Burst Suppression Pattern Recognition Using Time-Frequency Analysis

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Abstract: We developed a method to recognize EEG burst suppression in the joint time-frequency domain. We obtained the feature used in the proposed method from the joint use of the time and frequency domains, and we recognized the EEG samples as bursts or suppressions by a maximum likelihood estimation, which is an easier optimization than conventional methods. We evaluated the performance of the proposed method in terms of its accordance to the visual score and estimation of the burst suppression ratio. The accuracy was higher than the sole use of the time domain, as well as conventional methods conducted in the time domain. Quantification of burst suppression necessitated a precise recognition with an easy optimization; therefore, the proposed method using time-frequency analysis appears beneficial.

Keywords— **EEG, Burst suppression, Maximum likelihood estimation, Time-frequency analysis**

1. Introduction

Electroencephalogram (EEG) burst suppression (BS) is an inactivated EEG pattern, and is basically isoelectric pattern (suppression) alternating with high voltage pattern (burst), as shown in Fig. 1. BS pattern is observed in reduction of brain's activity and metabolic rate [1], e.g., anaesthesia, hypothermia, and coma. From the fact that more reductions result in a longer suppression duration, quantification of BS have developed based on measuring how suppressed the BS is. The first step for quantifying is to recognize BS (i.e., classify BS samples into burst and suppression). Current practices are based on visual-score, which is roughly guessed and time-consuming, thus algorithmic methods have developed.

Most of BS recognition have conducted in time domain only, and few basic frequency-domain features are used. In this study, we jointly use time and frequency domain to enhance the accuracy of BS recognition. Then, the distribution of time-frequency features was modelled as two-dimensional Gaussian, and maximum likelihood estimation (MLE) is applied to recognize. The result is more accurate than time-domain methods and conventional methods, and is more advantageous in terms of the optimization than the conventional methods.

2. Method

2.1 Data acquisition

In this study, we used 11 multichannel EEG data sets recorded from the Mokdong Hospital of Ewha Womens University. The 20 min duration of 11 EEGs came from patients suffering status epilepticus, and were identified the occurrence of BS patterns. The 11 EEGs were recorded from 21 electrode locations, based on the international 10-20 system with 200 Hz of sampling frequency.

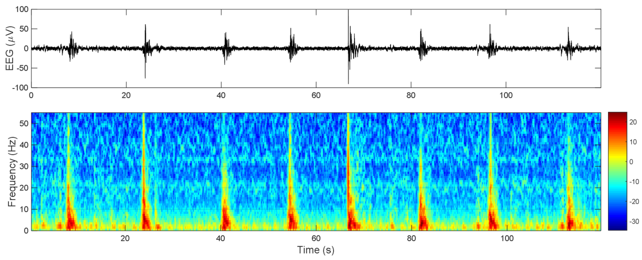


Figure 1. An example of EEG burst suppression and its PSD by spectrogram

2.2 Time-frequency representation of burst suppression

Let $\{x_n(i) : i = 1, 2, ..., L\}$ be the raw sampled EEG signal of the nth channel. To remove artifacts in the EEG signals, we take median value over all channels and denote the signal as $x(i)$. As in Fig. 1, the power spectral density (PSD), which is a representative of frequency-representation, is also informative to capture the difference of burst and suppression. Therefore, to conduct time-frequency analysis and obtain the power spectral density of the signal, we defined the mth block of $x(i)$ as:

$$\mathbf{x}_m = \{x(i) : i = 1 + m\Delta, 2 + m\Delta, ..., N + m\Delta\}, \quad (1)$$

where N denotes the block width and $\Delta < N$ means the step-size of sliding block. Then, PSD $\mathbf{P}_m$ is directly calculated by the short-time Fourier transform (STFT) as

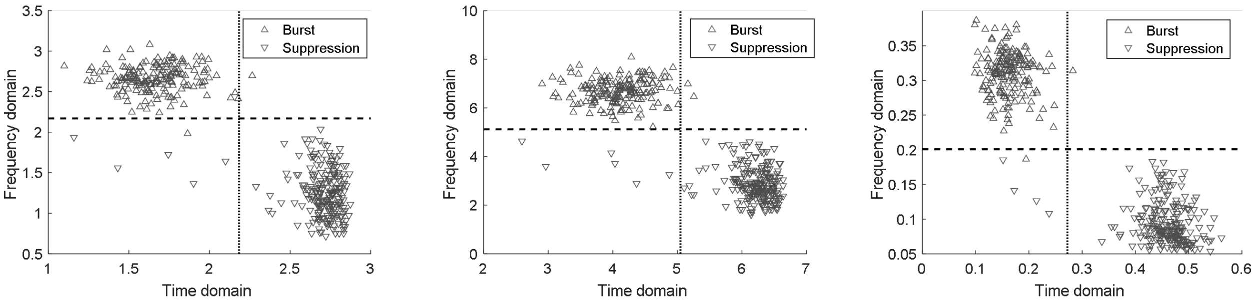
$$\begin{aligned} \mathbf{X}_m &= \mathrm{STFT}\{\mathbf{x}_\mathrm{m}\}, \\ \mathbf{P}_m &= |\mathbf{X}_m|^2. \end{aligned} \quad (2)$$

To analyse BS patterns in time-frequency domain, the time-frequency vector $\mathbf{f}_m$ for mth sliding window is newly defined as

$$\mathbf{f}_m = \begin{bmatrix} \mathbf{x}_m \\ \mathbf{P}_m \end{bmatrix}. \quad (3)$$

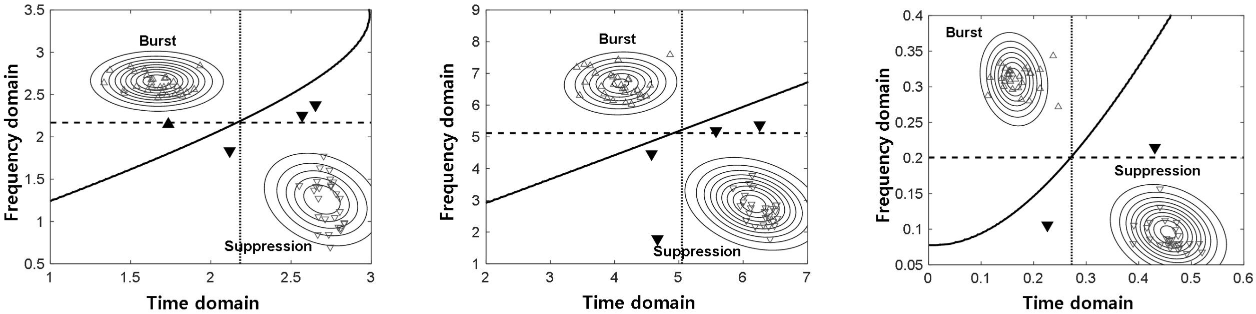
Conventionally in quantitative EEG analysis, many features were used for detecting transient events, such as bursts. In this study, conventional features we used were Shannon entropy $S(m)$, Tsallis entropy $T(m)$, and regularity $R(m)$, and they are applied to $\mathbf{f}_m$. The features are calculated as

$$S(m) = \begin{bmatrix} -\sum_{l=1}^{M_t} p_t(l) \ln p_t(l) \\ -\sum_{l=1}^{M_f} p_f(l) \ln p_f(l) \end{bmatrix}, \quad (4)$$



(a)Shannon entropy in time-frequency domain (b)Tsallis entropy in time-frequency domain (c)Regularity in time-frequency domain

Figure 2. Features distributed in time-frequency domain



(a)Gaussian models for Shannon entropy (b)Gaussian models for Tsallis entropy (c)Gaussian models for regularity

Figure 3. Gaussian models for features and MLE decision in time-frequency domain

$$T(m) = \frac{1}{q-1}\left[\begin{array}{c} 1-\sum_{i=1}^{M_t} p_t(l)^q \\ 1-\sum_{i=1}^{M_f} p_f(l)^q \end{array}\right], \tag{5}$$

and

$$R(m) = \left[\begin{array}{c} \sqrt{\dfrac{\sum_{i=1}^{N} i^2 d_t(i)}{\frac{N^2}{3}\sum_{i=1}^{N} d_t(i)}} \\ \sqrt{\dfrac{\sum_{i=1}^{N} i^2 d_f(i)}{\frac{N^2}{3}\sum_{i=1}^{N} d_f(i)}} \end{array}\right], \tag{6}$$

where $p_t(l)$ and $p_f(l)$ are estimated probability density functions of $\mathbf{x}_m$ and $\mathbf{P}_m$, respectively, q is a real positive number, and $d_t(i)$ and $d_f(i)$ are descending-ordered sequence of $\mathbf{x}_m^2$ and $\mathbf{P}_m$, respectively. The probability density function $p_t(l)$ and $p_f(l)$ are estimated by binning process with the numbers of bins M_t and M_f, respectively.

The example features are shown in Fig. 2. The burst clusters and the suppression clusters are clearly separated for all the features. However, the recognition performance can deteriorate by the segments deviated from their clusters, and a fixed threshold could result in errors (i.e., false alarms or missing). The optimal threshold are drawn by the vertical and the horizontal lines, and they always generate errors. Therefore, we considered probabilistic distributions of the features and applied non-linear decision boundary in the time-frequency domain.

2.3 Burst suppression segmentation

To consider the probabilistic distributions of features (4)-(6), the feature clusters are modelled as Gaussian. Let the mean and covariance of bursts (suppressions) as $\boldsymbol{\mu}_{B(S)}$ and $\mathbf{C}_{B(S)}$, respectively. Then, the Gaussian distribution $p_\theta(\mathbf{z})$ for $\theta \in \{B, S\}$ is

$$p_\theta(\mathbf{z}) = \frac{\exp\left\{-\frac{1}{2}(\mathbf{z}-\boldsymbol{\mu}_\theta)^{\mathbf{T}}\mathbf{C}_\theta^{-1}(\mathbf{z}-\boldsymbol{\mu}_\theta)\right\}}{|2\pi\mathbf{C}_\theta|^{\frac{1}{2}}}. \tag{7}$$

To recognize whether a new feature $\mathbf{z}$ is a burst or a suppression, MLE was used. The estimation $\hat{\theta}$ is formulated as

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}}\left\{p_\theta(\mathbf{z}) : \theta \in \{B, S\}\right\}. \tag{8}$$

In Fig. 3, examples of Gaussian distributions for all the three features are shown as loci plots. The means and the covariances are obtained from Fig. 2, and the decision boundaries by MLE are plotted as solid lines. The horizontal lines and the vertical lines are corresponding to optimal thresholds in the sole use of the time and the frequency domain, respectively. The newly extracted features plotted as triangles, and filled triangles are corresponding to errors evoked by the straight lines. However, these errors are recognized correctly by the MLE. In the case of Shannon entropy, the four errors in Fig. 3a are represented with the BS pattern on the time axis in Fig. 4. The blocks are detected burst periods, and the boxes mean errors. The correct classification of the proposed method is also verified.

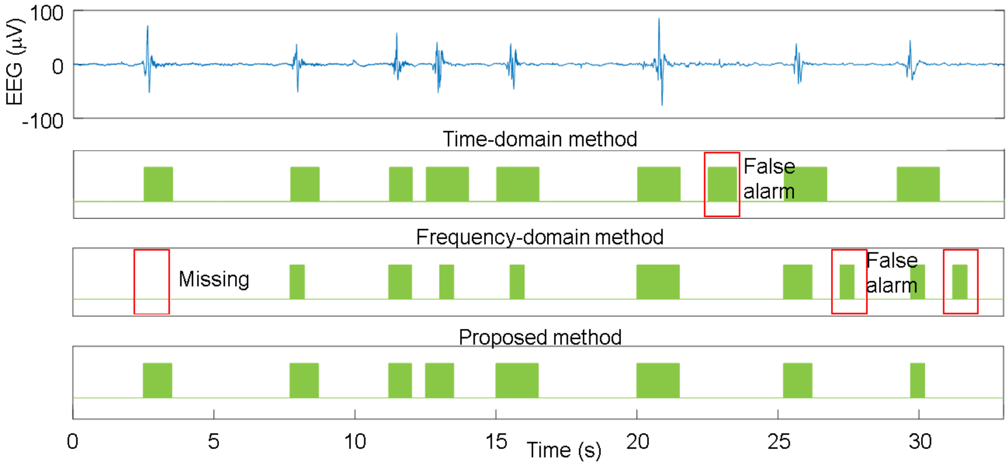


Figure 4. An example BS (top), time-domain recognition (second), frequency-domain recognition (third) and the proposed recognition (bottom). Filled blocks: detected burst periods, boxes: errors

Table 1. Mean and standard deviation (std) of sensitivity, specificity, and accuracy for various features

	Features	Sensitivity (%)		Specificity (%)		Accuracy (%)	
		mean	std	mean	std	mean	std
Proposed time-frequency domain	Shannon entropy	68.55	17.4	**88.66**	21.9	84.51	17.8
	Tsallis entropy	**69.81**	16.3	88.31	17.9	83.29	14.8
	Regularity	**74.42**	13.3	88.60	23.0	**84.82**	19.3
Time domain	Shannon entropy	51.90	15.1	87.91	7.0	83.72	9.0
	Tsallis entropy	50.99	14.4	83.92	6.0	80.97	8.3
	Regularity	62.76	11.5	88.20	8.0	77.71	8.1
Conventional methods	Line length [2]	68.12	31.3	**92.58**	12.9	**84.67**	13.4
	Envelope [3]	57.13	20.9	82.83	23.3	77.32	19.2
	NLEO [4]	56.40	21.9	83.60	22.2	77.83	18.7

*Bold faces are the highest two evaluations in columns

3. Results

Data used are 11 EEG BS patterns recorded from 21 electrode locations based on international 10-20 system, and each BS duration is about 20 min. For the time-frequency analysis, N and Δ were set to be 140 and 40, which are corresponding to 0.7 s and 0.2 s, respectively. For entropy features, M_t and M_f are 20 and 40, respectively, and $q = 0.5$. To set the Gaussian models in (5), initial 10 min samples of each BS is used. Then, the remaining BS is recognized and used to verify the performance of accordance and estimate burst suppression ratio (BSR), which is a quantification of BS.

3.1 Accordance to visual scores

To verify the agreement of the BS pattern recognition compared with visual scores, sensitivity, specificity, and accuracy are widely used [2-4]. These are evaluated as

$$\begin{aligned} \text{Sensitivity} &= \frac{\#(\text{Correctly detected bursts})}{\#(\text{All bursts})}, \\ \text{Specificity} &= \frac{\#(\text{Correctly detected suppressions})}{\#(\text{All suppressions})}, \\ \text{Accuracy} &= \frac{\#(\text{Correctly detected samples})}{\#(\text{All samples})}. \end{aligned} \tag{9}$$

Equation (9) is evaluated for various features, and compared in Table 1. The sole use of the time domain of Shannon entropy, Tsallis entropy, and regularity are compared, and conventional methods are also compared, which are line-length based method [2], envelope based method [3], and non-linear-energy-operator based method [4]. The proposed methods are better than time domain methods for all criteria, and are also better than conventional methods except for the line-length based method. Furthermore, all the compared conventional methods uses ROC-based optimizations, but the proposed method provides easier optimization by MLE, which is probabilistic optimal estimation.

3.2 Burst suppression ratio (BSR)

As a result of the BS recognition, BSR measures how suppressed the BS is. BSR is known most widely as the quantification of BS, and is calculated by the ratio of suppression sample to the number of sample in a certain interval of 15 s.

The estimated BSR is compared with true BSR, which is based on visual score, is in Fig. 5. The two different BS is exhibited, and true BSRs is high for the more suppressed BS and medium for the less suppressed BS. The absolute difference ΔBSR between the true BSR and the estimated BSR is also

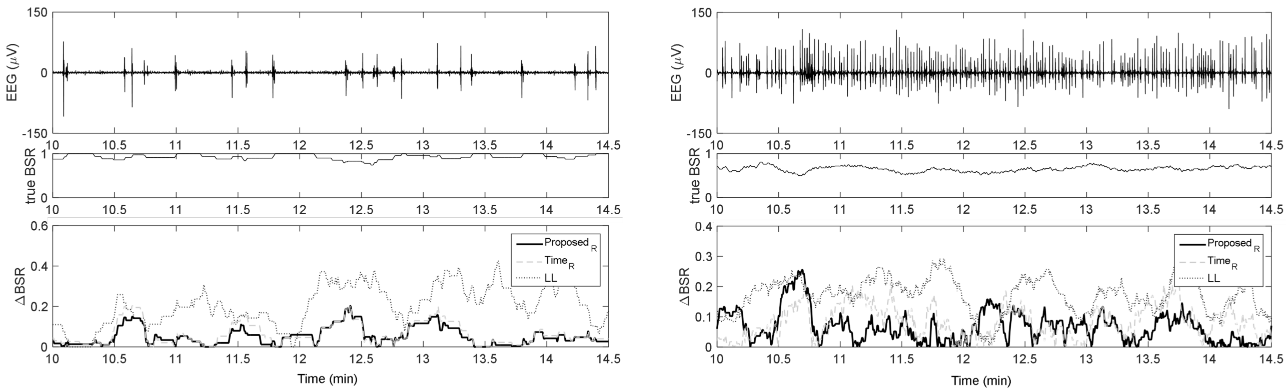


Figure 5. Example BSR estimations for different BS. BS are shown in the top, true BSR is exhibited in the middle, and ΔBSR is shown in the bottom. Proposed$_R$ means the proposed method using regularity, Time$_R$ is the sole use of time domain using regularity, and LL is line-length based method.

Table 2. Mean and standard deviation RMSE between true BSR and estimated BSR by diverse methods

RMSE	Features								
	Proposed time-frequency domain			Time domain			Conventional methods		
	Shannon entropy	Tsallis entropy	Regularity	Shannon entropy	Tsallis entropy	Regularity	Line length [2]	Envelope [3]	NLEO [4]
Mean	0.111	0.121	**0.094**	0.118	0.131	**0.098**	0.175	0.210	0.214
std	0.074	0.068	0.051	0.067	0.058	0.049	0.053	0.136	0.130

plotted in the bottom. The compared methods in Fig. 5 are the proposed method using regularity, the sole use of time domain using regularity, and LL based method, which were accurate in terms of accordance to visual scores. Generally, the proposed method accurately estimates BSR rather than other methods. The statistical results of root-mean-square-error between true BSR and estimated BSR were exhibited in Table 2. The mean RMSE was the smallest (0.094) for the proposed method using regularity, and the sole use of time domain using regularity provides the second smallest RMSE (0.098).

4. Conclusion and Discussion

In this study, the features, used in conventional time domain qEEG were reviewed in the time-frequency domain to recognize burst and suppression for EEG BS pattern. The features were derived from the $\mathbf{f_m}$ that was newly defined by the time-frequency analysis. To recognize BS, we considered the feature distribution of bursts and suppressions in time-frequency domain, and modeled the distributions as Gaussian. Finally, the MLE is conducted to recognize burst and suppression in BS.

The results was evaluated in two perspectives: accordance to visual scores of BS and the comparison between true BSR and estimated BSR. In terms of accordance, sensitivity, specificity, and accuracy are exhibited and the enhanced accordance to visual score is verified. In the comparisons of true BSR and estimated BSR, the proposed BS recognition estimates BSR accurately, so the proposed method is beneficial.

Another usefulness of the proposed method can be shown in terms of the optimization process. Conventional methods used an ROC-based optimization, which is very time-consuming and needs a huge amount of redundant calculations. However, the proposed BS recognition uses the feature distributions of bursts and suppressions and MLE, which is the probabilistically optimal decision, so the proposed method is advantageous.

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