Vigilance Differentiation from EEG Complexity Attributes

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Abstract. Vigilance is an ability to maintain concentrated attention on a particular event or target stimulus. Monitoring tasks require certainly high vigilance to properly detect rare occurrence or accurately respond to stimulation. Changes in vigilance can be reflected by EEG signal, so vigilance levels can be classified based on features extracted from EEG. Up to now, power spectral density was commonly employed as features to differentiate between vigilance levels in majority of previous studies. To the best of our knowledge, multifractal attributes for vigilance differentiation have not been exploited, and their feasibility still need to be investigated. In this study, we first extracted multifractal attributes based on wavelet leaders, and then selected statistically significant distinct attributes for the following classification (two vigilance levels). According to the results, classification accuracy was improved with increase of time window used for feature extraction. When time window was increased to 50 s, an averaged accuracy of 91.67 % was achieved, and accuracies for all subjects were higher than 85 %. Our results suggest that multifractal attributes are promising for vigilance differentiation.

Keywords: Vigilance classification · Sustained attention · Complexity attribute · Self-similarity · Feature selection

1 Introduction

In our daily life, vigilance plays an important role on interactive activities. High vigilance facilitates to perform stressful and hard tasks, and to reduce the rate of occurrence of mistakes. In contrast, vigilance decrement could lead to serious consequences, such as traffic accidents. A few psychophysiological signals

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have been utilized to estimate vigilance levels. EEG is the most common among them because it is directly recorded from the brain. In EEG studies, power spectral density is usually extracted to represent ongoing brain states [1–6]. For instance, J.N. Gu et al. extracted features of power spectral density and classified vigilance states by Gaussian mixture model [1]. Power spectral density in different bands was also investigated in [2–4, 6]. Before vigilance classification, principle component analysis was usually used to reduce dimension of features [2, 4, 7]. In general, components corresponding to first several largest variances are selected and features are projected onto the space spanned by these components. In [7], the authors proposed to calculate correlation between features and vigilance index for feature selection. By this way, the retained components are more relevant to vigilance. All papers mentioned above utilized power spectral density as features to estimate vigilance level, but vigilance information may also be encoded in EEG by other representations. As indicated in [8], EEG signal recorded under motor imagery has multifractal characteristics. The multifractal attributes can be used to successfully decode different motor imageries. In this case, both power spectral density and multifractal attributes encode relevant information of motor imagery. In this paper, we explore multifractal attributes in EEG recordings and investigate feasibility of vigilance differentiation. To this end, a monotonous task was designed to induce vigilance decrement with time. Multifractal attributes were compared between high vigilance and low vigilance states, and were used to classify vigilance levels.

2 Subjects and Experimental Environment

Twelve healthy volunteers (age: $20 \sim 31$) participated in the study. All of them self-reported no history of mental illness, neurological illness, and they were not on medication. Their sights were normal or corrected-to-normal by wearing glasses. All subjects gave their written consent before conducting the experiment. The experiment was approved by the Institutional Review Board (IRB) of the National University of Singapore.

Subject was seated in a comfortable armchair with an appropriate height. A simulated factory scene (see Fig. 1) was presented in front of the subject by a 21-inch computer screen. The distance from the screen to the plane of the subject's eyes was 50 cm. The subject was instructed to detect a rarely occurring intruder (marked by red circle in the Fig. 1) from civilians who were randomly walking in the scene (marked by blue circles). The intruder sneaked from an arbitrarily appeared location to another location and disappeared on reaching that location. Subject needed to detect the intruder by pressing the key 'Q'. During the experiment, 62 channels EEG, 2 channels EOG, and 1 channel ECG were recorded as referenced to the linked mastoids. The impedance of all electrodes was kept below 10 $k\Omega$. In addition, eye tracker was also used to track eyes' behaviour, but the data analysis is beyond the scope of this paper.

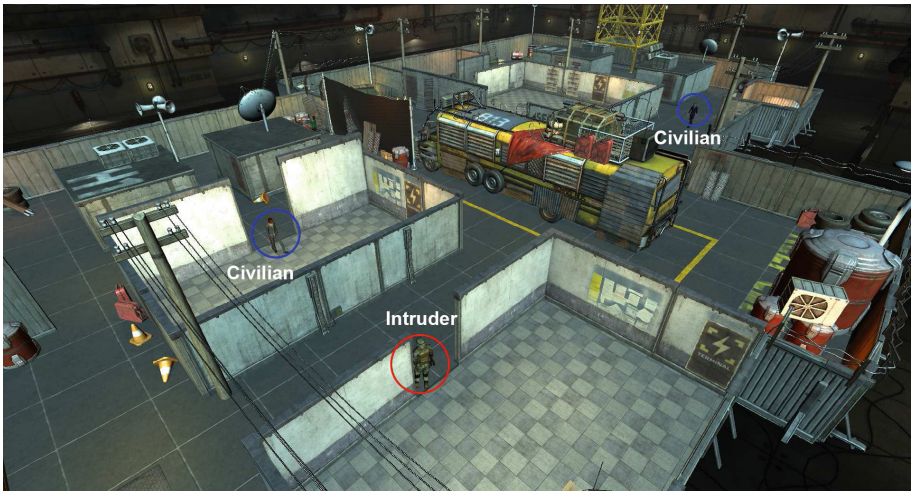

Fig. 1. Simulated factory scene. A few civilians are randomly walking in the scene (as indicated by blue circles). Intruder wearing military uniform infrequently appears at random location (marked by red circle) and then sneaks to another location (Color figure online).

3 Methodology

In this experiment, subjects performed saccades from one point to another point to detect the intruder. This results in obvious artefacts corrupting the EEG signals. At the first step, we should remove the effects of artefacts, such as EOG and EMG. Figure 2 shows the schematic of our methodology for vigilance classification. Least mean squares (LMS) was employed to remove EOG by subtracting weighted EOG signal from EEG signal [9]. Then, EEG signal was decomposed by canonical correlation analysis (CCA) to obtain components. Subsequently, EEG was projected onto a few maximally auto-correlated components to suppress the effect of EMG [10]. EEG signal plots at the upper right part of Fig. 2 show examples before and after artefacts removal.

After removing artefacts, we extracted multifractal attributes for each channel by the following procedure. Let $x(t)$ stand for time series of one channel in a sliding time window. $x(t)$ is first transformed into a time-scale representation (wavelet coefficients) by discrete wavelet transform (DWT). Because multifractal spectrum can be more accurately estimated based on wavelet leaders than based on the wavelet coefficients themselves according to the suggestion in [11,12], we adopted wavelet leaders in this study. Wavelet leader $L_x(j,k)$ is defined as the greatest value of adjacent wavelet coefficients, which includes wavelet coefficients in the time interval $[k-1, k+1]$ at scale 2^j and all smaller scales. Hölder exponent h is defined as the largest power that $x(t)$ is expanded into a polynomial at t_0 with error no more than the product of a constant and the power of $|t-t_0|$.

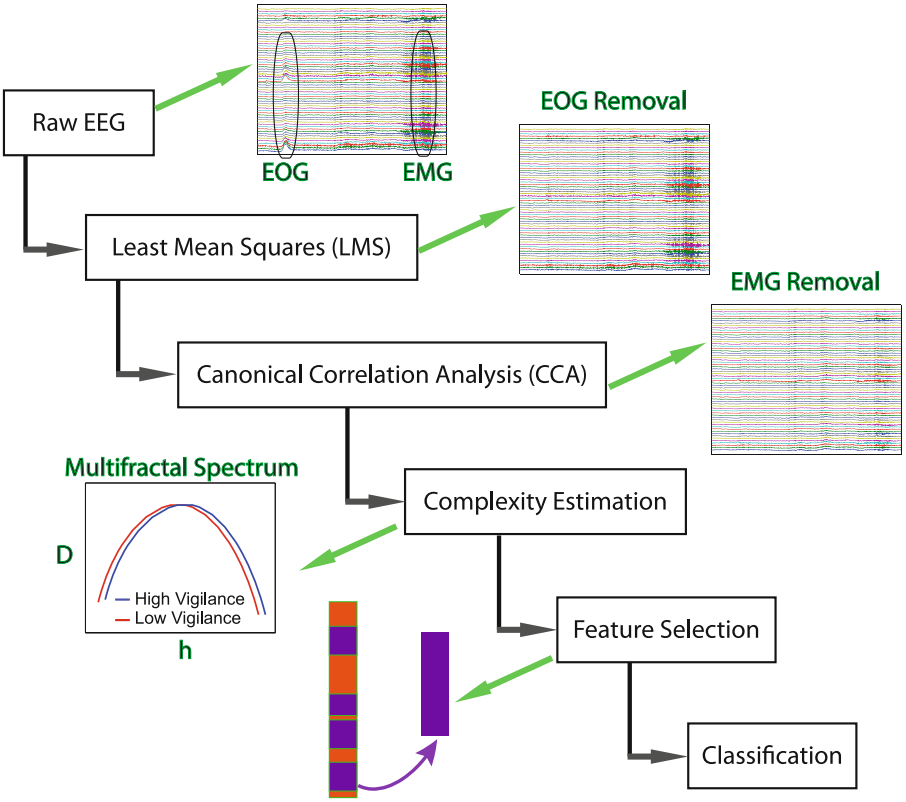

Fig. 2. Methodological schematic of vigilance differentiation. The middle flowchart shows each step to perform classification. The upper right subplots illustrate examples of artefacts removal. The bottom left subplot and diagram show multifractal spectrum and feature selection, respectively.

Under mild regularity condition, wavelet leaders exactly reproduce the Hölder exponent h of $x(t)$ at t_0 in the limit of fine scales ($2^j \to 0$) [12].

$$L_x(j,k) \leq C2^{jh}, \tag{1}$$

It means $h(t_0)$ is the supremum of all values h. The formula (1) shows that the wavelet leader structure functions $S^L(j,q)$ possess power law behaviour with respect to scales in the limit $2^j \to 0$ [12].

$$S^L(j,\,q) = \frac{1}{n_j}\sum_{k=1}^{n_j} L_x(j,\,k)^q = F_q 2^{j\zeta(q)}, \tag{2}$$

where n_j is the number of wavelet leaders $L_x(j,k)$ available at the scale 2^j, F_q is coefficient. $\zeta(q)$ is scaling exponents that indicate signal complexity. The higher order in $\zeta(q)$, the more complex the EEG signal is. It has been proven that the

Legendre transform of the scaling exponents $\zeta(q)$ provide an upper bound for the multifractal spectrum $D(h)$ [12],

$$D(h) \leq \min_{q \neq 0}(1 + qh - \zeta(q)). \tag{3}$$

For the most commonly used multifractal models [13], the inequality (3) becomes equality,

$$D(h) = \min_{q \neq 0}(1 + qh - \zeta(q)). \tag{4}$$

Hence, the multifractal spectrum $D(h)$ can be drawn with respect to the scaling exponents $\zeta(q)$ and Hölder exponents h. An example of multifractal spectrum is shown in the bottom left subplot in the Fig. 2. Two curves respectively represent multifractal spectra of high and low vigilance states. For further information about multifractal spectrum, readers could refer to [11–13]. In order to reduce the number of features, we did not use original multifractal spectrum as features, only three attributes are extracted from multifractal spectrum to be used as features. They are the location of maximum c_1, width c_2, and asymmetry c_3 of multifractal spectrum. The physical meaning of c_1 is self-similarity of signal over time. All attributes of all channels are assembled to form a feature vector

$$f = [c_{1,1}\ c_{1,2}\ c_{1,3}\ \cdots\ c_{n,1}\ c_{n,2}\ c_{n,3}], \tag{5}$$

where n is the number of channels.

The dimension of features is still high if attributes extracted from all channels are used, so we select a subset of features according to statistical evaluation (see the following pseudocode). Feature selection is performed for each individual. Then, selected features are normalized and fed into an SVM classifier with radial basis function (RBF) kernel [14]. Performance is evaluated by 4-fold cross-validation.

Feature Selection Procedure

```
Input: All Extracted Features
Output: Selected Features
   begin
    repeat
      channel = channel+1;
        repeat
          attribute = attribute+1;
          if difference is significant (p<0.05)
             keep current feature;
          else
             remove current feature;
          end
        until attribute = 3
     until channel = 62
   end
```

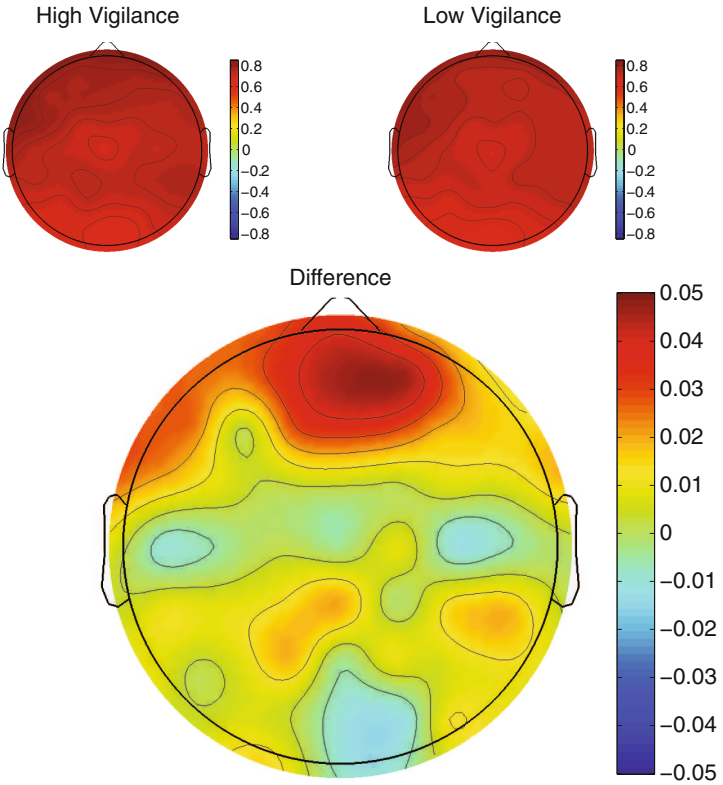

Fig. 3. Topographies at the upper row are averaged multifractal attributes (self-similarity) for the high and low vigilance states, respectively. Difference topography at the bottom is obtained by subtracting self-similarity values of low vigilance state from that of high vigilance state (Color figure online).

4 Results

Figure 3 shows the difference topography of multifractal attribute between high vigilance and low vigilance conditions. Areas in red color mean self-similarity value for the high vigilance condition is bigger than that of the low vigilance condition. The inverse situation is marked by blue color in the topography. The most dominant regions between high and low vigilances are located on the frontal and occipital cortices. A higher self-similarity is observed on the frontal cortex during high vigilance state. It becomes lower on the occipital cortex. Interestingly, the dominant spatial regions found in our study are matched with the findings with spectral power study, such as alpha band on occipital cortex is related to vigilance [15].

High vigilance and low vigilance portions are selected from the whole recording according to the protocol setting. Each portion is 12 min long, and is further partitioned into segments using specific time window length. Time window

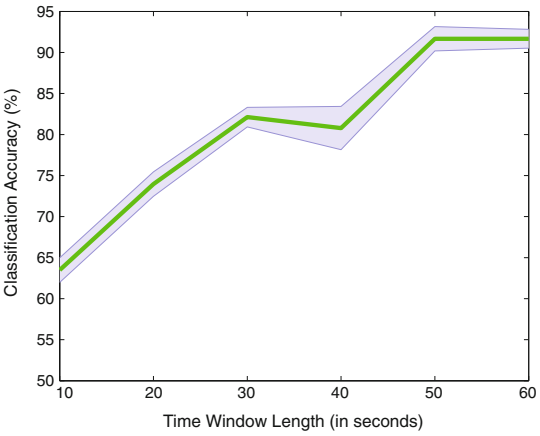

Fig. 4. The grand accuracies in different time window lengths. Horizontal axis represents window length while vertical axis represents classification accuracy. Bold green line stands for averaged accuracy across subjects. Standard error is shown as shaded region (Color figure online).

length is a crucial parameter in multifractal analysis. Different window lengths used for extracting multifractal attributes result in different classification accuracies. Therefore, we used different window lengths from 10 s to 60 s with an incremental step of 10 s. The results are shown in the Fig. 4. Grand accuracies averaged across all subjects are shown as bold green line. From the figure, we can see that classification accuracy is generally improved with increase in window length. The highest accuracy of 91.67 % is reached when window length is 50 s. Accuracies for every subject are higher than 85 %. Accuracies in 7 out of 12 subjects exceed 90 %. Variance over subjects are shown as shaded region. The largest inter-subject variance occurs at the window length of 40 s. The variances for the rest of window lengths are small.

4.1 Conclusion

In this study, we exploited a new representation of multifractal attributes for vigilance degree, rather than conventional representation of power spectral density. Three attributes derived from the location of maximum, width, asymmetry of multifractal spectrum are extracted as features. Then, the number of features was reduced by feature selection according to statistical evaluation. Classification accuracies demonstrate that multifractal attributes are feasible to differentiate vigilance levels. We further explored the spatial distribution of self-similarity attribute, and found that the most distinct difference between high and low vigilance levels is appeared on the frontal and occipital cortices.

Vigilance differentiation could be utilized to construct a passive brain computer interface (BCI) for monitoring the alertness of people. It could be integrated into an active BCI, such as motor-imagery wheelchair system [16], to assess mental state while people are manipulating by an active BCI.

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