r-Principal Subspace for Driver Cognitive State Classification

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***Abstract*— Using EEG signals, a novel technique for driver cognitive state assessment is presented, analyzed and experimentally verified. The proposed technique depends on the singular value decomposition (SVD) in finding the distributed energy of the EEG data matrix *A* in the direction of the *r*-principal subspace. This distribution is unique and sensitive to the changes in the cognitive state of the driver due to external stimuli, so it is used as a set of features for classification. The proposed technique is tested with 42 subjects using 128 EEG channels and the results show significant improvements in terms of accuracy, specificity, sensitivity, and false detection in comparison to other recently proposed techniques.**

I. INTRODUCTION

DRIVER distraction is one of the main causes of vehicles accidents [1],[2]. Many traffic safety organizations have reported that driver cognitive state is responsible of approximately 40% of car crashes and near crashes. Various measures are used to assess driver's cognitive distraction, among them driver biological measures, driver physical measures and driving performance measures. In this study we focus on the electroencephalogram (EEG) signals for the assessment of driver cognitive distraction.

Schier investigated the suitability of the EEG acquired signals in indicating driver cognitive state by measuring the activities in the alpha frequency band (8–13 Hz) during driving and driving-reply sessions [3]. Scheir found that Alpha band is the most dominant band to study attention and since attention is inversely proportional to the cognitive load, the dynamic changes in Alpha band can be used as index of driver cognitive distraction.

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In addition to alpha index, it is widely accepted in EEG studies of cognitive distraction that theta (4–8 Hz) and beta (14–35 Hz) bands are also good indicators of cognitive load [4], [5]. Theta and beta activities in brain frontal lobes are associated with cognitive processes such as judgment, problem solving, working memory, decision making, and mathematical problem solving [5]. The increasing amplitudes of these particular bands are often a result of brain engagement in such activities.

During the last decade many methods were proposed to detect driver cognitive distraction using EEG data. In [5], Lin *et. al* proposed to use the independent component analysis (ICA) to extract the power changes from frontal and motor cortex, then to use a self-organized map to investigate the presence of distraction in the EEG epochs. In [4], Lin *et. al* proposed to use EEG power spectra to capture the time-frequency brain dynamics then to use the ICA to divide the EEG raw data into dependent brain sources.

In this paper a novel technique for the assessment of driver cognitive distraction is proposed. The technique is based on the singular value decomposition (SVD) of the $A_{(m\times n)}$ EEG data matrix in finding the distributed energy into the r-principal subspace through the r largest singular values. This set of singular values is used with the support vector machine (SVM) classifier to assess the cognitive sate of the driver.

For clarity, an attempt has been made to adhere to a standard notational convention. Lower case **boldface** characters will generally refer to vectors. Upper case **BOLDFACE** characters will generally refer to matrices. Vector or matrix transposition will be denoted using $(.)^T$. $\mathbb{R}^n$ denotes the real vector space of n dimensions.

II. THE R-PRINCIPAL SUBSPACE TECHNIQUE

A. The r-Principal Subspace the Maximal Oriented Energy

Let $\boldsymbol{A} \in \mathbb{R}^{m\times n}$ and denote its n column vectors as $\boldsymbol{a}_k$, $k = 1, 2, \ldots, n$. The energy E_Q measured in a subspace $Q \subset \mathbb{R}^m$, is defined as:

$$E_Q[\boldsymbol{A}] = \sum_{k=1}^{n} \left\| P_Q(\boldsymbol{a}_k) \right\|^2 \quad (1)$$

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where $P_Q(\boldsymbol{a}_k)$ denotes the orthogonal projection of $\boldsymbol{a}_k$ into the subspace Q and $\|.\|$ denotes the Euclidean norm.
The singular value decomposition (SVD) of real matrices is based upon the following theorem [10], [11]:

Theorem 1. For any real $m \times n$ matrix $\boldsymbol{A}$, there exists a real factorization:

$$\boldsymbol{A} = \underset{m\times m}{\boldsymbol{U}} \times \underset{m\times n}{\boldsymbol{S}} \times \underset{n\times n}{\boldsymbol{V}^{T}} \tag{2}$$

in which the matrices $\boldsymbol{U}$ and $\boldsymbol{V}$ are real orthonormal, and matrix $\boldsymbol{S}$ is real pseudo-diagonal with nonnegative diagonal elements.

The diagonal entries σ_i of $\boldsymbol{S}$ are called the singular values of the matrix $\boldsymbol{A}$ and they are sorted in non-increasing order $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n$. The columns $\boldsymbol{u}_i$ and $\boldsymbol{v}_i$ of $\boldsymbol{U}$ and $\boldsymbol{V}$ are called respectively the left and right singular vectors of matrix $\boldsymbol{A}$. The space $S_U^r = [\boldsymbol{u}_1 \quad \boldsymbol{u}_2 \quad \ldots \quad \boldsymbol{u}_r]$ is called the r-th left principal subspace.

Theorem 2. Consider a sequence of m-vectors $\{\boldsymbol{a}_k\}$, $k = 1, 2, \ldots, n$ and the associated $m \times n$ matrix $\boldsymbol{A}$ with SVD as defined in Eq. (3) with $n \geq m$. Then:

$$E_{\boldsymbol{u}_i}[\boldsymbol{A}] = \sigma_i^2 \tag{3}$$

The oriented energy measured in the direction of the i-th left singular vector of the matrix $\boldsymbol{A}$, is equal to the i-th singular value squared.

With the aid of theorem 2, one can easily obtain, using the SVD, the directions and spaces of extremal energy, as follows [12], [13]:

$$\max_{Q^r \subset \mathbb{R}^m} E_{Q^r}[\boldsymbol{A}] = E_{S_U^r}[\boldsymbol{A}] = \sum_{\boldsymbol{i}=1}^{\boldsymbol{r}} \sigma_{\boldsymbol{i}}^2 \tag{4}$$

$$\min_{Q^r \subset \mathbb{R}^m} E_{Q^r}[\boldsymbol{A}] = E_{\left(S_U^{m-r}\right)^{\perp}}[\boldsymbol{A}] = \sum_{\boldsymbol{i}=\boldsymbol{m}-\boldsymbol{r}+1}^{\boldsymbol{m}} \sigma_{\boldsymbol{i}}^2 \tag{5}$$

where 'max' and 'min' denote operators, maximizing or minimizing overall r-dimensional subspaces Q^r of the space $\mathbb{R}^m$. S_U^r is the r-dimensional principal subspace of matrix $\boldsymbol{A}$ while $\left(S_U^{m-r}\right)^{\perp}$ denotes the r-dimensional orthogonal complement of S_U^{m-r}. Eq. 4 shows that the r-principal subspace S_U^r is, among all r-dimensional subspaces of $\mathbb{R}^m$, the one that senses a maximal oriented energy. Eqs (4) and (5) show that the orthogonal decomposition of the energy via the singular value decomposition is canonical in the sense that it allows subspaces of dimension r to be found where the sequence has minimal and maximal energy.

In the proposed algorithm, we use the distribution of the energy in the directions of the r singular vectors represented by the r-largest singular values, as features for the assessment of driver's cognitive distraction. This will effectively represents the variation in the signals with lower dimensionality subspace.

Having represented the EEG data of driver distraction with the largest r singular values (features), the SVM is used for classification.

III EXPERIMENT DESIGN AND DATA PREPROCESSING

A. Participants

Forty two healthy volunteers aged between 18 and 24 years old participated in the study. The selected participants have normal or corrected-to-normal vision and normal hearing and no history of psychiatric disorders. In addition, the participants have no experience in driving simulators; therefore they are allowed to practice driving in the driving simulator for approximately 10 minutes before the EEG net is mounted. The experimental procedures involving human subjects described in this paper were approved by the Institutional Ethical Committee.

B. Experiment Scenario

As a control session, participants are first instructed to drive for 30 minutes and pay attention to driving rules such as driving below 80 km/h speed, using indicator lights when needed, etc. Next, the participants are instructed to listen carefully to a secondary task administered by the experimenter standing beside while paying attention to the road over a time span of 30 minutes. The secondary task is a mix of logical reasoning in the form of analogies included in the experiment in order to create cognitive distraction among the participants. The two sessions are counter-balanced – half of the participants will start with the control session while the other half will start the driving with distraction session. The experiment scenario is shown in Figure 1-b.

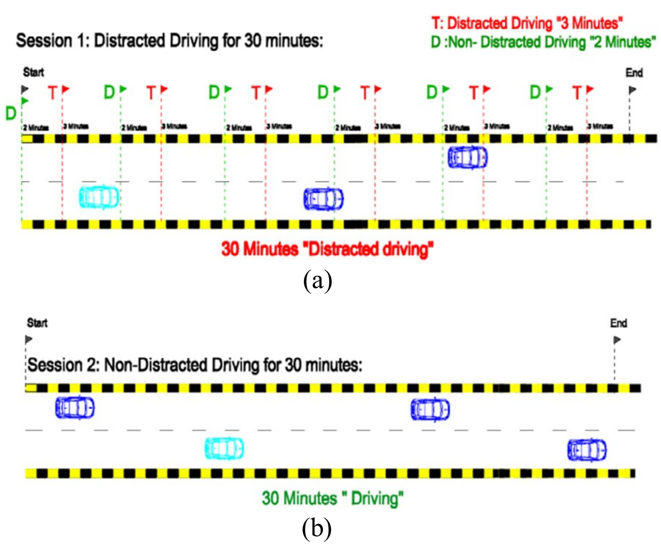

Figure 1. Experiment scenario: (a) 30-minute session of distracted driving (b) 30-minut control session

As illustrated in Figure 1, the distracted driving session is segmented into six intervals of "*attentive*" driving and six intervals of "*distracted*" driving. During this session the participants are asked to answer the questions as accurately as possible.

C. Data Collection

A 128-channel EGI Hydro-Cel GSN electrode net connected to NetStation 4.2 software is used to obtain the EEG signal. The physiological data acquisition employed 128 EEG electrodes with a vertical Cz reference electrode. Before acquisition, the contact impedance between EEG electrodes and the cortex was calibrated to be < 5 kΩ. The EEG data were recorded at a sampling rate of 250 Hz.

The measures of driving performance used in this study are the deviation between the center of the vehicle and the center of the cruising lane, number of accidents, and number of speeding offenses. These measures are used to indirectly quantify the level of the subject's attention. We compare the driving performance between control and distracted driving sessions. When the subject is distracted (as determined based on the subject's driving performance report), car deviation increased, speed awareness decreased, and a higher probability of causing an accident is observed.

D. EEG Data Pre-processing

The data is pre-processed by removing eye movements and high-powered eye blinking. EEG-data is off-line corrected from ocular and muscle artifact using the Gratton method [18]. This method is based on correcting the noisy EEG-data regarding to a pre-defined EOG channel (channel 14 at the upper right eyebrow) then subtracting the original signal from the defined one.

As most cognitive functions involved in making judgments and problem solving occur in the frontal lobe, only the 16 EEG electrodes from the frontal lobe are used for driver distraction analysis [4, 5].

III. RESULTS AND DISCUSSION

In the first experiment, the sensitivity of the singular values of the EEG signals at the 16 electrodes of the frontal lobe to the variations due to distraction is investigated. In this experiment the six segments of each of the 42 subjects are extracted for driving with distraction and driving without distraction. Then the segments are filtered at theta, alpha and beta bands and the six vectors of singular values for each driving scenario are obtained and averaged. The results are shown in Figure 2.

The results in Figure 2-b shows a significant increase in the theta and beta due to the increase in the driver distraction and significant increase in alpha because of the decrease in driver attention during distracted driving.Figure 2 show clearly the sensitivity of the singular values to the amount of distraction.

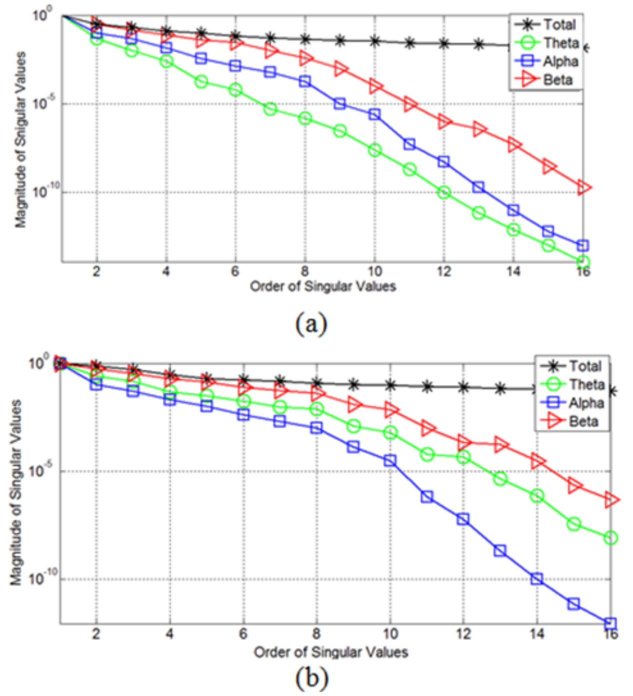

Figure 2Figure 2. The averaged variation in the 16 singular values due to driver distraction; (a) driving without distraction; (b) driving with distraction

In order to find the best value of the dimension of the principal subspace (r) the truncated energy from the EEG signal as a function of r calculated as

$$\text{truncated energy (\%)} = \left(\frac{\sum_{i=r+1}^{16} \sigma_i^2}{\sum_{i=1}^{16} \sigma_i^2} \right) \times 100 \quad (6)$$

is obtained and shown in Table I.

TABLE I.
THE TRUNCATED ENERGY AS A FUNCTION OF r

r	14	12	10	8
truncated energy (%)	0.35	0.79	1.40	2.1

TABLE I shows that the reduction in the dimensionality of the principal subspace from full rank to r = 8 will only affect 2.1% of the total energy of the EEG data matrix at the 16 sensors of the frontal lobe. With this reduced value of the dimension of the principal subspace, we have eight features represent the oriented energy in the directions of the first eight singular vectors and sense 97.90 % of the total energy of the original EEG data matrix $\boldsymbol{A}$.

In the second experiment the capability of the proposed technique in detecting the two different cognitive states of distracted and non-distracted driver, is addressed and compared with the technique in ref. [5]. Where the ICA components were clustered and labeled as good for the good components and bad for the noisy and bad components. After clustering, the total power of each component is calculated and averaged over all subjects for theta, alpha and beta bands.

Both techniques are implemented with the 16 EEG signals at the frontal lobe and the SVM is used as a classifier. The eight largest singular are used for the features of the proposed technique, whereas the total power in theta, alpha and beta bands are used as features for the technique in ref. [5]. With both techniques, the SVM classifier is trained with 40% of the features vectors of the 42 subjects (control) and tested with the rest (case). The results over theta, alpha, and beta bands are shown in TABLE II.

TABLE II
THE PERFORMANCE OF THE PROPOSED TECHNIQUE AND THE TECHNIQUE IN [6] INDICATED IN PERCENTAGE

Band		total	theta	alpha	beta
Accuracy (%)	Proposed	94.5	95.88	93	88.25
	Ref. [5]	75.68	83.33	91	82.13
Sensitivity (%)	Proposed	98.89	97.7	95.92	88.25
	Ref. [5]	71.64	85.45	85.71	82.13
Specificity (%)	Proposed	96.52	95.68	93.75	92.25
	Ref. [5]	82.14	80.85	90.62	68.24
FDR (%)	Proposed	3.48	4.32	6.25	7.75
	Ref. [5]	17.86	19.15	9.38	31.36

The results in TABLE II show clearly the better capability of the proposed algorithm in detecting the driver mental state than the algorithm in [5] over the various bands. In general, the results in TABLE II verify that the proposed algorithm can be implemented with both theta and alpha bands for the detection of the driver mental state without significant difference in performance. On the other hand, the algorithm in [5] shows it is best performance with alpha band and exhibits poor performance with theta.

IV. CONCLUSION

In this paper a set of a predominant features represented by the r singular values of the EEG data matrix are used to assess the mental distraction state of the driver. The SVD is applied on the EEG data segments of driving without and with distraction and the 16 singular values of the frontal lobe signals are obtained. The largest eight singular values are selected as features and used with the SVM classifier to assess the mental state of the driver. The capability of the proposed technique in detecting the cognitive distraction of the driver is tested using data collected from 42 subjects and the results indicate high accuracy, sensitivity, specificity and low FDR value over theta, alpha and beta bands.

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