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Efficient Classification Techniques for Predicting Eeg Level

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ABSTRACT: In today's busy and complex society driving is an important activity, and it requires physical and mental abilities, collectively known as driving workload. For safe and comfortable driving, it is useful to detect when drivers are overloading. Analysing the driver workload using an electroencephalograph (EEG) is useful for this purpose. However, obtaining an EEG during actual driving can be very inconvenient because the measuring device must be attached to the driver. In this paper, we will develop a model to assess a driver's EEG level using basic information obtained while driving a vehicle. We have divided the EEG values into two classes, "normal" and "overload" and collected useful features from vehicle driving information such as engine RPM, vehicle speed, lane changes and turns. The classification model was constructed using a support vector machine to estimate normal and overload conditions during actual driving. We examine the performance of the proposed method using field-off-test data collected while driving on actual roads and suggest directions for future research based on the analysis of experimental results.

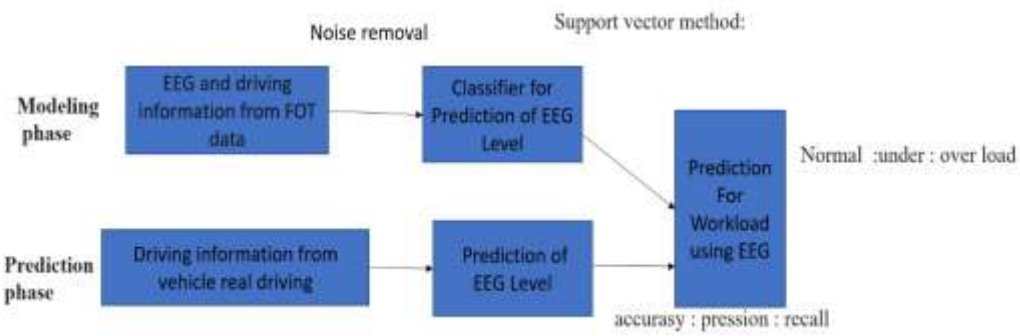
Keywords: workload, driver behaviour, driver workload, electroencephalograph, support vector machine.

I. INTRODUCTION:

Driving has become an important activity in today's busy and complex society. People use cars to travel and manage their personal affairs on a daily basis. Driving a car is a dynamic and complex activity involving visual, cognitive and manual tasks. Driving work requires physical and mental workload, collectively known as driving workload. In general, the term "workload" refers to the load of an operator required to perform a specific task. However, even when doing the same work, the actual workload may vary depending on the characteristics of the driver and the road environment and They showed that optimal function performance occurs at intermediate levels of physical or mental stimulation, which leads to relatively poor performance, Driver workload levels can be classified as underload, normal and overload states, reflecting the load on the driver. Drivers who drive for a long time on a normal road with less traffic usually fall into an overloaded state, which is characterized by boredom and monotony. If they are talking on the phone or listening to the radio in an environment where traffic conditions are constantly changing, they may enter an overload situation that exceeds their limits. Recent studies measure the accuracy of lane keeping and speed control, driving performance in a variety of ways traffic violations and response time to pop-up events. Relationship between driving workload. The green line indicates the ability to do driving work and the red line indicates the need for ADAS. driving performance is highest in normal condition and performance is degraded in underload or overload state. In our previous study we developed a technology that blocks incoming smartphone calls or text messages when the driver is overloaded, and then informs the driver of the blocked information when the driver returns to the steady state.The driver's mental workload can be measured by self-report, performance measurement or physical measurement. Detailed driving information such as minute revolutions (RPM) of the automobile engine, vehicle speed, wheel angle, indicators, intersection turns and curves can be obtained based on navigation and on-board diagnostics (OBD-II). Vehicle data collection equipment. To assess physical conditions.

II. BLOCKDIAGRAM:

➢ **Modelling and prediction process.**



Electroencephalography (EEG), a representative measurement technique, can be used to capture brain activity that reflects a person's dynamic mood. Current studies have concluded that EEG is an effective way to estimate and classify workload obtaining an EEG can be very inconvenient when the driver is engaged in driving, as the measuring device must be attached to the active driver.

In this study, we developed a model to assess a driver's EEG level using specific driving and behaviiural information obtained from a vehicle while driving. Using the EEG data and driving information collected while driving on a real road, a taxonomic model was trained to learn the relationship between driving conditions and EEG values.A trained classification model was used to assess whether the driver had a low or high EEG based on driving information. Fig. 2 describes the modelling and prediction process in our system. The section beyond the dotted line, which refers to the context in which workload is estimated using an EEG, is developed as future work.Driving We have proposed a method for estimating the EEG level of an active driver using driving and behaviour information. Using this model, the driver's EEG level can be estimated without direct measurement. As far as we know, this is the first paper to use the classification method to determine the driver's EEG level.Driving We used Field of Test (FOT) data collected in the actual driving environment rather than the data collected in the simulator environment.I have defined three effective feature groups that significantly affect a driver's EEG level assessment: driving information, information about changing driving conditions, and driving behaviour information. In addition, using video analysis, other factors affecting high-level EEG conditions were explored.This paper is organized as follows. In the relevant works are reviewed and describes the characteristics of the data used in this paper, including driving information and EEG measurements collected from FOT data. I propose a method for assessing a driver's EEG levels based on driving information analyse the factors that affect the expected performance

Review of related studies: Much research has been done to measure and calculate a driver's condition, including workload, stress, fatigue, and drowsiness, based on physical signals obtained from the driver. Physical data such as EEG, electrocardiogram (ECG) and electromyogram (EMG) were used separately or in combination. Table I summarizes some recent studies on driver status analysis using various physiological data. Some research [12] - [15] analyzed workload using EEG data. Lee et al. [12] Presented a study indicating mental workload using EEG data. The researchers analysed the workload by comparing diffusion changes in the EEG. In another study [13], the authors performed a combined T-test on EEG data generated during straight and left turn driving and showed that EEG activity was higher on the left turn than on direct driving. In [14], the cognitive characteristics of the driving workload caused by drivers' behaviour were analysed. Five types of driving behaviours are classified into categories: left and right turn, rapid acceleration and deceleration and lane change sections. For each of these driving behaviours, the driving section and the reference section are defined using driving information and GPS data. Using statistical analysis of EEG variation rates, EEG values were found during this timeThe periods of the driving behaviour sections are longer than the reference sections. In other research [15], task load levels and task memory levels were altered at both angles of work memory load. They compared changes in EEG power when doing lane change and N-back tasks simultaneously.

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Test vehicle and data configuration:

Cognitive workload depends on the driver's characteristics and driving conditions. When analysing cognitive workload, it is more effective to use the collected data while driving on the actual road instead of the simulated environment. In this study, we used Driver-Vehicle Interaction (DVI) DB based on FOT data which was collected once per second while traveling on the actual road.

Data Composition

Data	Description
Time	Speed
SAS_Angle	Steering wheel
SAS_speed	Steering Wheel speed
RPM(Revolution per Minute)	Engine speed
Speed	Vehicle speed (km/h)
Break _Act	Break operation
EEG	Brain wave information
Turn signal LH and RH	Left turn & right turn signal

TRAINING SET:

Driving info

Detail Features	Meaning
Wheel angle	Steering wheel angle
Wheel speed	Steering wheel speed
RPM 200 intervals (<1000 to 1400)	Engine speed
Speed (km/h 10 – 30)	Vehicle speed

Driving conditions

Detail Features	Meaning
Diff- angle	Difference in the Steering wheel angle one second intervals
Diff -RPM	Difference in the RPM atone second intervals
Diff-Speed	Difference in the Vehicle speed one second intervals

Driver driving behaviour

Detail Features	Meaning
Straight	Run straight(true/false) (1-0)
ACC-Diff	Increment in the speed of more than 4km/h during 1 second
Diff-Diff	Decrement in the speed of more than 4km/h during 1 second
curve	Right curve turn(t/f)

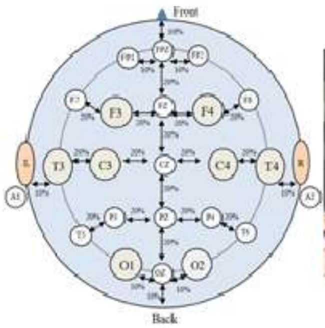
EEG(electroencephalogram)

The EEG is a recording of electrical activity on the scal. The EEG measures the voltage fluctuations in which ionic current flows through neurons in the brain. The potential variation of EEG data is very small, ranging from one V to hundreds of V. These signals usually appear constant to the same person, although the difference in frequency frequency of the primary wave depends on the individual's physical and mental state . EEG signals are very important indicators to measure the activity of the brain, and as indicated in Table IV, each signal looks different depending on the physical and mental state of the person measuring it. EEG signals are classified into five types, ranging from the slowest vibrating part to the fastest oscillating part. For example, "arousal" is a term used to describe a state of physical and mental awakening or perception of the senses.

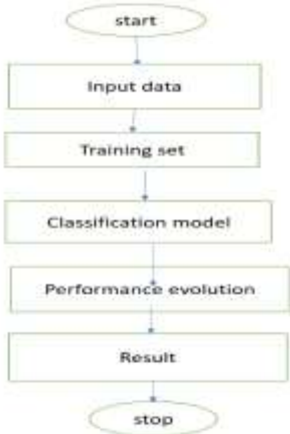
Band	Frequency	Characteristics
Delta	0.2 TO 3.99 Hz	Sleep
Theta	4 To 7.99 Hz	Drowsiness
Alpha	8 To 12.99 Hz	Relaxed
Beta	13 To 30 Hz	Active ,Busy
Gamma	40 To 100+ Hz	Arousal and excited state

. EEG bands and characteristics

EEG data were obtained using the non-invasive method by attaching EEG electrodes to the scalp. It is necessary first to spread the gel, which is a good conductor of electricity, well on the scalp, and then attach the electrodes in specific positions. The fine electrical capacity is amplified and recorded. The EEG was measured using the International 10-20 system, and the brain signal data of the test participants were collected from a total of eight channels: two frontal lobes (F3 / F4), two temporal lobes (T3 / T4), two parietal lobes (C3 / C4) and Two on occipital lobes (O1 / O2) (Fig. 3). The EEG measurement device is a poly G-I model sample of brain wave signals is set at 250 Hz.Information about the preprocessing of EEG data, such as sampling and frequency analysis, can be found in detail [13]. When collecting FOT data in a real driving environment, the frequency range of thegama waves overlaps the secondary vibration characteristics of the vehicle engine. It is the largest excitation source in the vehicle, and it produces



Flow chart:



A. Experimental approach

We designed the following experiment to evaluate the performance capabilities of taxonomic models constructed with different combinations of feature groups described training and test data are not duplicated to obtain reliable performance evaluation results. We used the leave-one-out cross-certification Leave-one-out cross-certification is just n-fold cross-certification, where n is the number of examples in the dataset. Each instance is gradually dropped and in all other cases the learning plan is trained. We created a classification model using a training set with data from 27 drivers, and then evaluated the performance of the classification model using data from the remaining one driver as a test set. We performed this procedure 28 times so that each driver data was used only once in the performance evaluation. The final performance measurement is calculated by integrating the performance results. The problem of class size imbalance between overload and normal classes arises because by definition the overload status is defined by the first 20% of each driver's EEG values. To solve this problem, we used an under-sampling strategy Since 80% of the data is in the general class and 20% in the overload class, we randomly collected one-fourth of the data samples from the normal state class so that the size of the general and overload classes in the training set is equal.To find out what kind of symptoms affect EEG levels the most, we did three types of experiments using the feature groups. The first classification model was trained only on the basis of the characteristics of group A, the second was trained using the characteristics of group A and B groups, and the third classification was formed from all the characteristics of groups A, B and C. This was done to find out which feature group is best in relation to the classification model performance.

SVM classification model:

Learning the taxonomic model is carried out with a training set consisting of data samples known to class labels. Once the model is built, it is applied to a test set to evaluate its performance. The class labels of the datasamps in the test set are evaluated and compared with the actual class labels.

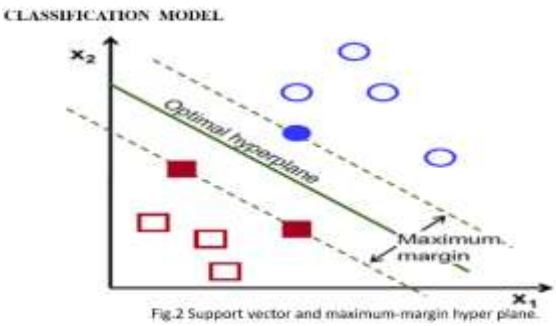


Fig.2 Support vector and maximum-margin hyper plane.

$D = \{(x_i, y_i) | x_i \in RP, y_i \in (-1,1)\}n \;\; i=1$

$$\min \frac{1}{2}\|W\|^2$$

We used the Support Vector Machine (SVM), which is known to be superior in performance and training speed invarious classification models. SVM is successfully applied using the soft margin and kernel method across different application areas. In the experiments presented in Chapter 5, we used the linear SVM classification

Metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

$$\text{Precision } (P) = \frac{TP}{TP + FP}$$

$$\text{Recall } (R) = \frac{TP}{TP + FN}$$

- True positive (TP) : Number of samples predicated to be positive when belongs to passive class
- False positive (FP) : Number of samples predicated to be positive when belongs to are negative class
- True negative (TN) : TN and FN are defined similarly
- False negative (FN) : TN and FN are defined similarly

Estimated results

When data from each of Compares 10 accuracy and F1 values shows the accuracy display F1 values when the normal class is set to a positive class and the overload class to a positive class. Accuracy is higher when using attributes than when using only the attributes. Each time we added a feature group, the expected accuracy for most drivers increased. when the normal class is set to a positive class, the F1 values are higher when there are more features in the classification model. In contrast, the F1 value is highest properties when the overload group is a positive class. It makes average estimated results for all test drivers. This shows that it is very difficult to estimate the overload status compared to the normal state.

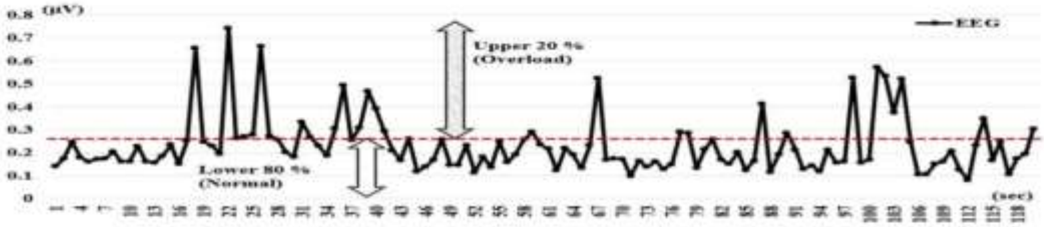
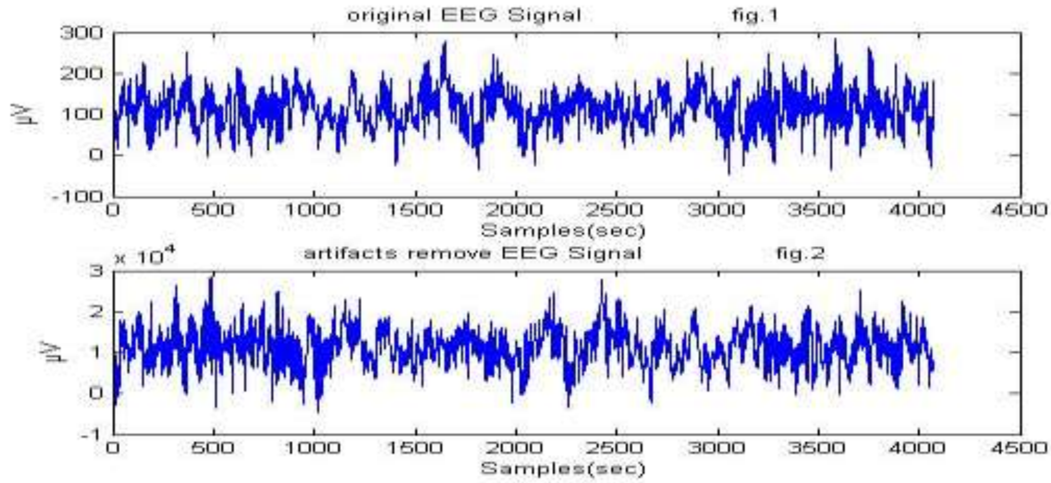
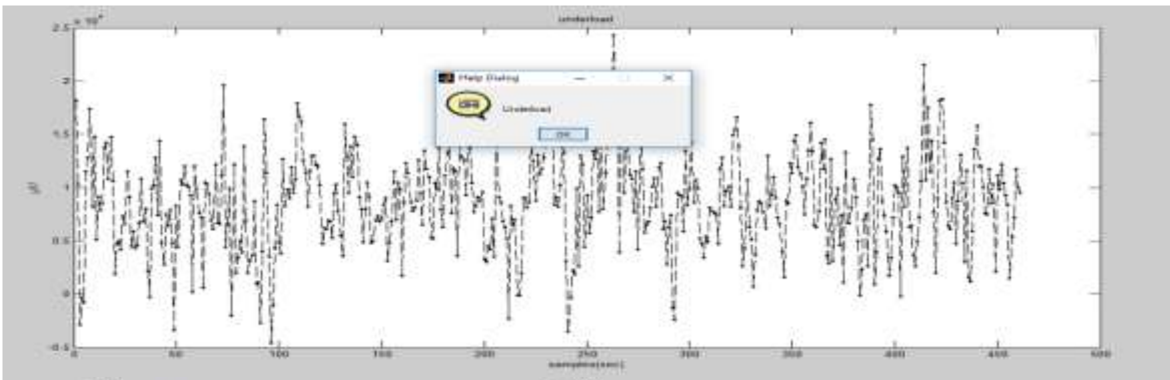
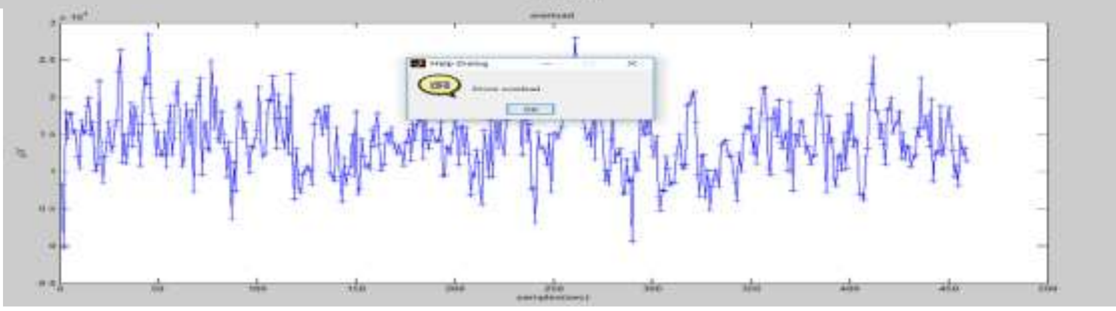


Fig.3 Driver EEG levels normal and overload



consider the driver driving conditions and EEG levels to predict the driver workload in given results driver normal load graph and driver over load graph and driver fully over load on based the svm classification method to calculate the accuracy value and precision value, recall values and f1 value to predict the driver workload





Bellow the table represent FOT database based driver condition DN(driver normal load) data ,DO(driver overload) , DF(driver fully overload)

TABLE CONFUSION MATRIX				
S.No	ACCURACY	PRECISION	RECALL	F MESURE
DN	90.61	1	0.110	0.0218
DO	91.40	1	0.0109	0.0216
DF	94.84	1	0.0150	0.0209

III. CONCLUSION :

Efficient classification technique for predicting EEG level based on FOT datathis EEG data generate driver workload and it contain normal load and over load peaks are appear on driver conditions is displayed.This data is used to major implementations for road safety and one of the complementary methods for road accidents prevention.It is very useful to prediction of driver condition and safe driving

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