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Driver Drowsiness Monitoring System Using Visual behaviour And Machine Learning

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***Abstract*- One leading cause of traffic accidents is drivers who are either sleepy or too distracted to pay attention. It is possible to identify sleepiness and exhaustion by monitoring physiological signals while driving; this information is crucial for alerting the driver to avoid accidents. One way to think of sleepiness is as a transition between the "alert" and "drift-off" stages, when one's capacity to actively reduce their inspection and examination abilities occurs. Extracting as much sleep-related data as possible from a database of electroencephalogram (EEG) recordings is the primary goal of this research. This thesis develops four feature extraction approaches to detect driver drowsiness/fatigue states by extracting the most important information. The relevant brain physiological signals are analyzed to do this. In order to mitigate its consequences, the thesis delves into strategies that have been created to classify the various sleepy stages and notify the user at certain moments. There are two other types of methodology: supervised and unsupervised. Supervised methods include WPTBNN, FRFTNN, and FRFTABCS, while unsupervised methods include STFTIPSF and optimization with optimized particle swarms and fuzzy classifiers. An EEG signal downloaded from physionet.org serves as the data set for the study. The procurement of the database is the starting point for each of the described approaches. Next, the obtained signal is broken down into its component parts using WPT, FRFT, and STFT. From there, the coefficients or frequency band characteristics are created, and optimization is performed to choose the most suitable ones. Next, NN, Sparse, and Fuzzy classifiers are used to further classify these optimized best features. Using a number of performance indicators obtained from ROC graphs specific to each methodology, we further examine how well the approaches we developed performed. Results from the ROC graphs are used to do the performance analysis, which takes into account the following metrics: sensitivity, specificity, accuracy, FPR, PPV, NPV, FDR, and MCC. To achieve high-accuracy classification that would precisely discriminate between alert and departure from alert states, an efficient feature extraction method based on Wavelet Packet Transforms and Bootstrap Optimization and Neural Network Classifier (WPTBNN) is suggested. With the help of a Neural Network (NN) classifier, this suggested approach optimizes a Wavelet Packet Transform (WPT) program, retrieves frequency band information from a provided database, and then sorts the different states of awareness. The features are optimized using Bootstrap approach after frequency band feature creation. Then, they are sent to neural network classification using the Perceptron Learning algorithm. Additionally, the DWTBKNN (Discrete Wavelet Transform + Bootstrap optimization + k-Nearest Neighbor classification) approach has been used to validate the findings**.

Keywords: **EEG, WPT, FRFT, and Discrete Wavelet Transform.**

I. INTRODUCTION

It is possible to use the adjectives "drowsy" and "sluggish" interchangeably, and both of these terms reflect a tendency to drop out of consciousness. A loss in one's ability to examine and evaluate is a consequence of the transition from the "alert" stage to the "drift-off" stage.

The reduction is significant. There are signs of tiredness in both the motor function of the brain, which reduces the capacity to adapt to new information, and the visual activity of the eyes, which reduces the threshold of perception. Both of these functions show signs of sleepiness. Slower response times, less attentiveness, and deficiencies in information processing are some of the key variables that contribute to driving impairments that are induced by fatigue. In the United States, the National Highway Traffic Safety Administration (NHTSA) estimates that tiredness among drivers is responsible for over 100,000 accidents that are reported to the authorities each year. According to an initial estimate, the indirect repercussions of this incident include around 1,650 fatalities, 73,000 injuries, and a loss of economic value of approximately $13.5 billion.

A key factor in around 35–45 percent of all automobile collisions is the presence of weariness among drivers. It is possible that being idle and relaxing might help reduce exhaustion; yet, these activities can make sleepiness worse. It has been shown via recent research that accidents that are attributed to exhaustion are responsible for around 1,200 fatalities and 76,000 injuries each year. One of the most significant challenges that the area of accident-avoidance systems faces is the creation of technology that can detect and alleviate the effects of driver weariness.There have been a great number of research investigations carried out on the topic of driver fatigue. If a motorist experiences drowsiness while behind the wheel, the following potential outcomes may take place:

There is an increase in the amount of time it takes to respond to situations, which may lead to longer delays.When driving a car, especially when going at high speeds, the probability of being involved in a collision is drastically increased.

. A decrease in attentiveness, which is defined by a lack of responsiveness or delayed response when fatigue hinders the capacity to focus on activities being performed. The insufficient transmission of information, which may put the precision and accuracy of decision-making at risk when it is made.

Drowsiness or fatigue while driving can be caused by a number of factors, including not getting enough sleep, driving for long periods of time, drinking alcohol, taking sedative medication, and certain driving habits, such as driving late at night, early in the morning, in the middle of the afternoon, and especially in a driving environment that is repetitive. To a large extent, it is also dependent on the modifications that are made to the driver's capacity to execute. Previous research has suggested a wide variety of approaches to identifying signs of fatigue. The two unique groups that they may be placed into are the primary and secondary categories. In the first method, the emphasis is on the physiological changes that occur as a result of weariness. These changes include the driver's head tilting to the side, relaxed posture, and decreased grip on the steering wheel.

It is possible to directly detect the motions of the driver's body with the use of sensors or video cameras. One of the benefits of these procedures is that they do not result in any discomfort for the driver, and they furthermore give a diagnosis of weariness without the need for any physical contact. As a consequence of this, the driver is very likely to accept the utilization of these methods in order to assess tiredness. On the other hand, it is important to keep in mind that these standards could change based on the kind of vehicle and the circumstances under which it is being driven.

circumstance. The second method focuses on analyzing the physiological changes that occur in drivers. This includes the measurement of the drivers' heart rate, skin conductance, eye movement data, and electroencephalogram (EEG) activity. Many studies have shown that.There are two metrics that are greatly impacted by tiredness, and those are the length of eye blinks and the frequency of eye blinks. Through the use of a more condensed moving-averaged window, the EEG-based technique has the potential to monitor real-time changes in the subject's performance in a visual compensatory situation. In order to determine alertness, this is based on a comparison of techniques that are based on ocular activity and those that are based on EEG.

II LITERARURE SURVEY

As a result of the tremendous advancements that have been made in Brain-Computer Interface (BCI) technology, researchers are working hard to find ways to improve the effectiveness of the many BCI techniques that are now being used. The following is a condensed summary of a handful of the strategies that were used.

Several different biopotentials were evaluated with the use of a Brain-Computer Interface (BCI), which was also utilized to measure degrees of weariness and drowsiness. In the year 2003, Xiaorong Gao and his colleagues developed an environmental controller that is based on steady-state visual evoked potential and is intended for those who have restricted mobility. A trainable infrared remote controller, a digital signal processor, and a stimulator are the components that make up the system. Among its remarkable characteristics are the minimal training requirements, the rapid information transmission rates, and the capability to successfully record signals without causing any interference.

Based on the findings of the tests, it was discovered that this system is capable of achieving a transmission rate of up to 68 bytes per minute and is able to discern between a minimum of 48 targets. In order to make the process of routing electrical equipment more efficient, an effective system has been brought into place.

The authors Qiang Ji et al. (2004) developed a probabilistic model for human fatigue, in which they also produced predictions regarding weariness by using visual data. A far more robust and precise definition of exhaustion was achieved by the use of a multitude of visual cues and the careful organization of those clues, without depending on any one particular indication. The system was comprised of a hardware system that was capable of capturing real-time video pictures of the driver, as well as a variety of software and hardware implementations for computer vision algorithms. Real-time eye tracking, calculation of eyelid movement parameters, estimate of eye-gaze, determination of face position, and analysis of facial expressions were all accomplished with the help of these algorithms. For the purpose of integrating all visual signals together with pertinent contextual information into a cohesive and representational structure, a Bayesian Network (BN) model is developed. Using real-time exhaustion circumstances, the suggested method was verified on human volunteers who came from a variety of different ethnic backgrounds.

Among the elements that might potentially influence the look are the individual's gender, age, the lighting circumstances, and whether or not they are wearing eyeglasses. The technique for validation was broken down into two distinct phases. In the first case, the precision of the methods used for computer vision was shown to exceed expectations.

The precision of the fatigue measures that are used to assess exhaustion is the second aim that has to be accomplished today. A high degree of resilience, accuracy, and dependability was established by the probabilistic model in the process of characterisation of fatigue. The authors Chin-Teng Lin et al. (2005) proposed a technique for evaluating the mental state of a driver by using electroencephalogram (EEG) in conjunction with Independent Component Analysis (ICA), power-spectrum analysis, correlation assessments, and a linear regression model. The use of a virtual reality (VR)-based dynamic simulator was the primary motivation for the development of this approach. When performing the lane-keeping driving task, the amount of driving error is measured by the differences between the midpoint of the vehicle and the midpoint of the lane that is specified for the vehicle.

Through the use of ICA-based multi-stream EEG spectra, the findings of the experiment give proof that it is possible to quantitatively determine the amount of weariness. When applied to the power spectrum of ICA components, the ICA-based approach that was suggested was shown to have the capability to carry out the following tasks: After removing the majority of EEG artifacts, the ideal configuration for placing EEG electrodes was proposed, and the deviation of the driver's alertness to tiredness was identified based on the driving performance measure. All of these things were accomplished. The average accuracy of estimating inside a session for five participants was found to be 86.2%, while the average accuracy of estimating across sessions was found to be 88.2%. These findings were derived via comparative research and testing. The ICA component-based evaluations of alertness have an accuracy that is equivalent to that of scalp-EEG-based assessments, despite the fact that they seem to be not quite as accurate. The reason for this is because the ICA training that was made use of in this particular instance does not need the acquisition of additional EEG channel data. Between the years 2007 and 2008, Azim Eskandarian and Ali Mortazavi presented a discrete approach for detecting tiredness. Through the provision of timely alerts or warnings, this technology has the ability to prevent mishaps that might have catastrophic consequences.

Offering support to the drivers of the vehicles. During the course of the research, an investigation was carried out to investigate the experimental experiences that drivers had when feeling fatigue in a truck driving simulator. Additionally, it evaluated the effectiveness of an algorithm that was based on neural networks.

III WPT-BASED FEATURE EXTRACTION USING BOOTSTRAP OPTIMIZATION AND NN CLASSIFIER

The purpose of the technique is to construct an automated tool that makes use of the EEG database that is accessible for download on the internet in order to discern between the two states of consciousness, which are referred to as "alert" and "deviation from alert."

To develop the crucial frequency band characteristics that demonstrate a substantial relationship with alertness and the various degrees of exhaustion, the Wavelet Packet Transform is specially used. This is done in order to generate the characteristics. The capability of WPT to efficiently handle unplanned fluctuations, surges, patterns, and deviations, as well as the non-constant or transient properties of various signals, is the primary justification for the use of this technique. As part of this study, the Daubechies Wavelet Transform (DaWT), which is an ideal Discrete Wavelet Transform (DWT), is chosen and used in order to automatically find the frequency components that are most suited for evaluating the features of sleepiness and alertness. Only a limited characterisation of the states of sleepiness, such as alertness and drowsiness, has been offered by the approaches that are now in use. Furthermore, some algorithms tend to have a high degree of categorization accuracy. However, due to the fact that these systems are dependent on the capture of pictures that are able to adapt to changing environmental circumstances, there may be a significant disparity between the actual and predicted warning states. It is essential to make use of an appropriate method that is capable of recognizing different levels of drowsiness in order to achieve a high level of accuracy when categorizing exhaustion. The Daubechies Wavelet Transform (DaWT), which is based on the WPT, makes it possible to determine the frequency of the signal and to divide the signal frequency range in a uniform manner. Due to the fact that DaWT is only a particular implementation of WPT, the differences and similarities between DaWT and WPT are equivalent in this instance.In particular, the Daubechies1 Wavelet Transform (Da1WT), which is the same sort of wavelet transform that was used in this work, is the subject of primary attention in this investigation. The Daubechies 1 Wavelet Transform, often known as the Da1WT, is used due to its ability to perform the function of a low pass filter in an effective manner, hence successfully decreasing noise and reconstructing signals for low frequency signals.

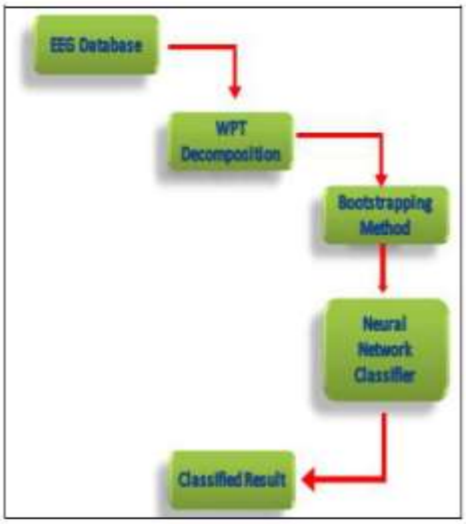

Figure 1: Block diagram of the proposed WPTBNN methodology

A. *Feature Extraction Using Wavelet Packet Transform*

The formation of biomedical signals often involves the combination of components that are low-frequency and long-lasting, and that are closely spaced in frequency, with components that are high-frequency and transitory, and these components are tightly separated in time. In theory, wavelets are thought to

since of their limited capacity to precisely measure time and their strong ability to accurately measure frequency, these signals are suitable for assessment since they have both of these capabilities. In other words, after they have identified the low-frequency components of the signal, they are able to detect the high-frequency components of the signal. By doing more research into the connection that exists between wavelets and multi-resolution approximations, Coifmanetal came up with the wavelet-packet transform, which is often referred to as WPT. Through the use of WPT, we are able to develop characteristics that exhibit a significant link with alertness as well as the various degrees of deviation from the typical level of alertness. Mathematician Ingrid Daubechies, who was born in Belgium, is credited with developing the Wavelet Packet Transform in the year 1988. A technique that is developed from the Wavelet Packet Transform (WPT) is known as the Discrete Wavelet Transform (DWT). In order to do this, recurrence relations are used in conjunction with discrete samples of a mother wavelet function that are more exact. In addition, the resolution has been raised by a factor of two in comparison to the scale that was previously used

A visual representation of the processes involved in signal processing is shown in Figure 2.1. The initial step in the process is to gather the necessary information for the construction of the model. As a consequence of this, a database is created in order to record EEG signals that are associated with sleep, and a raw EEG signal is produced specifically for the specific database. In order to get the properties of the frequency band, the signal must first be segmented into individual samples. The basic goal of feature extraction is to perform an effective representation of a large quantity of data while using a limited number of resources. As a result of the extensive size of the EEG database, it is quite probable that a significant number of variables will be included. As a consequence of this, it will be necessary to conduct a thorough investigation that calls for a significant amount of memory and significant amounts of computer capacity. As a result, feature extraction is an essential step in the process of doing additional database analysis. It is essential to carry out feature extraction and feature selection in order to achieve a high degree of accuracy in identifying weariness and accurately measuring the amount of attention shown by the driver. The Daubechies Wavelet packet Transform (DaWT) is the method that shows the most potential for success when it comes to extracting the appropriate properties from the database that is provided. This approach, which is developed from discrete wavelet transform (DWT), recovers the frequency time of the signals and splits the frequency range of the signal in an equal manner. One way in which Da1WT and WPT are comparable is because Da1WT is only the particular implementation of WPT, which is the requirement that is absolutely necessary.

IV **FRFT-BASED FEATURE EXTRACTION USING NN CLASSIFIER**

Figure 2 depicts the process that is described in more detail in the way that is suggested. The initial stage is to carry out the process of acquiring EEG data. Following this, the next stage requires the use of FRFT in order to generate FRFT coefficients for the end goal. Additional signal processing is used in order to drastically lessen the amount of noise and to function as a filter with several resolutions. The frequency band characteristics that have been created are now prepared for categorization after their generation. In this approach, the neural network classifier that is employed is the same as the one that was utilized in the technique that came before it; however, it accumulates information via the utilization of the Back Propagation (BP) Learning Algorithm.

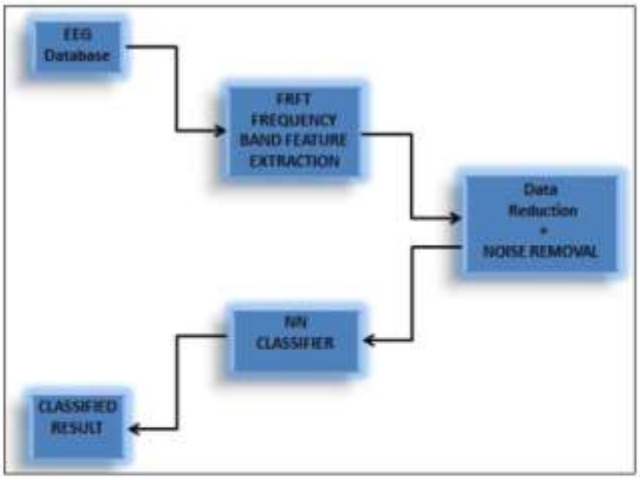

Figure 2 : Block diagram of the proposed FRFTNN methodology

A. Preprocessed Signal

To get started, the first thing that needs to be done is to take a raw EEG signal from the directory that is being investigated.

The initial, unprocessed condition of EEG signals is the state in which they are created or received, and subsequently they are subjected to preprocessing.

This analysis of the signal is shown in Figure 3. The samples are taken at a frequency of 256 hertz.

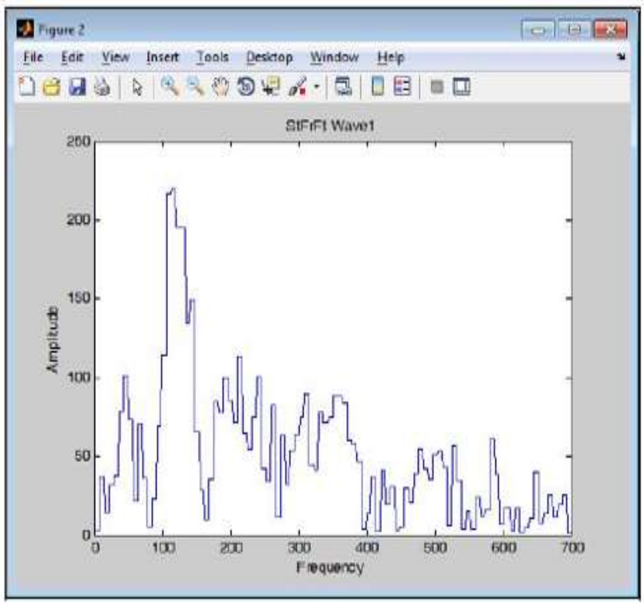

Figure 3 : FRFT Decomposed signal- FRFTNN methodology

B. Classified Results

Figure 4: Classified results- FRFTNN methodology

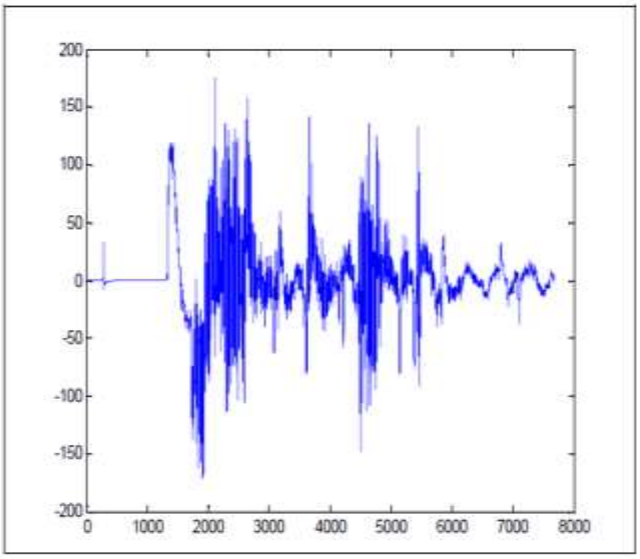

Figure 5 : A sample alert signal – FRFTNN methodology

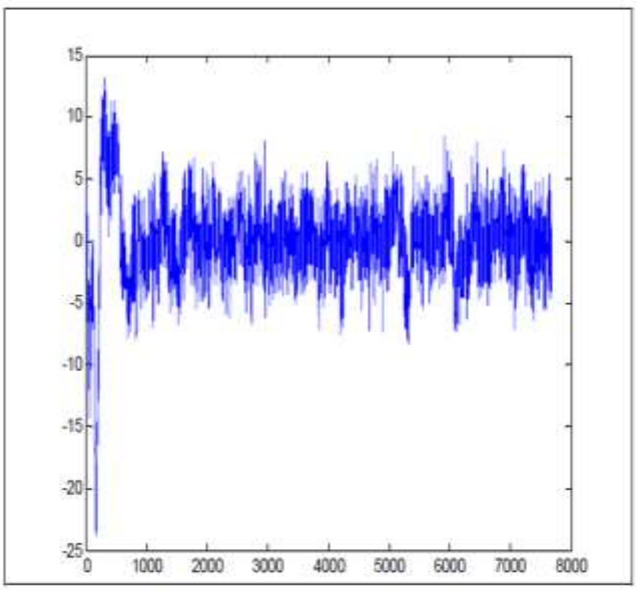

Figure 6 : A sample drowsy signal – FRFTNN methodology

IV CONCLUSION

The huge number of automotive accidents that occur each year is significantly influenced by drowsiness, which is a key contributing factor. The cognitive state of the driver should thus be monitored on a constant basis in order to drastically minimize the number of accidents.

There is a strong connection between the occurrence of the EEG signal and the degree of awareness that a person has. An increase in dominant frequency is seen in the electroencephalogram (EEG) in conjunction with a drop in amplitude when activity levels rise. An increase in alpha wave activity may be seen on the electroencephalogram (EEG) while the eyes are closed. There is a drop in the main EEG frequency that occurs as you fall asleep. Individuals are able to have dreams and display active eye movements while they are in a certain stage of sleep known as rapid eye movement (REM) sleep. There is a distinct EEG signal that may be used to identify this stage. The electroencephalogram (EEG) exhibits considerable and progressive deflections known as delta waves when the subject is in a profound sleep state. The absence of any discernible cerebral activity is the hallmark of a patient who has experienced full brain death.

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REFERENCES

1. Ahmet Ozkis & Ahmet Babalik 2013, ‘Accelerated ABC (A-ABC) Algorithm for Continuous Optimization Problems’, Lecture Notes onSoftware Engineering, vol. 1, no. 3, pp. 262-266.
2. Alper Kutay, M, Haldun M Ozaktas, Orhan Ar⍰kan & Levent Onural 1997, ‘Optimal Filtering in Fractional Fourier Domains’, IEEE ransactions On Signal Processing, vol. 45, no. 5, pp. 1129-1143.
3. Artem A Lenskiy & Jong-Soo Lee 2012, ‘Driver’s Eye Blinking Detection Using Novel Color and Texture Segmentation Algorithms’,International Journal of Control, Automation, and Systems, vol. 10,no. 2, pp. 317-327.
4. Ashok Narayanana, V & Prabhu, MM 2003, ‘The Fractional Fourier transform: Theory, Implementation and Error analysis’, Elsevier,Microprocessors and Microsystems, vol. 27, pp. 511–521.
5. Ayumi Tsuchida, Shoaib Bhuiyan, Md & Koji Oguri 2009, ‘Estimation of Drowsiness LevelBased on Eyelid Closure and Heart Rate Variability’, 31st Annual International Conference of the IEEE EMBS,pp. 2543-2546.
6. Azim Eskandarian & Ali Mortazavi 2007, ‘Evaluation of a Smart Algorithm for Commercial Vehicle Driver Drowsiness Detection’,Proceedings of the IEEE Intelligent Vehicles Symposium, pp. 553-559.
7. Balaji Krishnapuram, Lawrence Carin, Fellow, Ma´ rio A.T.Figueiredo & Alexander J Hartemink 2005, ‘Sparse Multinomial Logistic Regression: Fast Algorithms and Generalization Bounds’,IEEE Transactions On Pattern Analysis And Machine Intelligence,vol. 27, no. 6, pp. 957-968.
8. R Chai et al.,2017Improving EEG-Based Driver Fatigue

ISSN: 2582-1431 (Online), Volume-6 Issue-2, June 2024
Classification Using Sparse-Deep Belief Networks, , Front Neuroscience, Vol11,pp.103.
9. Bernard Ng & Rafeef Abugharbieh 2011 , 'Generalized Group Sparse Classifiers with Application in fMRI Brain Decoding', The University of British Columbia,2366 Main Mall, Vancouver, BC, V6T 1Z4.
10. Bernard Ng, Viviana Siless, Gael Varoquaux & Rafeef Abugharbieh 2012, 'Connectivity-informed Sparse Classifiers for fMRI Brain Decoding', Pattern Recognition in Neuroimaging.
11. Chin-Teng Lin , Li-Wei Ko, I-Fang Chung, Teng-Yi Huang, Yu-Chieh Chen, Tzyy-Ping Jung & Sheng-Fu Liang 2006, 'Adaptive EEG-Based Alertness Estimation System by Using ICA-Based Fuzzy Neural Networks', IEEE Transactions On Circuits And Systems - I: Regular Papers, vol. 53, no. 11, pp. 2469-2476.
12. Chin-Teng Lin, Ruei-Cheng Wu, Sheng-Fu Liang, Wen-Hung Chao,Yu-Jie Chen & Tzyy-Ping Jung 2005, 'EEG-Based Drowsiness Estimation for Safety Driving Using Independent Component Analysis', IEEE Transactions On Circuits And Systems-I: Regular Papers, vol. 52, no. 12, pp. 2726-2738.