km/hr and the car is randomly and automatically drifted away from the center of the cruising lane to



mimic the consequences of a non-ideal road surface.

We asked the subject to keep the car on the third cruising lane (from left to right counted). While the subject is alert, his/her response time will be short and deviation of the car will be small; otherwise the subject's response time and the car deviation will be slow and long. In this driving experiment, the VR-based freeway scene provides only one car driven on the road without any other event stimuli to simulate a monotonous and unexciting task that make drivers fallen asleep.

#### A. Alertness Measurement

In order to investigate the relationship between the measured EEG signals and subject's cognitive state and to quantify the level of the subject's alertness, the subject's alertness level is defined which indexes the deviation between the center of the vehicle and the center of the cruising lane as an indirect measurement of the drivers alertness level. The pilot studies shown that when the drivers is drowsy (checked from video recordings and subjects' reports), the derivation error of car drift increases, and vice versa. Since the fluctuates of drowsiness level with cycle lengths were longer than 4 min the alertness level index were smoothed using a causal 90-sec. square moving-average filter advancing at 2-s steps to eliminate variance at cycle lengths shorter than 1–2 min. It is noted that the step size of eye-activity based approaches is about 10sec. It means that the temporal resolution of our method is 5 times higher than that of the eye-activity based approaches denotes the distance between the center sampling rate, and of the vehicle and the center of the cruising lane at time. Figure 1 shows the designed VR-based freeway scene and the smoothed alertness level index. The red numbers depict the widths in pixels of the four lanes from left to right in VR frontal scene. In this case, each lane covers 60 pixels and the width of the car is 32 pixels. The distance of each pixel is converted into the width of the real road. The plots the time course of deviation (alertness level) across time (in seconds). Each experiment lasted about 45-min (2700 s). The vertical axis represents the deviation of the car in pixel. When the deviation is greater than 32 pixels [horizontal dashed line in Figure.I] the car was completely off the cruising lane which could easily lead to accidents. Participants who demonstrated waves of drowsiness containing two or more micro-sleeps in both sessions were selected as successful subjects. Based on these criteria, five participants (ten sessions) have been selected for further modeling and cross-session testing.

#### B. Alertness level estimates for training/testing

Two types of learning such as structure and parameter learning are used concurrently to construct the ICAFNN. The on-line ICA mixture model is used to realize the Precondition and consequent structure identification of the proposed FNN. For the parameter learning, the parameters of the linear equations in the consequent parts are adjusted by the back propagation rule to minimize a given cost function and the parameters in the precondition part are adjusted by the online

Alertness level estimates for training/testing sessions of subject 2, based on a linear regression model (dot line, top panels) with sub band log power of ICA components at 8–12 Hz, over plotted against actual driving performance time series for the session (solid line). it is shown Figure 3. The correlation coefficient between the two time series is  $r = 0:91$  in the training session and  $r = 0:89$  in the testing session. Bottom panels show the results in the same subject based on ICAFNN, the correlation coefficient between the two time series (dot and solid lines) increase to 0.989 in the training session, and 0.94 in the testing session, respectively.

### IV. ACCIDENT HELDING PARAMETER

Rapid Eye Movement (REM) sleep is a normal stage of sleep characterized by the random movement of the eye. REM sleep in adult humans typically occupies 20–25% of total sleep and about 90–120 minutes of a night's sleep.

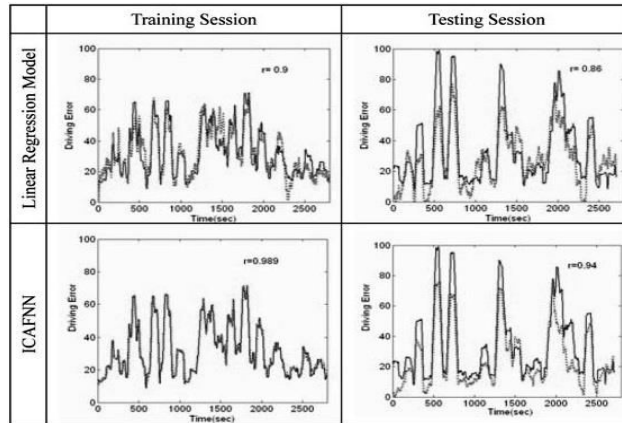


Figure 2.REM Analysis

During a normal night of sleep, humans usually experience about four or five periods of REM sleep and they are quite short at the beginning of the night and longer toward the end. Many animals and some people tend to wake, or experience a period of very light sleep, for a short time immediately after a bout of REM. The relative amount of REM sleep varies considerably with age. A newborn baby spends more than 80% of total sleep time in REM.

#### A. Correlation Analysis

In order to find the relationship between the brain activities and the subject’s alertness level and to extract the effective frequency bands of drowsiness related components, the correlation coefficient is completed between two time courses of the alertness level index and the concurrent power changes at each frequency of the ICA components by using the Pearson correlation coefficient to form a correlation spectrum.

#### B. Clustering Outline

There are several steps in the independent component clustering process.

1. Identify a set of epoched EEG datasets containing ICA weights to form the STUDY to be clustered.
2. Specify the subject code and group, task condition, and session for each dataset.
3. Identify the components in each dataset to cluster.
4. Specify and compute ("pre-clustering") measures to use in clustering.
5. Perform component clustering using these measures.
6. View the scalp maps, dipole models, and activity measures of the component clusters.
7. Perform signal processing and statistical estimation on the clusters.

There are two types of clustering methods available. One is the original (PCA) method and the other one is the new. Both methods produce reasonable clusters, but the new MP method requires less parameter tuning (it has only one parameter) and is therefore recommended. The PCA method is older and its implementation is more stable though.

#### C. Subjects

A total of ten subjects (ages from 20 to 40 years, old) participated in the VR-based highway driving experiments. Each subject completed a training session in one day and testing sessions on the other days. To maximize the opportunities to get valuable data for our study, all the experiments were conducted in the early afternoons after lunch. Statistical reports showed that people often get drowsy within one hour of continuous driving during these periods, indicating that drowsiness is not necessarily caused by long driving-hours. On the first day, participants were told of the general features of the driving task, completed necessary informed consent material, and then started with a 15 to 45-min practice to keep the car at the center of the cruising lane by maneuvering the car with the steering wheel. Subjects reported this amount of practice to be sufficient to train participants to asymptote on the task. After practicing, participants were wired with EEG electrodes and began a 45-min lane-keeping driving task. Participant’s re- turned on a different day to complete the other 45-min driving session for cross-session test.

## V. SAMPLING PROCESS

Frequency range vary from, 500 Hz recording are down-sampled to sampling rate.250 Hz for the simplicity of data processing in up sampling rate. Cut-off frequency of 50 Hz to remove the line noise (60 Hz and its harmonic).

### A. Independent Component Analysis

Two Independent Component Analysis (ICA) the driving performance and controlling of vehicle done. Due to this the hardware implementation is giving very less performance than the theoretical part.

#### B. A. Principal Component Analysis

PCA of a multivariate Gaussian distribution centered at (1,3) with a standard deviation of 3 in roughly the (0.878, 0.478) direction and of 1 in the orthogonal direction. The vectors shown are the eigenvectors of the covariance matrix scaled by the square root of the corresponding Eigen value, and shifted so their tails are at the mean.

Principal Component Analysis is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables.

This transformation is defined in such a way that the first principal component as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn the highest variance possible under the constraint that it be orthogonal to (uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen–Loeve Transform (KLT), Proper Orthogonal Decomposition (POD).

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable).

PCA can supply the user with a lower-dimensional picture, a "shadow" of this object when viewed from its (in some sense) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced. PCA is closely related to factor analysis; indeed, some statistical packages (such as Stata) deliberately conflate the two techniques.

True factor analysis makes different assumptions about the underlying structure and solves eigenvectors of a slightly different matrix.

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Define a data matrix,  $X^T$ , with zero empirical mean (the empirical (sample) mean of the distribution been subtracted from the data set), where each of the  $n$  rows represents a different repetition of the experiment, and each of the  $m$  columns gives a particular kind of datum (say, the results from a particular probe). (Note that what we are calling  $X^T$  is often alternatively denoted as  $X$  itself.) The singular value decomposition of  $X$  is  $X = W\Sigma V^T$ , where the  $m \times m$  matrix  $W$  is the matrix of eigenvectors of  $XX^T$ , the matrix  $\Sigma$  is an  $m \times n$  rectangular diagonal matrix with nonnegative real numbers on the diagonal, and the  $n \times n$  matrix  $V$  is the matrix of eigenvectors of  $X^T X$ . The PCA transformation that preserves dimensionality (that is, gives the same number of principal components as original variables) is then given by:  $V$  is not uniquely defined in the usual case when  $m < n - 1$ , but  $Y$  will usually still be uniquely defined. Since  $W$  (by definition of the SVD of a real matrix) is an orthogonal matrix, each row of  $Y^T$  is simply a rotation of the corresponding row of  $X^T$ . The first column of  $Y^T$  is made up of the "scores" of the cases with respect to the "principal" component; the next column the scores with respect to the "second principal" component, and so on.

If a reduced-dimensionality representation, the Paper  $X$  down into the reduced space defined by only the first  $L$  singular vectors,  $W_L$ .

The matrix  $W$  of singular vectors of  $X$  is equivalently the matrix  $W$  of eigenvectors of the matrix of observed covariance's  $C = X X^T$ . Given a set of points in Euclidean space, the first principal component corresponds to a line that passes through the multidimensional mean and minimizes the sum of squares of the distances of the points from the line. The second principal component corresponds to the same concept after all correlation with the first principal component been subtracted out from the points. The singular values (in  $\Sigma$ ) are the square roots of the Eigen value of the matrix  $XX^T$ . Each Eigen value is proportional to the portion of the "variance" (more correctly of the sum of the squared distances of the points from their multidimensional mean) that is correlated with each eigenvector. The sum of all the Eigen value is equal to the sum of the squared distances of the points from their multidimensional mean.

PCA essentially rotates the set of points around their mean in order to align with the principal components. This moves as much of the variance as possible (using an orthogonal transformation) into the first few dimensions.

## VI. SYSTEM IMPLEMENTATION

The present a methodology and a wearable system for the evaluation of the emotional states and eye blinking condition. The proposed approach performs an assessment of the emotional states using fuzzy logic, Discrete Walsh-Hadamard Transform (DWHT). The system consists of the following are multisensory wearable module, centralized computing module, system's interface. It supports Adaptive Neuro-Fuzzy Inference System (ANFIS) have been used for the classification. The overall classification rates achieved by using tenfold cross validation are for the ANFIS.

Wireless BCI based on customized Electroencephalogram recording and signals processing modules the advantage of ultimate portability, wear ability and usability. Integrates a mobile and wireless EEG system and a signal-process platform based on a Bluetooth into a truly wearable BCI. Its implications for BCI were demonstrated through the module programmed to assess steady-state, visual-evoked potentials in response to flickering visual stimuli to make a Bluetooth module directly.

## VII. SYSTEM SPECIFICATION

### A. Hardware requirements

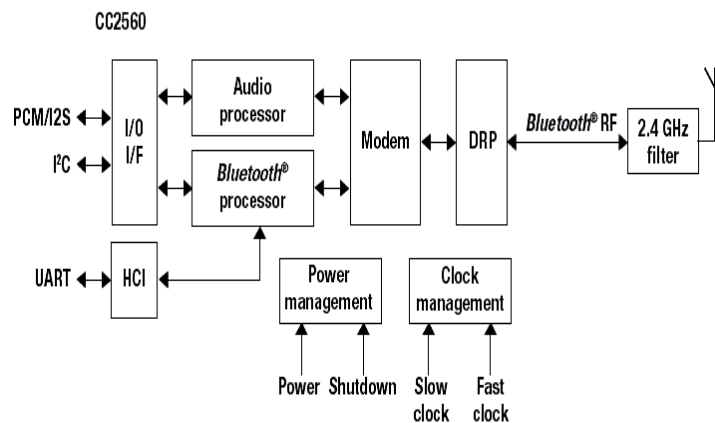


Figure 3 CC2560 Bluetooth single-chip solution

The CC2560 from Texas Instruments is a complete Bluetooth Host Controller Interface (HCI) solution enabling ease of design as well as decreased time to market for Bluetooth-enabled devices in medical, industrial and consumer electronics applications. Based on TI's seventh-generation Bluetooth core, the CC2560 brings a product-proven solution that supports the Bluetooth 2.1 + EDR release, while the CC2564 is upgradable to Bluetooth Version 3.0 and Bluetooth low energy Version 4.0.

The CC2560 is the industry's first Bluetooth solution manufactured with TI's cutting-edge 65-nm CMOS process and DRP technology, delivering the industry's smallest single-chip solution along with low power and cost.

### A. RF Performance

The CC2560 offers best-in-class Bluetooth RF performance for Tx power, Rx sensitivity and blocking. In addition, internal temperature detection and compensation ensures minimal variation in RF performance over temperature.

The CC2560 RF transmitter is capable of receiving -95 dBm or transmitting up to +12 dBm (with level



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control) without the need for external power amplifiers or a Tx/Rx switch.

Table I  
CC2560 Bluetooth Single chip solution

Parameter	Value	Conduction nodes
Power sPower Supply voltage	1.7 to 4.8V	Battery or DC to DC
Operating ambient temperature range	-40 to 85C	Industrial temperature range
Output power	+12 dBm	GFSK typical
Receiver sensitivity	-95 dBm	GFSK typical dirty Txon
eSCO	8.3 mille Amps	2-EV364Kbps

TI has tried to eliminate the need for customers to be Bluetooth experts by reintegrating Bluetooth to the MSP430 and by providing example source code applications in the platform.

Turning Bluetooth on making the device discoverable performing inquiry pairing the devices Flash Read Error and Susceptibility for MSP430F54xxA

*C Technical Performance*

Flash read errors can be minimized by customizing the linker file used to build the Paper to avoid using the affected areas of the flash. The modified linker file may be used as a temporary

Possible workaround till the new MSP430 devices are released. The flash in the MSP430F54xxA is divided into four banks. Two of these banks are susceptible to the Flash read errors. The modifications to the linker file involve trying to place the code and constant data into the unaffected regions of the flash.

*D. Proposed System*

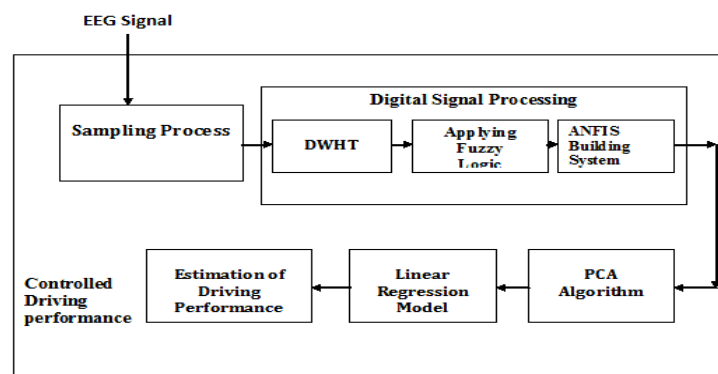


Figure III  
Reception process of EEG signal



In this Paper a new approach to Principal Component Analysis (PCA), Adaptive Neuro Fuzzy Interference System (ANFIS) and automatic Pattern recognition is carried out using

Fuzzy Clustering non-Stationary bio signals. A wireless embedded system with real-time bio signals processing ability to remove effective noise in bio-signals by means of Discrete Walsh Hadamard Transform (DWHT) with help of fuzzy logic system is proposed in this paper.

The EEG signal is first acquired by signal-acquisition and amplification unit, and then, transmitted from wireless data transmitter to wireless data receiver. Using Ag/AgCl EEG/ECG signals were gathered and processed with the help of DWHT to remove excessive noise in bio-signals, then processed results were further transmitted to the sensing system for data storage. The results shows noise is removed completely with the help of our proposed system. Adaptive Neuro Fuzzy inference system, integration of fuzzy logic and neural networks and have the potential to capture the benefits of both these fields in a single framework.

## VIII. RESULTS AND DISCUSSION

### A. Adaptive Feature Selection

After PCA training and spectral analysis for each ICA components, we computed the spectral correlations between changes in the ICA log sub band power spectrum and alertness level index. We then applied the proposed AFSM (Section III-D) to automatically select the features for drowsiness estimation. The selected features for five different subjects are shown in Table I. The features selected by the method in are also included in Table I for comparison. As can be seen, two methods might select different components.

In general, the drowsiness-related regions are mainly in the parietal and occipital lobes. In, the optimal frequency bands were selected according to the correlation coefficients between ICA power spectra and drowsiness index and iteratively testing alertness level estimation, as shown in Table II. The mean correlation between actual alertness level time series and within-session estimation by using the features selected by AFSM is 90%, whereas the mean correlation coefficient between actual alertness level and cross-session estimation is 86.6%. The average performance of the AFSM is closed to the performance using the optimal features. It can also be found that some testing results are better than the performance of the training sessions due to the repeatedly testing procedure, the estimated alertness level of training/testing sessions of subject 2 obtained by the linear regression model with the feature selected by AFSM technique. These results demonstrate that the feature selected by the one-path selection method AFSM can also reach excellent performance in estimating driving error without the repeatedly testing process.

The performance of the proposed ICA-based AFSM is also compared favorably to the Principal Component Analysis (PCA) based approach developed in that used 50 PCA components as the input features of the linear regression model for drowsiness estimation.

The mean correlation coefficient between actual alertness level and cross-session estimation of the PCA for the same 10 sessions. EEG-Based PCA-Mixture-Model-Based Fuzzy Neural Networks (PCAFNN) for Driver Alertness Estimation:

In this study, we fed the features selected by AFSM into the ICAFNN for subject's alertness level estimation. The PCA weight matrices obtained from the training sessions were used to spatially

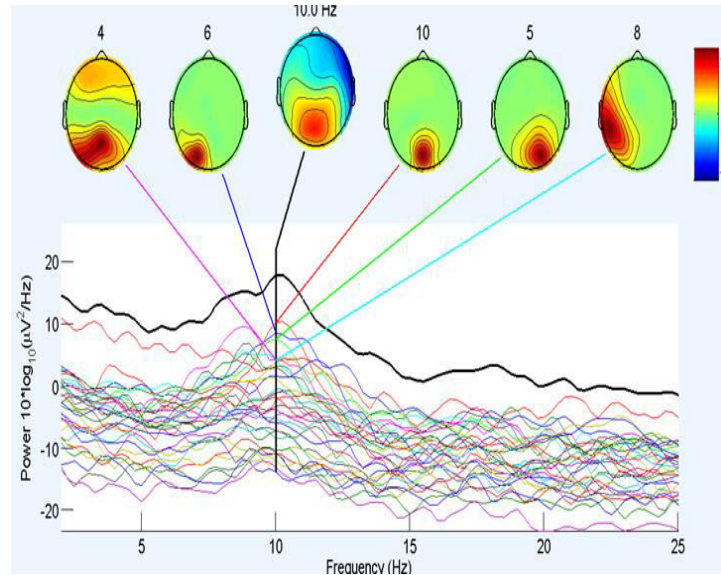


Figure IV Signal analysis

filter the features in the testing sessions so that training/testing data were processed in the same way before feeding to the estimation models for the same subject. Figure. 4 shows that the estimated and actual alertness level index of training/testing sessions of subject 2 etched well with the actual alertness level (% in the training session and 94% in the testing session, respectively). Table II (bottom row) summarizes the performance of alertness level estimation obtained by the PCAFNN model across ten sessions of five subjects. The mean correlation between actual and estimated alertness level time series is%, whereas the mean correlation coefficient in cross-session testing is 98.1%.

## IX. CONCLUSION

In this study, an adaptive EEG-based drowsiness estimation technology that combines PCA, power-spectrum analysis, AFSM, Is proposed to continuously, indirectly estimate/predict fluctuations in human alertness level indexed by alertness level measurement, expressed as deviation between the center of the vehicle and the center of the cruising lane in a virtual-reality based driving environment. The AFSM can automatically select effective features based on the correlation analysis between the power spectra of drowsiness related components and the driving errors. The proposed ANFIS can accurately estimate driver’s individual alertness level using ten sub-band power spectra of two PCA components selected by ANFIS. The computational methods developed in this study can lead to on-line monitoring of human operators’ cognitive state in attention-critical settings.

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