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Vigilance Detection Based on Sparse Representation of EEG

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Abstract— **Electroencephalogram (EEG) based vigilance detection of those people who engage in long time attention demanding tasks such as monotonous monitoring or driving is a key field in the research of brain-computer interface (BCI). However, robust detection of human vigilance from EEG is very difficult due to the low SNR nature of EEG signals. Recently, compressive sensing and sparse representation become successful tools in the fields of signal reconstruction and machine learning. In this paper, we propose to use the sparse representation of EEG to the vigilance detection problem. We first use continuous wavelet transform to extract the rhythm features of EEG data, and then employ the sparse representation method to the wavelet transform coefficients. We collect five subjects' EEG recordings in a simulation driving environment and apply the proposed method to detect the vigilance of the subjects. The experimental results show that the algorithm framework proposed in this paper can successfully estimate driver's vigilance with the average accuracy about 94.22 %. We also compare our algorithm framework with other vigilance estimation methods using different feature extraction and classifier selection approaches, the result shows that the proposed method has obvious advantages in the classification accuracy.**

Index Terms— **Electroencephalograph (EEG), Vigilance, Brain Computer Interface, Continuous Wavelet Transform, Sparse Representation**

I. INTRODUCTION

Keeping the vigilance at a certain level is necessary for those people who engaged in the monotonous and long time attention-demanding jobs such as guarding task, driving a car and machinery operations. So designing a real-time system that can accurately and fast assess the driver's vigilance degree has become a necessity. Many biological characteristics and behavioral characteristics such as eye-closure, face expression, head position, heart beating, brain activity and reaction time, etc. have been used for developing automated ways and devices for vigilance detection. In general, these systems collect the operators' biological or behavior data and then analyze these information to determine the mental states of the operator and finally give the corresponding instructors to the controlling system to prevent the potential disaster[1]-[2].

It has been found that EEG recordings have close relationships with the person's vigilance degree and many previous studies have confirmed that the rhythm of brain waves varies with the change of the mental states[3]-[4]. Many research works have achieved considerable experiment results based on the power spectral density (PSD) distribution or the energy changes of specific rhythm of EEG recordings. For example, when the vigilance states are divided into two states–the clear headed state and the sleeping state, the classification accuracy can almost get to 96% [5]. Now much effort has been made to detect vigilance with more states, in this paper, we consider the vigilance degree which is divided into three states: the first state is labeled clear-headed, the second state is labeled sleeping and the third state is the transition from alert to sleepy states, denoted drowsy, which is just the state we need to determine and used to prevent the occurrence of the potential disaster.

EEG is a non-stationary and extremely sensitive signal, even a small movement from eyes or body can contaminate it. So removing the polluted signal segments or contaminated channels and reducing the noise influences from EOG,EMG and other channels are all necessary in the EEG signal preprocessing work. Independent component analysis(ICA) is a useful tool in separating the independent component from a mixed signal.If the assumption of the data from each channel are statistically independent,blind ICA separation of a mixed signal can gives very satisfactory results. In this paper, we use blind ICA separation to get the relatively pure data of each channel.

Because of the great amount of EEG data, feature extraction and data dimension reduction are needed, many transform techniques such as FFT[6], STFT[7] and wavelet transform[8]-[10] have been utilized to describe the minute and detailed changes of the vigilance in the research based on EEG combined with various classifier performing classification task, considerable progresses have been achieved in the previous studies. Support vector machine (SVM)[11], artificial neural networks (ANN)[6]-[7] and autoregressive(AR)[12] etc. are the most commonly used classifiers in the EEG research domain.

In this paper,a sparse representation method combined with the wavelet coefficients of EEG recordings extracted as EEG features is utilized to estimate the subjects' vigilance states. Our experiment results show the sparse representation's superiority in estimating driver's vigilance level and comparisons with other classifiers are also made to test the classification ability of our method.

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This paper is structured as follows: for EEG data acquisition is explained in section II, and in section III the EEG preprocessing methods are given, Then the method for vigilance analysis is presented in section IV. Section V presents the experimental results. Finally,conclusions and future work are discussed.

II. Data acquisition

Five healthy young men aged 18-28 participated in our EEG vigilance analysis data collection experiments. The subjects were required to wearing a EEG recording cap with 64 electrodes connected to the amplifier of the NeuroScan system and sitting on chair when driving a car in a simulation driving environments. The electrodes are arranged based on the international 10/20 standard, and the EEG signals were recorded in a computer and the sample rate of brain potential is 100Hz per second. The room used in our experiments was designed to be a dark, quiet, isolated room, the temperature was set to 24 degrees and the humidity was between 40 % and 60 %. The subjects manipulate the steering wheel and the simulated driving scenes were displayed before them with a LCD screen. A DV camera was also placed in front of the subjects to record the facial expression of the subjects for state labeling later [5]. Every subject was required to practise for ten minutes to get used to the operational processes before the beginning of experiments. The whole experiment lasts about for one hour and data labeling was completely by hand according to the monitoring video.In the first several minutes of the experiments the subject was clear-headed with eyes open and situation changes over the experiment duration,when blink frequency increases, which indicates the subject entering drowsy state and finally goes to sleep with eyes closed.

III. Data Preprocessing

In the process of data preprocessing, we first remove the EEG signals from the damaged channels, as well as the signal segments which are contaminated by EMG or EOG signal manually. Then,the EEG signals are filtered by a band-pass FIR filter to eliminate the noise. As the brain potential is generally between 1Hz and 40 Hz, so the band-pass filter cut-off frequencies are set to 1Hz and 40Hz, respectively. Subsequently, the ICA method is applied to the filtered EEG signals to find the approximate independent components from all available channels and all of components are used in the the following procedure.

IV. Feature extraction and classification

A. Feature extraction with CWT

Due to the non-stationary nature of the EEG signal from each electrode of the NeuroScan system, the sampling data of EEG are divided into many overlapping epochs and each epoch contains 250 new sampling data and 250 duplicate data from the previous epoch, so each epoch corresponds to EEG signal of 5 seconds. After that, the Continuous Wavelet Transform (CWT) is used to calculate the wavelet coefficients of each epoch. In this way, we can get the transient components of the signal in both time (or position) and frequency domains. The wavelet function we used in our experiment is the complex Morlet wavelet function defined [9] by

$$\psi(x) = \frac{1}{\sqrt{\pi f_b}} \exp\{2i\pi f_c x\} \exp\{-\frac{x^2}{f_b}\} \qquad (1)$$

where f_c denote the central frequency,and f_b is a bandwidth parameter, f_c and the variance σ_f are related by $f_b = \frac{1}{2\pi^2\sigma_f^2}$.The Morlet wavelet has very special characteristics that both of its time-domain waveform and frequency-domain waveform are Gaussian shape. So, we can accurately extract the desired signal frequencies by adjusting the parameter values of the Morlet wavelet function, and besides it also has good resolution both in time domain and frequency domain. That's why we chose Morlet wavelet function in our method.

As in previous literature [5], we divide the EEG signal into the following five bands: δ rhythm ($\leq$ 4Hz), θ rhythm(4-7Hz),α rhythm (8-13Hz), β rhythm (14-25Hz) and γ rhythm ($> 26Hz$). The change of the rhythms in the brain wave has close relationships with the driver's vigilance, so the complex Morlet wavelet is mainly used to compute the coefficients of these five bands of rhythms in this paper. The parameters of five wavelet functions of the complex Morlet wavelet with respect to the five bands are given in Table 1 which are used in our latter experiments.

TABLE I

The parameters of wavelet function used in our experiments

Frequency Band (Hz)	Central Frequency (f_c /Hz)	Bandwidth Parameter (f_b /Hz)
$\delta(< 4.0Hz)$	2.5	1.5
$\theta(4.0-8.0Hz)$	6.0	1.0
$\alpha(8.0-13.0Hz)$	10.0	2.0
spindle(11.0-13.0Hz)	12.0	1.0
$\beta(13.0-30.0Hz)$	21.0	9.0
$\gamma(> 30.0Hz)$	35.0	5.0

B. Classification with sparse representation

Conventional Shannon's sampling rate theorem is the basis of the all signal acquisition protocols: the sampling rate must be at least twice the maximum frequency present in the signal. However, the emergence of compressed sensing breaks the limitation. It has been forty years since it was discovered by the seismologists when constructing images of reflective layers within the earth based on the data that did not seem to satisfy the Nyquist-Shannon criterion. The theory of compressed sensing believes that some natural signals have compact and condense representation in some domain, the property which is called sparsity. Sparse signals contain many coefficients close to or equal to zero that can be discarded and so that the sparse representation of signal can use as little as possible amount of data to represent the original data and then to recover it without any significant information loss [13]. Suppose that signal $f(t) \in R^n$ is a time series and we can expand it in an orthonormal basis

$\Psi = [\psi_1, \psi_2, ..., \psi_n]$ as follows:

$$f(t) = \sum_{i=1}^{n} x_i \psi_i(t) \quad (2)$$

where $x_i = \langle f, \phi_i \rangle$ (ϕ_i is also an orthonormal basis and used for sensing the signal) is the coefficient sequence of f and the coefficient sequence vector can be denoted by $X = [x_1, x_2, x_3, ..., x_n]$. In the domain if the coefficient x_i is sufficiently sparse then we can discard the x_i that are near or equal to zero, and therefore get a new coefficient vector $\widehat{X} = [\hat{x}_1, \hat{x}_2, \hat{x}_3, ..., \hat{x}_m](m < n)$ where $\widehat{X}$ is the sparse representation of X. Accordingly, the sensing number also decrease from n to m. By using the equation $\hat{f} = \Psi\hat{X}$ we can easily recover the original signal without perceptual information loss. However,mathematically the $\hat{X}$ should satisfy the following restriction:

$$\min_{x \in R^n} \|x\|_0 \quad \text{subject to} \quad \hat{x}_k = \langle \phi_k, \Psi X \rangle, \;\; k = 1, 2, ..., m. \quad (3)$$

where $\|\cdot\|_0$ is the l_0 norm of a vector. Solving the above optimization problem is NP-hard [14]. [15] proved that as long as the solution x is sparse enough, the solution of the above l^0-minimization problem is equal to the solution to the following l_1-norm minimization problem:

$$\min_{x \in R^n} \|x\|_1 \quad \text{subject to} \quad \hat{x}_k = \langle \phi_k, \Psi X \rangle, \;\; k = 1, 2, ..., m. \quad (4)$$

where $\|\cdot\|_1$ is the vector l_1 norm. In [16], sparse representation is firstly used to realize classification task in the face recognition problem and robust performance has been reported. Inspired by the work of [16], in this paper we adopt sparse representation method to estimate driver's vigilance degree. As stated in the previous section, we extract wavelet features from EEG recordings by CWT which forms feature vectors $a_i \in R^m$, $i = 1, 2, 3, ..., k$, where m is the number of CWT features in the ith channel and k is the number of available channels. Then we stack all the vectors a_i into one column vector $a \in R^n$, $a = [a_1^T, a_2^T, ..., a_k^T]^T$, where $n = mk$. All the feature vectors a of all classes from the training data are used as a column vector to construct a matrix $A \in R^{n \times h}$, where $h = cp$, where c and p are the number of classes (the number of vigilance states in this paper) and the number of samples used for training in each class respectively. For a test vector $y \in R^n$, we find its sparse representation as the linear combination of the columns of A. So the problem is transformed into solving the sparse solution of the linear equation: $y = Ax$ as:

$$(l^1): x_1 = \arg\min_{x \in R^n} \|x\|_1 \quad \text{subject to} \quad y = Ax \quad (5)$$

(5) can be solved in polynomial time by standard linear programming methods[17]. As done in [16], the residual $r(y)$ is computed by $r(y) = \|Ax_1 - y\|_2$, the test sample is classified to the class with which the residual $r(y)$ is the smallest.

V. Experiment Results and discussions

EEG recordings collected from 5 subjects in a driving simulation environment are used in our experiment. For each data set, we select the first half recordings in different vigilance degree (alert, drowsy and sleep) for training and the other half for testing. To test the classification performance of the sparse representation, we analyze the validation results versus the training sample number. In our experiments, some data of certain subjects were contaminated by the EMG (electromyography), in order to guarantee sufficient data for test, we just select only a part of the data for testing. The available data still give satisfactory accuracy. Fig.1 shows the classification performance of the sparse representation method versus number of training samples. The results show that as long as there are enough training samples, our algorithm can achieve very high accuracy rate. More training samples can help to enhance the recognition performance. Data set from subject 5 lack sufficient training data but still a high recognition rate is achieved with only 200 training samples for each class. Data from subject 4 are contaminated, so the accuracy with increase of the number of training samples decreases. However the recognition accuracy is still high (about 85%) with only 50 training samples.

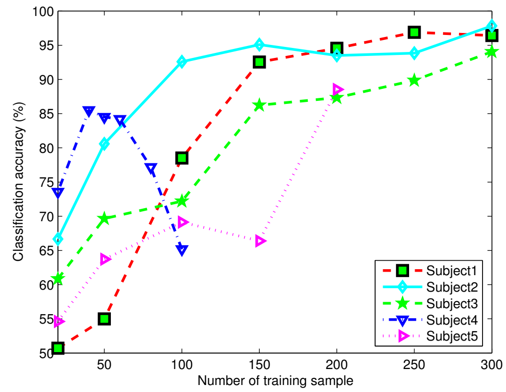

Fig. 1. The vigilance classification accuracy of sparse representation method versus the number of training samples

The cross-validation method was adopted in our experiments to explore the classification ability of the proposed algorithm. We divide the whole data for each class into 4 sets, three of which are used as the training set and the remaining set is for testing. The classification result for test samples is given in Table II. The results is good. We also make comparisons with the Support Vector Machine (SVM) classifier, the same wavelet coefficient feature vectors of EEG data are as the input to the SVM classifier [18], the test result

TABLE II

Classification accuracy of sparse representation method obtained by using cross-validation

DataSet	1	2	3	4	average accur
sub1	0.7470	0.8715	0.9518	0.9639	0.8836 ± 0.010
sub2	09108	0.9812	0.9437	0.9718	0.9519 ± 0.001
sub3	0.7073	0.8862	0.9512	0.6992	0.8110 ± 0.016
sub4	1.0000	0.7467	0.9733	0.9733	0.9233 ± 0.014
sub5	1.0000	1.0000	1.0000	1.0000	1.0000 ± 0.000

is given in Table III, from the result we can see that the sparse representation method outperforms the SVM classifier in terms of classification accuracy.

TABLE III

CLASSIFICATION ACCURACY USING SVM

Data Set	1	2	3	4	average accuracy
subject1	0.7510	0.8795	0.9799	0.8514	0.8656 ± 0.0089
subject2	0.9109	0.9718	0.8404	0.9733	0.9285 ± 0.0046
subject3	0.7561	0.9593	0.9350	0.8943	0.8862 ± 0.0082
subject4	1.0000	0.7333	0.9467	0.9733	0.9133 ± 0.0149
subject5	0.9875	1.0000	0.9875	1.0000	0.9938 ± 0.0000

Some other features are also extracted to make further comparisons with our proposed algorithm. We use two other types of features: the short-time Fourier transform (STFT), and the time series data of EEG directly treated as feature, and then sparse representation is used to these feature vectors. Table IV illustrates the results. We can see that the wavelet feature achieved significantly better result. In [16] the author assert that "if sparsity in the recognition problem is properly harnessed, the choice of feature is no longer critical". However, our results do not support this point of view. From table IV we can see that the feature selection in our EEG vigilance estimation problem is still very important, time series data can't be directly applied into the sparse representation framework. Using STFT coefficients as feature also get a poor recognition accuracy. Through the comparison experiment with time series and STFT coefficient, we can see that a prerequisite for use of the sparse representation framework is that the signal is sparse, if the feature we extract is not sparse,the classification result might be poor. Obviously the wavelet feature we use has good sparsity.

TABLE IV

COMPARISON OF THREE DIFFERENT FEATURES USING SPARSE REPRESENTATION FRAMEWORK

Data Set	Wavelet coefficient	Time series	STFT feature
Subject1	**96.43%**	79.43%	54.41%
Subject2	**94.06%**	60.38%	44.16%
Subject3	**97.83%**	100.00%	86.36%
Subject4	**88.54%**	59.50%	56.14%

VI. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this paper, we study driver's vigilance detection based on EEG recordings. The continuous wavelet transform was used to extract the brain wave rhythm features which are related to the vigilance states. The sparse representation method was then applied to accomplish classification task with CWT coefficients to estimate three vigilance levels: alert, drowsy and sleep. Five data sets from five subjects were used in our experiments to test the algorithm. The experimental results show that our algorithm has a good advantage in the detection of the driver's vigilance degree. Comparisons with the SVM classifier and other features are also made, which show that the proposed method have more advantages than the methods mentioned.

B. Future Works

The ultimate objective in the research of vigilance estimation is to design a small and easy system which can quickly and accurately estimate the state of driver's vigilance. The proposed sparse method has achieved a high accuracy rate, however, the sparse representation method is inferior to SVM in the computation cost. Reducing the computation complexity, improve the recognition accuracy and study the sparsity of the EEG signal are our future work on vigilance detection using sparse representation.

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