A Vigilance Estimation Method Based on EEG Differential Entropy Postprint

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Abstract

To improve the real-time estimation accuracy of human vigilance, a real-time vigilance estimation method based on differential entropy (DE), improved moving average, and bidirectional two-dimensional principal component analysis (TD-2DPCA) is proposed. First, the total frequency band is decomposed into multiple sub-bands with a certain bandwidth, and DE is extracted from each sub-band. Then, combining the temporal dynamic characteristics of vigilance, the traditional moving average method is improved, and the improved moving average is used to smooth the DE. Subsequently, TD-2DPCA is employed to reduce the dimensionality of DE, and least squares support vector machine (LS-SVM) is adopted to establish a regression model between the feature matrix and vigilance, thereby achieving real-time accurate estimation of vigilance. Finally, experimental validation was conducted using the SEED-VIG dataset, and the results demonstrate that processing the data with the improved moving average and TD-2DPCA methods can enhance the accuracy of vigilance estimation and reduce estimation time. When the total frequency band is within 0-35 Hz and the decomposition bandwidth is 1 Hz or 2 Hz, the extracted DE for vigilance estimation can achieve the highest estimation accuracy, with a Pearson correlation coefficient of approximately 0.91 and an RMSE of approximately 0.09, which is superior to existing vigilance estimation methods.

Full Text

Preamble

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A Vigilance Estimation Method Based on Differential Entropy of EEG

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Abstract: To improve the real-time estimation accuracy of human vigilance, this paper proposes a method based on differential entropy (DE), improved moving average, and two-directional two-dimensional principal component analysis (TD-2DPCA). First, the total frequency band is decomposed into multiple sub-bands with a fixed bandwidth, and DE features are extracted from each sub-band. Then, traditional moving average is improved by incorporating the temporal dynamic characteristics of vigilance, and the improved method is used to smooth the DE features. Subsequently, TD-2DPCA is employed for dimensionality reduction, and least squares-support vector machine (LS-SVM) is adopted to construct a regression model between the feature matrix and vigilance levels, enabling accurate real-time estimation. Experimental validation on the SEED-VIG dataset demonstrates that the proposed smoothing and dimensionality reduction approach enhances estimation accuracy while reducing computation time. When the total frequency band is within 0–35 Hz and the decomposition bandwidth is 1 Hz or 2 Hz, the extracted DE features achieve the highest estimation accuracy, with a Pearson correlation coefficient of approximately 0.91 and RMSE of approximately 0.09, outperforming existing vigilance estimation methods.

Keywords: EEG signal; differential entropy; improved moving average; two-directional two-dimensional principal component analysis

0 Introduction

Vigilance refers to the degree of alertness exhibited when an individual concentrates on performing a task. Lower vigilance significantly increases the probability of errors during task execution [?]. Numerous high-risk professions—such as long-distance bus drivers, chemical transporters, heavy equipment operators, and pilots—require sustained high vigilance levels. Any decline in vigilance can lead to catastrophic consequences [?]. Consequently, vigilance estimation has become a critical research topic in human-computer interaction and proactive safety systems.

Common vigilance estimation methods include self-assessment, eye-tracking measurements, and electroencephalogram (EEG) measurements. Among these, EEG-based approaches demonstrate superior accuracy and stability [?]. EEG signals record scalp potential variations that reflect cognitive activity [?]. Typically, EEG signals are divided into five frequency bands: δ (0.5–4 Hz), θ (4-8 Hz), α (8-14 Hz), β (14-30 Hz), and γ (30-50 Hz), though exact divisions may vary across studies [?]. Research indicates that drowsiness states exhibit increased δ and θ power alongside decreased α and β power [?]. Wang et al. [?] utilized power spectral density ratios of $\theta/(\alpha+\beta)$, attention-to-relaxation ratios, and blink frequency as fatigue detection features for real-time monitoring, but this method only classified fatigue into three categories, preventing precise vigilance tracking. Zhang et al. [?] extracted 37 features per channel and employed random forests for fatigue detection; however, the lack of feature processing resulted in high dimensionality and limited recognition accuracy.

Both approaches extracted features from only the five conventional EEG bands, failing to maximize the information contained in EEG signals. While decomposition methods such as empirical mode decomposition and wavelet transform can extract additional useful features [?, ?], the resulting components lack clear physiological meaning, and redundant features may interfere with existing ones, compromising estimation performance [?]. Moreover, fatigue state evolution is a dynamic process that cannot be simply categorized into discrete classes, making real-time vigilance assessment more practical [?]. Studies have shown that differential entropy (DE) outperforms traditional EEG features for vigilance estimation [?, ?], motivating our adoption of DE as the primary feature.

Building upon existing research, this study further investigates vigilance estimation methods. For feature extraction, we first divide each channel' s EEG signal into multiple sub-bands and extract DE from each sub-band, analyzing how different division strategies affect estimation accuracy to identify the optimal DE extraction approach while comparing it with traditional methods. For feature smoothing, we improve conventional moving average by incorporating vigilance' s temporal dynamics, proposing an edge data smoothing method that combines variable-window averaging with short-term prediction to enhance correlation between edge and overall data. For dimensionality reduction, we compare traditional principal component analysis (PCA) with two-directional two-dimensional PCA (TD-2DPCA) for EEG feature compression. Finally, we construct a regression model between EEG features and vigilance levels using least squares-support vector machine (LS-SVM) to achieve accurate estimation, validated on real datasets.

1.1 Feature Extraction

Previous studies demonstrate that DE performs better than traditional power spectral density and other time-frequency features for vigilance estimation [?]. Therefore, this paper adopts DE as the feature metric. DE describes the complexity of continuous variables and is calculated as:

$$DE = -\int_{-\infty}^{+\infty} f(x)\log(f(x))\,dx$$

where $f(x)$ represents the probability density function of random variable X.

Within a fixed frequency band, EEG signals can be approximated as following a Gaussian distribution $N(\mu, \sigma^2)$, allowing DE to be simplified to:

$$DE = \frac{1}{2}\log(2\pi e\sigma^2)$$

We employ two DE extraction methods: (1) For each channel, extract DE from the five conventional bands (δ, θ, α, β, γ); (2) For each channel, divide a portion of the frequency band into equal sub-bands at a specified bandwidth. For example, on the 0–50 Hz band with 2 Hz bandwidth, the signal can be decomposed into 25 sub-bands: [0,2], [2,4], ···, [48,50] Hz, with DE extracted from each sub-band. All DE features are computed using short-time Fourier transform with 8-second non-overlapping Hanning windows, yielding a feature matrix of dimension $N \times M \times L$, where N represents the number of channels, M the number of sub-bands, and L the total number of feature extractions (equal to the EEG signal length divided by window length).

1.2 Feature Smoothing

Most vigilance estimation research maps EEG signals to static discrete fatigue states, but human vigilance evolution is fundamentally a temporal dynamic process [**?**]. Smoothing extracted features not only mitigates measurement errors but also enhances temporal continuity, thereby improving estimation accuracy. Moving average is a common smoothing technique. Assuming an odd window length l, for an EEG feature sequence x_i, where features before and after have equal weight:

$$z_i = \frac{1}{l}\sum_{j=-(l-1)/2}^{(l-1)/2} x_{i+j}$$

where x_i is the original data, z_i the smoothed data, and L the data length. However, Equation (3) cannot process data in the intervals $[1, (l-1)/2]$ and $[L-(l-1)/2, L]$, causing potential jumps at both ends that significantly impact the vigilance estimation model. Since vigilance exhibits dynamic temporal characteristics that allow short-term prediction, we improve traditional moving average as follows:

Step 1: Apply conventional moving average to obtain smoothed data z_i for the central region.

Step 2: Starting from $i = (l-1)/2 + 1$, compute backward smoothing results using a variable window:

$$z_i = \frac{1}{s}\sum_{j=1}^{s} x_{i+j-1}, \quad s = i$$

Starting from $i = L - (l-1)/2$, compute forward smoothing results:

$$z_i = \frac{1}{s}\sum_{j=1}^{s} x_{i-j+1}, \quad s = L - i + 1$$

Step 3: For intervals $[1, s]$ and $[L-s, L]$ where windows remain too small for adequate smoothing, apply short-term prediction using already-smoothed data:

$$z_i = z_{i+n_1} - n_1 \cdot \frac{z_{i+n_1} - z_{i+n_2}}{n_2 - n_1}$$

where n_1 and n_2 are variables requiring adjustment based on actual data; in this paper, both are set to 4.

1.3 Feature Dimensionality Reduction

Decomposing each channel' s EEG signal extracts more information, but redundant features may degrade training accuracy and increase computation time. Dimensionality reduction thus improves estimation accuracy and reduces time costs. This paper introduces two methods: PCA and two-directional two-dimensional PCA (TD-2DPCA) [**?**], comparing their performance for vigilance estimation.

Traditional PCA uses orthogonal transformation to map high-dimensional data to a lower-dimensional space [**?**], reducing estimation time to some extent. However, PCA requires reshaping high-dimensional data into row vectors. For EEG features of dimension $N \times M \times L$, each time window yields an $N \times M$ matrix where rows represent different brain regions or channels and columns represent different sub-bands. PCA cannot distinguish between these two dimensions during reduction. TD-2DPCA directly reduces dimensions along both matrix axes, offering greater flexibility for extracting channel and frequency information. Moreover, TD-2DPCA' s covariance matrices have far lower dimensions than PCA' s, yielding higher computational efficiency better suited for real-time vigilance estimation.

In 2DPCA, for M training samples A_i of size $n \times m$, a projection matrix X maps them to principal component space:

$$Y_i = A_i X, \quad i = 1, 2, ..., M$$

where Y_i represents the i-th sample' s projection. The projection matrix X is selected to maximize inter-class scatter after projection, defined by the objective function:

$$J(X) = \mathrm{tr}(S_x) = \mathrm{tr}\{E[(Y - E(Y))(Y - E(Y))^T]\}$$

where S_x is the covariance matrix of Y and tr denotes the trace. X is an $n \times d$ matrix. The training samples' overall scatter matrix G_t is:

$$G_t = \frac{1}{M}\sum_{i=1}^{M}(A_i - \bar{A})^T(A_i - \bar{A})$$

where $\bar{A}$ is the mean image. G_t is an $m \times m$ non-negative definite matrix. Computing its standard eigenvectors in descending eigenvalue order yields the optimal projection matrix $X = [x_1, x_2, ..., x_d]$, where x_i is the i-th eigenvector. The projection result $Y_i = A_i X$ reduces sample dimension from $n \times m$ to $n \times d$, performing row-direction projection.

TD-2DPCA extends 2DPCA by additionally projecting along the column direction. The column projection matrix Z is solved similarly by transposing samples A_i, yielding the overall scatter matrix $\hat{G}_t = \frac{1}{M}\sum_{i=1}^{M}(A_i - \bar{A})(A_i - \bar{A})^T$, an $n \times n$ non-negative definite matrix. Its eigenvectors are computed and sorted to obtain the optimal column projection matrix $Z = [z_1, z_2, ..., z_q]$. Simultaneous row and column projection yields the final result:

$$C_i = Z^T A_i X$$

The original matrix dimension $n \times m$ is reduced to $q \times d$, achieving effective compression. Covariance matrix dimensions become $m \times m$ and $n \times n$, far smaller than PCA' s $(nm) \times (nm)$, improving computational efficiency.

Two common methods control projection dimension: (1) directly setting the projected dimension (number of eigenvectors); (2) calculating cumulative contribution rate from eigenvalues, selecting the number where the rate first exceeds a threshold. Fixed dimensions affect generalization, while cumulative contribution may cause information loss if one eigenvalue dominates. This paper combines both: primarily using cumulative contribution rate for generalization, but applying fixed-dimension reduction when the resulting dimension falls below a minimum allowed value.

1.4 Least Squares Support Vector Machine

Support Vector Machine (SVM) offers fast computation and high accuracy for small-sample classification and prediction, suitable for real-time vigilance estimation. Least Squares SVM (LS-SVM) simplifies computation further and runs faster, making it ideal for constructing regression models between EEG features and vigilance. The LS-SVM kernel function uses a Gaussian kernel:

$$K(\mathbf{x}, \mathbf{z}) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{z}\|^2}{2\sigma^2}\right)$$

where σ represents the kernel bandwidth.

1.5 Vigilance Estimation Method

The core vigilance estimation procedure is:

Step 1: For N channels of EEG signals, decompose each channel into M components using a fixed bandwidth.

Step 2: Extract differential entropy from each component via short-time Fourier transform with non-overlapping Hanning windows.

Step 3: Smooth the extracted DE features using improved moving average and reduce dimensions via TD-2DPCA.

Step 4: Feed the processed features into an LS-SVM regressor to obtain vigilance estimation results.

The method' s framework is illustrated in Figure 1.

2.1 EEG Dataset

The dataset is the publicly available SEED-VIG driving fatigue dataset from Shanghai Jiao Tong University' s Brain-Like Computing and Machine Intelligence Center [?]. Experiments were conducted in a virtual driving system where subjects operated a real vehicle (without unnecessary engine components) facing a screen displaying synchronized driving scenes, primarily monotonous straight roads to induce fatigue. Twenty-three subjects (12 females, mean age 23.3 ± 1.4) participated, all in good health. Most experiments began around 13:30 to facilitate fatigue onset, with each session lasting approximately 2 hours.

Eighteen channels of EEG signals were recorded using the international 10-20 system: FT7, FT8, T7, T8, TP7, TP8, CP1, CPZ, CP2, P1, PZ, P2, PO3, POZ, PO4, O1, OZ, O2 (Figure 2). CPZ served as the reference electrode, leaving 17 EEG channels. Additionally, 7 channels of eye and forehead signals were recorded (Figure 3). Channels 1-4 followed conventional EOG placement, while channels 5-7 were unique to SEED-VIG, capturing signals that can be considered EEG heavily contaminated by EOG. To reduce noise and computational load, the 17 EEG channels were downsampled to 200 Hz and bandpass-filtered at 1-75 Hz; the 7 eye/forehead channels were downsampled to 125 Hz.

Vigilance levels were annotated using the PERCLOS index calculated from eye-tracking glasses data:

$$\text{PERCLOS} = \frac{\text{blink} + \text{CLOS}}{\text{time}}$$

where time is the interval duration (8 seconds in SEED-VIG), blink is blink time, and CLOS is eye closure time. PERCLOS ranges from 0 to 1, with higher values indicating lower vigilance and greater fatigue.

2.2 Vigilance Estimation with Different Data Processing Methods

All experiments used 17 EEG channels plus 4 forehead channels (21 total channels), validated across all 23 subjects. The 0-50 Hz band was divided into 50 sub-bands at 1 Hz intervals. DE features were extracted using 8-second non-overlapping Hanning windows, yielding 885 data points from 118 minutes of recording per subject, resulting in a DE feature dimension of $21 \times 50 \times 885$.

Two smoothing methods (conventional and improved moving average) and two dimensionality reduction methods (PCA and TD-2DPCA) were compared. Since vigilance fluctuations typically exceed four-minute cycles [?], the smoothing window width was set to 4 minutes. After extensive experimentation, PCA' s contribution rate was set to 0.9, TD-2DPCA' s row/column contribution rates to 0.9 and 0.85 respectively, with minimum allowed dimension of 4 for both. LS-SVM regression models were trained with γ and σ set to 50000 and 3000. Performance was evaluated using:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

$$\text{Pearson} = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2 \sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}})^2}}$$

where y_i is the measured PERCLOS index, $\hat{y}_i$ the estimated value, and N the number of samples. Five-fold cross-validation was used: for each subject, 885 data points were divided into five segments, with four segments for training and one for validation, repeated five times. Results were concatenated in original order for final RMSE and Pearson correlation calculation.

Table 1 shows the impact of smoothing and dimensionality reduction, reporting averages across 23 subjects and total time for all tests. Direct use of raw features yielded only 64.08% Pearson correlation and the longest runtime, failing practical requirements. After smoothing and dimensionality reduction, Pearson correlation exceeded 85% and runtime halved, confirming their benefits. Improved moving average outperformed conventional methods, increasing Pearson correlation by ~2% and reducing RMSE by ~0.5%. The combination of improved moving average with TD-2DPCA achieved the highest Pearson correlation (87.83%) and shortest runtime, with RMSE only 0.04% higher than the minimum. TD-2DPCA thus offers advantages over PCA, particularly as feature dimensionality increases.

2.3 Vigilance Estimation with Different DE Extraction Methods

To further improve accuracy, we systematically investigated DE extraction methods. The total bands 0–15 Hz, 0–20 Hz, and 0–50 Hz were divided at bandwidths of 1 Hz, 2 Hz, 3 Hz, 4 Hz, and 5 Hz, yielding 105 DE extraction configurations. For example, dividing 0–25 Hz at 2 Hz bandwidth produces 12 sub-bands: 0–2 Hz, 2–4 Hz, ···, 22–24 Hz. Feature extraction used short-time Fourier transform, smoothing used improved moving average, dimensionality reduction used TD-2DPCA, and regression used LS-SVM, with parameters identical to the first experiment.

Results are shown in Table 2. The 1 Hz bandwidth achieved the highest Pearson correlation (87.45% average), while the 2 Hz bandwidth yielded the lowest RMSE (9.07% average), demonstrating clear advantages over 3–5 Hz bandwidths across all total bands. The maximum Pearson correlation reached 91.50% at 1 Hz bandwidth, and the minimum RMSE was 8.67% at 2 Hz bandwidth. Analysis of optimal total bands across bandwidths revealed that highest accuracy consistently occurred in ranges starting at 0 Hz and ending at 20–30 Hz, indicating that 0–30 Hz EEG contains most vigilance-related information, while excessive feature extraction degrades performance.

Table 3 lists all experiments achieving Pearson correlation > 0.9, showing corresponding RMSE, bandwidth, and total band. Nine DE extraction methods achieved high-precision vigilance assessment, with RMSE values near 0.09. Among them, four methods used 1 Hz bandwidth, four used 2 Hz, and one used 3 Hz; no methods with 4 Hz or 5 Hz bandwidths achieved this threshold. Notably, none of the nine methods used total bands exceeding 35 Hz, confirming that the optimal total bandwidth for DE-based vigilance estimation lies within 0–35 Hz.

2.4 Comparison with Existing Methods

Table 4 compares our method with existing approaches. Our method extracts DE from components obtained by dividing 0–35 Hz at 2 Hz bandwidth. The five-band method extracts DE from conventional frequency bands, while Zheng et al. [?] divided 0–50 Hz at 2 Hz bandwidth. Our method achieves 0.91/0.09 (Pearson/RMSE), surpassing the best existing result of 0.85/0.09. Comparison with the five-band method further confirms that fine-grained EEG decomposition yields more effective features than conventional band extraction.

3 Conclusion

To improve real-time vigilance estimation accuracy using EEG DE features, this paper systematically investigated DE extraction, data smoothing, and dimensionality reduction methods, proposing an approach combining improved moving average, TD-2DPCA, and optimal DE extraction. By incorporating vigilance' s temporal dynamics, we enhanced traditional moving average with variable-window smoothing and short-term prediction, strengthening edge-central data correlation. TD-2DPCA was introduced for dimensionality reduction, offering modest improvements in computational speed and information extraction over PCA. Comprehensive experiments revealed that dividing the total band within 0–35 Hz at 1 Hz or 2 Hz bandwidth yields high estimation accuracy (Pearson 0.91, RMSE 0.09), outperforming existing methods (0.85/0.09). Future work will integrate transfer learning for cross-subject vigilance estimation.

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Note: Figure translations are in progress. See original paper for figures.