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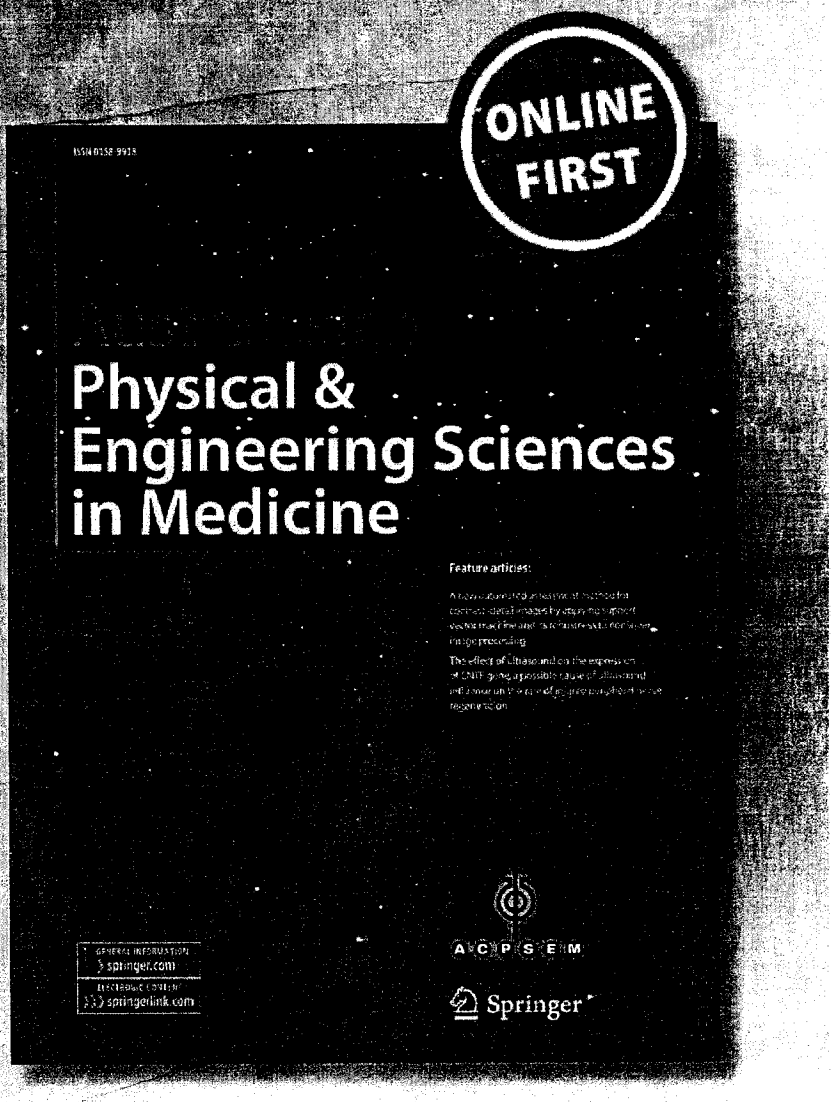

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SCIENTIFIC PAPER

Performance of epileptic single-channel scalp EEG classifications using single wavelet-based features

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Abstract Classification of epileptic scalp EEGs are certainly ones of the most crucial tasks in diagnosis of epilepsy. Rather than using multiple quantitative features, a single quantitative feature of single-channel scalp EEG is applied for classifying its corresponding state of the brain, i.e., during seizure activity or non-seizure period. The quantitative features proposed are wavelet-based features obtained from the logarithm of variance of detail and approximation coefficients of single-channel scalp EEG signals. The performance on patient-dependent based epileptic seizure classifications using single wavelet-based features are examined on scalp EEG data of 12 children subjects containing 79 seizures. The 4-fold cross validation is applied to evaluate the performance on patient-dependent based epileptic seizure classifications using single wavelet-based features. From the computational results, it is shown that the wavelet-based features can provide an outstanding performance on patient-dependent based epileptic seizure classification. The average accuracy, sensitivity, and specificity of patient-dependent based epileptic seizure classification are, respectively, 93.24%, 83.34%, and 93.53%.

Keywords Electroencephalogram · Seizure · Classification · Wavelet transform · Patient dependent

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Introduction

Epilepsy, one of the most common neurological disorders, remains a challenging topic to researchers in many aspects. In epilepsy, the normal pattern of neuron activity is disturbed, and sometimes clusters of neurons in the brain signal abnormally [1]. Epilepsy is characterized by recurrent seizures that are physical reactions to sudden, usually brief, excessive electrical discharges in clusters of nerve cells [2]. There are many possible causes for seizures ranging from illness to brain damage to abnormal brain development [1]. Approximately 50 million people worldwide have epilepsy and most of the people with epilepsy live in low- and middle-income countries [2]. In Thailand, there are between 380,000 and 470,000 people estimated to have epilepsy [3]. EEGs that quantify electrical activity of the brain are the most fundamental diagnostic test for epilepsy. Typically, EEGs are recorded using electrodes placed on the scalp. Scalp EEGs have several advantages including simplicity, non-invasiveness and also inexpensiveness. Scalp EEGs are however very sensitive to artifacts and have a poor spatial resolution. Intracranial EEGs are an alternative approach to measure the electrical activity of the brain by placing electrodes on the cortex. As intracranial EEGs provide better temporal and spatial characteristics of electrical activity of the brain compared to scalp EEGs, intracranial EEGs are more suitable for comprehensive diagnosis of epilepsy. Therefore, intracranial EEGs are used in most of studies, in particular, epileptic seizure classification and detection which are one of the most crucial tasks in diagnosis of epilepsy.

In epileptic seizure classification, corresponding states of the brain epochs of EEGs associated with, namely, ictal state (during epileptic seizure activity), and pre-ictal and post-ictal states (during non-seizure periods), are identified

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based on specific features and patterns of EEGs such as monomorphic waveforms, polymorphic waveforms, spike and sharp wave complexes, or periods of reduced electrocerebral activity [4–6]. A variety of quantitative features extracted from either scalp EEGs or intracranial EEGs have been shown to be useful for epileptic seizure classification and detection. A wide range of success on epileptic seizure classification and detection has been reported. The superior performance on epileptic seizure classification and detection using intracranial EEGs can in general be obtained.

In particular, the quantitative features applied for epileptic seizure classification and detection using scalp EEGs can be classified into a number of categories. Various time-domain features [7–10] such as line length, zero crossing, RMS, higher order moments, entropies, and Hjorth parameters are fundamental and simple quantitative features applied for epileptic seizure classification. Energy based features [4, 8–14] derived from Fourier transform and wavelet transforms are the most common quantitative features applied for various applications of EEG analysis including epileptic seizure classification and detection. Quantitative features derived from nonlinear methods [9] including Lyapunov exponents are novel quantitative features applied to epileptic seizure classification and detection.

Furthermore, a number of computational techniques and tools have beeen applied for classifying quantitative features of scalp EEGs into classes corresponding to physiological states, basically, seizure and non-seizure periods. Such computational techniques and tools ranging from simplest techniques such as thresholding to complex and advanced approaches based on concepts of computational intelligence, artificial neural networks, and machine learning. Support vector machines (SVMs) are one of the most common classifiers applied for epileptic seizure classification and detection [4, 8, 10, 12–15]. Evolutionary neural networks is another approach recently applied for epileptic seizure classification and detection [9].

In this study, wavelet-based features of scalp EEGs of children subjects with epilepsy are applied for patient-dependent based epileptic seizure classification. The wavelet-based features used are computationally relevant to the power spectral density (PSD) [16]. The wavelet-based approach however allows an unbiased estimate [16]. It is focused on assessing the performance of epileptic seizure classification using only single quantitative feature of single-channel scalp EEG rather than using multiple and complex quantitative features of single or multiple channels of scalp EEGs. Accordingly, as opposed to complicated classifiers, a simple thresholding technique can be applied to classify scalp EEGs into their corresponding states. The performance of three schemes of epileptic scalp EEG classifications using wavelet-based features is examined.

Materials and methods

EEG data and subjects

Scalp EEG data of twelve children subjects (3 males and 9 females) with intractable seizures examined in this study were obtained from the CHB-MIT Scalp EEG Database (available online at http://www.physionet.org/pn6/chb-mit/). The database was collected at the Children's Hospital Boston [17] and originally studied in Refs. [4, 12]. All subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention [17]. All protected health information (PHI) in the original recordings was replaced with surrogate information in order to protect the privacy of the subjects [17].

The subjects are referred to as chb01, chb02, chb05, chb08, chb09, chb10, chb13, chb14, chb16, chb20, chb22 and chb23, and age between 2 and 11 years old. A chosen single channel of scalp EEG signals is examined for each subject. The scalp EEG signals were acquired using a sampling rate of 256 Hz with 16-bit resolution [17]. The international 10–20 system of EEG electrode positions and nomenclature was used for the recordings [17]. There are a total of 79 epileptic seizure events. Segments of scalp EEG signals around epileptic seizure events (12 min before seizure onset and 12 min after seizure offset, unless limited by the beginning and the end of recording) are used in this study.

The scalp EEG segments are divided into epochs with length of 512 samples (2 s) and with 50% overlap. Scalp EEG epochs associated with epileptic seizure event are categorized as an SZ class while scalp EEG epochs associated with pre-ictal and post-ictal states are categorized as Pr and Po classes. The description of all twelve subjects and the number of SZ, Pr and Po epochs for each subject are summarized in Table 1.

Discrete wavelet transform

The discrete wavelet transform (DWT) is certainly one of the most powerful and widely used signal processing techniques. The DWT is a representation of a signal using a countably-infinite set of wavelets that constitutes an orthonormal basis [18]. The wavelet transform can be interpreted as a generalized filter bank [19] and also in the context of multiresolution analysis (MRA) [20]. The MRA generally consists of a sequence of successive approximation spaces [21]. Furthermore, the multiresolution analysis leads to a hierachical scheme for the computation of the wavelet coefficients of a given function [21].

Table 1 Description of subjects and scalp EEG data

Subject	Age (year)	Channel	No. of EEG epochs		
			Pr	SZ	Po
chb01	11	FT9-FT10	4633	421	4517
chb02	11	FP2-F4	1564	163	1484
chb05	7	P4-O2	3287	543	3595
chb08	3.5	F4-C4	3590	904	3185
chb09	10	F4-C4	2872	264	2494
chb10	3	T7-FT9	5026	426	4566
chb13	3	F7-T7	7504	499	8106
chb14	9	C4-P4	5744	145	5372
chb16	7	F8-T8	6594	54	6771
chb20	6	F8-T8	4788	270	5752
chb22	9	F3-C3	2154	195	1277
chb23	6	F7-T7	4631	403	5033

A signal $x[n]$ is decomposed into approximations and details using scaling functions ϕ and wavelet functions ψ that, respectively, correspond to halfband lowpass filter and halfband highpass filter. This can be expressed as

$$\begin{aligned} x[n] &= \sum_k a_0[k]\phi_{0,k}[n] \\ &= \sum_k a_1[k]\phi_{1,k}[n] + \sum_k d_1[k]\psi_{1,k}[n] \end{aligned} \tag{1}$$

where the scaling function $\phi_{1,k}[n]$ and the wavelet function $\psi_{1,k}[n]$ are, respectively, an orthonormal basis for the space V_1 and the orthogonal complement of V_1, denoted by W_1, and the space $V_0 = V_1 \oplus W_1$. The approximation coefficients $a_1[n]$ and the detail coefficients $d_1[n]$ can be obtained by

$$a_1[n] = \sum_k a_0[k]h[k-2n] \tag{2}$$

$$d_1[n] = \sum_k a_0[k]g[k-2n] \tag{3}$$

where $h[n]$ and $g[n]$ are, respectively, the impulse response of halfband lowpass filter and halfband highpass filter.

For a single-level discrete wavelet decomposition at level l, the approximation coefficients $a_l[n]$ can be obtained by convolving the approximation coefficients $a_{l-1}[n]$ with the time-reversed filter of $h[n]$, i.e., $\tilde{h}[n]$, followed by the downsampling and, similarly, the detail coefficients $d_l[n]$ can be obtained by convolving the approximation coefficients $a_{l-1}[n]$ with the time-reversed filter of $g[n]$, i.e., $\tilde{g}[n]$, followed by the downsampling. Therefore, there are L detail coefficients, i.e., $d_1, d_2, \ldots, d_L$, and one approximation coefficients, i.e., a_L, obtained from the L-level discrete wavelet decomposition.

Wavelet-based features and data analysis

Quantitative features examined in this study are obtained from the detail coefficients $d_l[n]$ and the approximation coefficients $a_l[n]$. The proposed wavelet-based features λ_i are the logarithm of variance of detail coefficients and approximation coefficients. The wavelet-based features obtained from the detail coefficients d_l are denoted by λ_k where $k = l$ and the wavelet-based feature obtained from the approximation coefficients a_L is denoted by λ_{L+1}. Therefore, the wavelet-based features are given by

$$\lambda_k = \log_2\left(\mathrm{var}(d_l)\right), \quad \text{where } k = \{l | l = 1, 2, \ldots, L\} \text{ and} \tag{4}$$

$$\lambda_{L+1} = \log_2\left(\mathrm{var}(a_L)\right). \tag{5}$$

Scalp EEG epochs are decomposed into five levels, that yield five detail coefficients d_1, d_2, d_3, d_4, and d_5 and one approximation coefficients a_5, using the 6th order Daubechies wavelets. The Daubechies wavelet family is one of the most commonly used wavelet families which hass several nice characteristics including orthogonality and finite compact support. A higher order Daubechies wavelets corresponds to higher regularity and also a number of vanishing moments. Furthermore, the five levels of wavelet decomposition is the maximum number of levels of wavelet decomposition of scalp EEG epochs with length of 512 samples (2 s) using the 6th order Daubechies wavelets. The coefficients d_1, d_2, d_3, d_4, d_5, and a_5 approximately correspond to 64–128, 32–64, 16–32, 8–16, 4–8, and 0–4-Hz subbands, respectively, which coincide with conventional EEG bands, namely, γ, β, α, θ, and δ. The frequency responses of the 6th order Daubechies wavelets corresponding to the coefficients d_1, d_2, d_3, d_4, d_5, and a_5 are shown in Fig. 1.

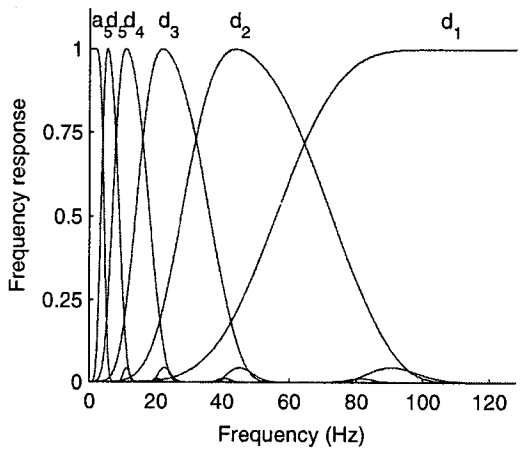

Fig. 1 The corresponding spectral subbands of the 6th order Daubechies wavelets

EEG classification and validation

A single feature λ_k is applied to classify corresponding scalp EEG epochs into one of classes, i.e., SZ, Pr, Po, and NS (non-seizure period) classes using a thresholding technique. Three classifications performed in this study include (1) classification between scalp EEG epochs associated with the SZ class and those associated with the Pr class; (2) classification between scalp EEG epochs associated with the SZ class and those associated with the Po class; and (3) classification between scalp EEG epochs associated with the SZ class and those associated with the Pr or Po classes (NS class).

The classification is performed by a subject-by-subject basis. The scalp EEG epochs obtained from within the same subject are applied for each classification. Performance of epileptic seizure classification is evaluated using three conventional classification performance measures: accuracy, sensitivity, and specificity. The accuracy (Ac), the sensitivity (Se), and the specificity (Sp) are given, respecitvely, by

$$Ac = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$
$$Se = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \text{ and}$$
$$Sp = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

where TP, TN, FP, and FN denote a number of true positives, a number of true negatives, a number of false positives, and a number of false negatives, respectively. In addition, the product of sensitivity and specificity is also determined as a performance measure that justifies both the true positive rate and the true negative rate.

The 4-fold cross validation is used to validate the performance of classifications. For each subject, the set of wavelet-based features of scalp EEG epochs associated with various classes are divided into four subsets. Three subsets of wavelet-based features are used to as a training set while another subset of wavelet-based features is used to as a testing set. A threshold τ is determined from the training set of wavelet-based features corresponding to both positive and negative classes, respectively, denoted by Z_P and Z_N as follows:

$$\tau = \begin{cases} \frac{\max Z_P + \min Z_N}{2} & \text{if } \bar{Z}_P < \bar{Z}_N \\ \frac{\min Z_P + \max Z_N}{2} & \text{if } \bar{Z}_P > \bar{Z}_N \end{cases} \tag{6}$$

where $\bar{Z}_P$ and $\bar{Z}_N$ are, respectively, the means of wavelet-based features corresponding to positive and negative classes. The positive class refers to the SZ class and the negative class refers to either the Pr, Po, or NS class.

The classification is simply performed using a thresholding technique with the following rules of logical comparison. In the first case, i.e., $\bar{Z}_P < \bar{Z}_N$, a scalp EEG epochs of testing set is classified to belong to a positive class if the corresponding wavelet-based feature λ_k is less than or equal to the threshold; and a negative class, otherwise. On the contrary, in another case, $\bar{Z}_P > \bar{Z}_N$, a scalp EEG epochs of testing sets is classified to belong to a positive class if the corresponding wavelet-based feature λ_k is greater than or equal to the threshold; and a negative class, otherwise. The cross validation is repeated 4 times with each of the four subsets of wavelet-based features is used once as the testing set. The performance of 4-fold cross validation is determined from all four classifications.

Results

Characteristics of wavelet-based features

The wavelet-based features, i.e., λ_1, λ_2, λ_3, λ_4, λ_5 and λ_6, of scalp EEG epochs associated with the SZ, Pr and Po classes of subjects chb01, chb02, chb05, chb08, chb09, chb10, chb13, chb14, chb16, chb20, chb22, and chb23 are compared in box plots shown in Fig. 2a–l. A variety of charateristics of wavelet-based features of scalp EEG epochs are observed. It is shown that the wavelet-based features vary corresponding to subjects, classes, and even levels of wavelet decomposition. In most of cases, the wavelet-based features λ_k of scalp EEG epochs associated with the SZ class tend to be greater than those of scalp EEG epochs associated with the Pr and Po classes. In addition, means and standard deviations of wavelet-based features of scalp EEG epochs associated with any class of all subjects are summarized in Table 2.

For comparative purposes, the one-way analysis of variance (ANOVA) is performed to assess differences in the wavelet-based features of scalp EEG epochs associated with various classes, i.e., SZ, Pr, and Po classes. The p-values and the F-statistic (shown in parentheses) yielded from the ANOVA are summarized in Table 3. In general, it is shown that probabilities of the identical means of wavelet-based features of scalp EEG epochs associated with various classes are very low, except for the wavelet-based features λ_2 of scalp EEG epochs of the subject chb13, and the wavelet-based features λ_1 and λ_6 of scalp EEG epochs of the subject chb16. This therefore suggests that there are significant differences among the wavelet-based features of scalp EEG epochs associated with SZ, Pr, and Po classes in most cases.

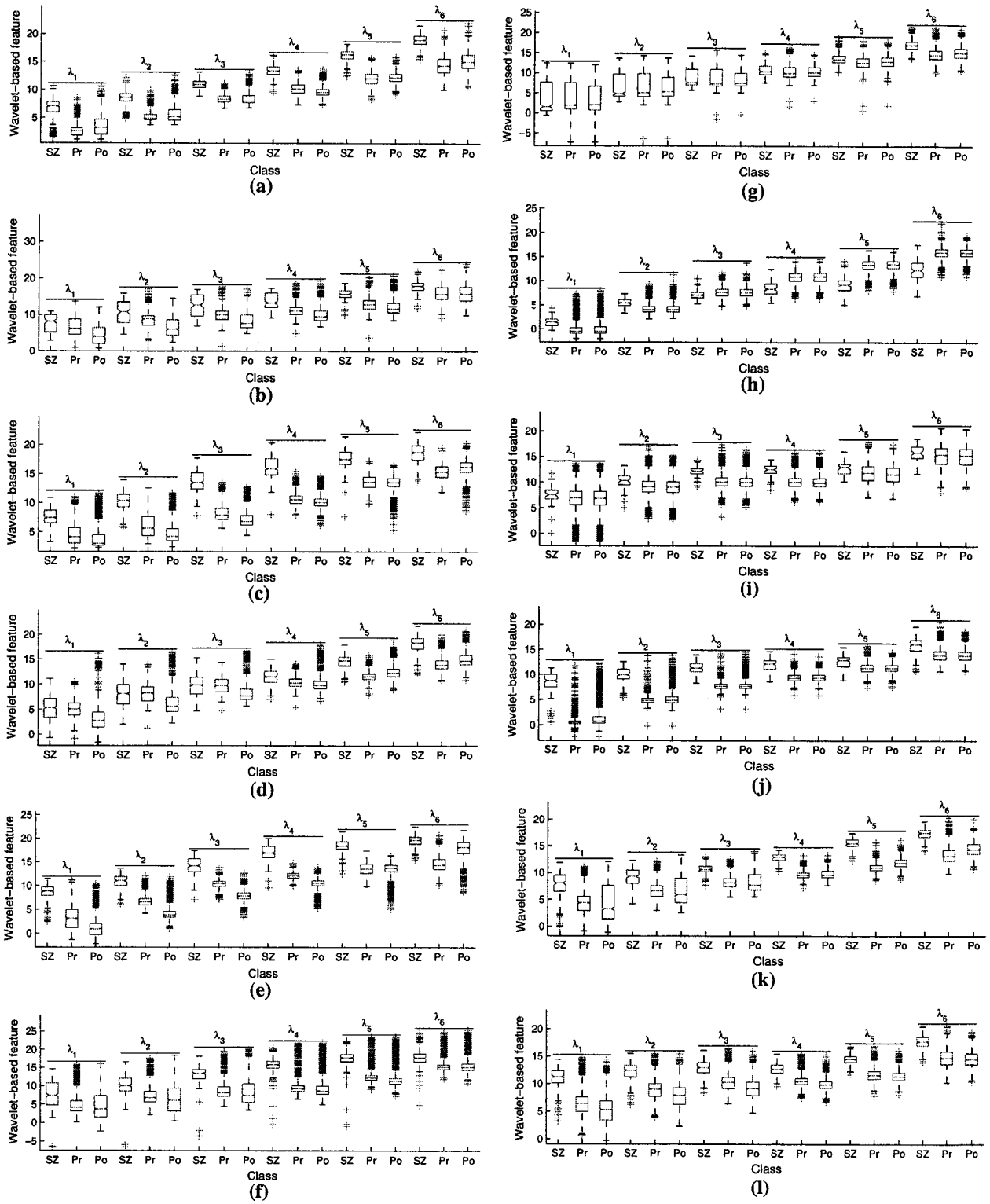

Fig. 2 Comparison between the wavelet-based features of scalp EEG epochs associated with the SZ, Pr and Po classes

Table 2 Statistical values (Mean±S.D.) of wavelet-based features of scalp EEG epochs

Subject	Class	Feature					
		λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
chb01	SZ	6.6287	8.4568	10.9442	13.4406	16.1876	18.9825
		±1.9952	±1.3919	±0.8740	±1.0615	±0.9209	±1.0896
	Pr	2.5195	5.0179	8.3729	10.2162	12.0625	14.4906
		±0.8310	±0.6443	±0.6299	±0.9968	±1.2072	±1.6421
	Po	3.4485	5.6258	8.5076	9.6827	12.2851	15.2157
		±1.5918	±1.3538	±1.1643	±0.8727	±0.9218	±1.5378
chb02	SZ	7.5183	10.4664	12.4426	13.8604	15.6579	17.8267
		±2.5635	±3.1395	±3.0063	±2.0935	±1.4272	±1.4808
	Pr	6.5488	8.4669	9.8869	11.1460	12.9414	15.8717
		±2.5090	±2.0734	±1.7713	±1.5153	±1.8095	±4.8464
	Po	4.4578	6.6188	8.4059	10.0235	12.2254	16.0619
		±2.6892	±2.6555	±2.4001	±2.1643	±2.1518	±2.6234
chb05	SZ	7.4822	10.3704	13.7127	16.1397	17.6216	18.6036
		±1.5232	±1.5979	±1.7393	±1.7906	±1.5899	±1.5878
	Pr	4.4955	6.0566	8.2006	10.5811	13.5692	15.3415
		±1.7468	±1.9404	±1.3950	±0.9618	±1.1351	±1.2584
	Po	3.8382	4.8550	7.2079	10.1620	13.4400	16.1543
		±1.8498	±1.9213	±1.5165	±0.9982	±1.1931	±1.3207
chb08	SZ	5.1461	8.0370	9.8464	11.4802	14.5328	18.1211
		±2.5616	±2.4900	±2.1613	±1.4573	±1.3318	±1.5930
	Pr	5.0728	8.1933	9.8271	10.3745	11.5928	14.0999
		±1.7320	±1.8753	±1.6315	±1.0427	±0.9133	±1.3089
	Po	3.6598	6.6884	8.7140	10.3888	12.5549	15.0254
		±4.1051	±3.4106	±2.8057	±2.1327	±1.4987	±1.4438
chb09	SZ	8.5817	10.8286	14.2112	16.9356	18.4499	19.0741
		±1.5432	±1.3744	±1.7586	±1.6716	±1.3911	±7.5684
	Pr	3.2773	6.7227	10.2232	12.0630	13.6581	14.6536
		±2.5508	±1.1438	±0.9907	±0.6813	±1.2994	±1.6843
	Po	1.2433	4.1909	7.8570	10.3876	13.4543	17.8999
		±2.2626	±1.4220	±1.0153	±1.0744	±1.5118	±1.8689
chb10	SZ	7.6707	10.2179	13.1721	15.6550	17.5727	17.3363
		±3.2603	±2.4969	±2.0693	±2.0022	±2.2325	±8.3229
	Pr	4.7488	7.2206	8.5943	9.6048	12.4542	15.4374
		±2.4495	±2.3524	±2.1326	±1.8392	±1.4837	±1.4495
	Po	4.5996	6.6639	8.3200	9.4948	11.9262	15.7294
		±4.1748	±4.0700	±3.4590	±2.9585	±2.5411	±2.2504
chb13	SZ	3.8395	6.6823	8.8202	10.7626	13.7026	17.2294
		±3.9457	±3.1561	±2.2190	±1.3935	±1.4292	±1.4242
	Pr	3.8632	6.6297	8.5787	10.3618	12.7589	14.7254
		±3.5257	±3.0752	±2.3645	±1.4723	±1.4141	±2.4477
	Po	3.5740	6.4785	8.4499	10.4186	12.9909	15.2597
		±3.3259	±2.7703	±2.0833	±1.3236	±1.4111	±1.5976
chb14	SZ	1.4103	5.4052	7.1245	8.4113	9.2893	12.4497
		±0.9324	±0.8706	±0.9527	±1.4289	±1.6622	±2.1553
	Pr	-0.1081	4.1840	7.6330	10.7932	13.2712	15.9291
		±1.3834	±0.8909	±1.0076	±1.1977	±1.2022	±1.1348
	Po	0.0721	4.2333	7.6250	10.8245	13.3803	15.9608
		±1.5816	±0.9645	±0.9498	±1.1625	±1.1167	±1.0589
chb16	SZ	7.6381	10.2524	12.0917	12.4086	12.8099	15.6339
		±1.9693	±1.4677	±1.0787	±1.2311	±1.2756	±1.6457
	Pr	6.5017	9.0354	10.0736	10.1094	11.8267	15.1486
		±2.8348	±1.8989	±1.4435	±1.3242	±1.7293	±2.9055

Table 2 (continued)

Subject	Class	Feature					
		λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
	Po	6.4623	8.9670	9.9779	10.0265	11.6523	15.0727
		±2.8486	±1.9430	±1.4698	±1.3488	±1.7038	±2.0498
chb20	SZ	8.5072	9.9786	11.3826	11.9010	12.5947	15.7773
		±1.8207	±1.4231	±1.1572	±1.2846	±1.3902	±1.6482
	Pr	0.4535	4.8787	7.7156	9.4214	11.3773	13.9828
		±0.8160	±0.7171	±0.6819	±0.8185	±0.9555	±1.2480
	Po	1.3325	5.1767	7.7903	9.4593	11.3899	13.9077
		±1.9545	±1.2828	±0.8855	±0.8129	±0.8866	±1.1633
chb22	SZ	7.5442	9.0416	10.6315	12.8188	15.4922	17.3781
		±2.5117	±1.8639	±0.9496	±0.7455	±0.9696	±1.0162
	Pr	4.1816	6.5538	8.2137	9.5921	11.0114	13.3812
		±2.3785	±1.7431	±1.2103	±0.7063	±0.8402	±1.5822
	Po	4.2253	6.6122	8.3653	9.7752	11.8681	14.4637
		±3.7632	±2.7824	±1.9898	±0.9327	±0.9552	±1.3435
chb23	SZ	11.0134	12.2340	12.8540	12.6699	14.4533	17.7460
		±1.7954	±1.5732	±1.3631	±1.0328	±0.8681	±1.1313
	Pr	6.3472	8.8818	10.2033	10.5132	11.6496	14.7702
		±2.3357	±1.8823	±1.5718	±1.0520	±1.1174	±1.5334
	Po	5.1976	7.6905	9.0974	9.8769	11.3606	14.5662
		±2.7825	±2.2764	±1.7954	±1.0073	±1.0075	±1.4255

Table 3 Results of one-way ANOVA using the wavelet-based features

Subject	Feature					
	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
chb01	0	0	0	0	0	0
	(2151.83)	(2089.45)	(1482.91)	(3116.24)	(2886.07)	(1633.33)
chb02	$\ll 0.0001$	$\ll 0.0001$	$\ll 0.0001$	$\ll 0.0001$	$\ll 0.0001$	< 0.0001
	(292.12)	(333.18)	(358.26)	(371.38)	(240.16)	(19.14)
chb05	0	0	0	0	0	0
	(995.05)	(2028.19)	(4552.60)	(7592.90)	(2967.20)	(1499.17)
chb08	$\ll 0.0001$	$\ll 0.0001$	$\ll 0.0001$	$\ll 0.0001$	0	0
	(207.51)	(282.31)	(229.87)	(182.17)	(2123.19)	(2978.87)
chb09	0	0	0	0	0	0
	(1343.46)	(4708.45)	(6337.20)	(6689.72)	(1537.83)	(1428.09)
chb10	$\ll 0.0001$	$\ll 0.0001$	$\ll 0.0001$	0	0	$\ll 0.0001$
	(161.78)	(238.97)	(579.79)	(1293.33)	(1452.77)	(116.41)
chb13	< 0.0001	0.0034	< 0.0001	< 0.0001	$\ll 0.0001$	$\ll 0.0001$
	(14.09)	(5.68)	(11.20)	(20.29)	(134.57)	(424.05)
chb14	$\ll 0.0001$	$\ll 0.0001$	< 0.0001	$\ll 0.0001$	0	$\ll 0.0001$
	(87.88)	(123.49)	(19.08)	(294.14)	(863.91)	(699.64)
chb16	0.0084	< 0.0001	$\ll 0.0001$	$\ll 0.0001$	< 0.0001	0.0667
	(4.78)	(13.55)	(61.42)	(88.97)	(27.77)	(2.71)
chb20	0	0	0	0	$\ll 0.0001$	$\ll 0.0001$
	(3551.56)	(2881.03)	(2647.23)	(1157.04)	(221.72)	(305.09)
chb22	$\ll 0.0001$	$\ll 0.0001$	$\ll 0.0001$	0	0	$\ll 0.0001$
	(119.00)	(119.20)	(226.38)	(1476.23)	(2391.63)	(762.51)
chb23	0	0	0	0	0	0
	(1068.48)	(1102.86)	(1235.99)	(1591.51)	(1608.61)	(878.46)

Table 4 The product of sensitivity and specificity of epileptic seizure classification using the wavelet-based features

Subject	Class.	Feature					
		λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
chb01	SZ-NS	72.55	49.63	53.02	90.16	**94.08**	60.58
	SZ-Pr	85.30	82.91	86.21	86.70	**93.15**	79.78
	SZ-Po	69.28	44.29	50.86	92.51	**94.68**	60.18
chb02	SZ-NS	38.31	44.84	47.35	43.31	**59.58**	40.06
	SZ-Pr	31.85	43.96	48.77	43.68	**63.46**	46.92
	SZ-Po	47.98	47.28	47.37	41.64	**59.35**	31.36
chb05	SZ-NS	43.91	76.31	89.70	**93.89**	51.64	68.79
	SZ-Pr	46.57	80.86	89.96	**91.57**	54.50	76.95
	SZ-Po	42.21	75.21	89.28	**93.64**	43.60	63.03
chb08	SZ-NS	15.58	24.20	25.91	25.88	51.94	**76.07**
	SZ-Pr	24.65	25.89	24.35	44.08	79.55	**81.06**
	SZ-Po	15.19	26.65	29.06	23.23	48.52	**71.13**
chb09	SZ-NS	86.37	**89.14**	87.63	63.84	63.77	58.00
	SZ-Pr	81.39	**85.58**	81.35	43.05	42.16	67.59
	SZ-Po	91.32	**92.67**	95.26	79.34	66.40	33.74
chb10	SZ-NS	43.95	43.03	56.65	**84.47**	43.85	47.72
	SZ-Pr	43.78	33.31	48.58	**85.76**	29.96	41.52
	SZ-Po	43.53	47.91	58.08	**82.78**	57.63	47.98
chb13	SZ-NS	25.63	25.23	21.19	14.63	24.07	**35.67**
	SZ-Pr	25.14	18.18	20.12	13.91	24.70	**36.73**
	SZ-Po	26.34	26.57	24.80	25.51	27.73	**39.94**
chb14	SZ-NS	1.33	0.00	37.82	64.76	**86.62**	76.10
	SZ-Pr	1.99	16.18	38.68	65.54	**85.49**	75.57
	SZ-Po	1.31	0.00	37.82	64.61	**87.83**	76.51
chb16	SZ-NS	39.02	27.76	12.67	**57.42**	8.47	26.94
	SZ-Pr	33.95	29.12	10.92	**59.15**	8.42	27.48
	SZ-Po	33.89	36.00	19.68	**60.73**	16.37	30.48
chb20	SZ-NS	**87.17**	60.48	48.91	68.92	57.21	56.69
	SZ-Pr	**91.82**	62.44	53.58	69.29	57.61	54.85
	SZ-Po	**85.77**	62.23	48.69	72.83	47.17	59.83
chb22	SZ-NS	59.85	51.84	35.74	91.48	**93.19**	54.77
	SZ-Pr	61.56	61.36	73.36	92.64	**95.59**	58.75
	SZ-Po	53.64	44.92	31.98	89.93	**92.30**	59.76
chb23	SZ-NS	**79.30**	73.61	64.48	51.98	55.13	63.35
	SZ-Pr	**78.63**	71.67	63.15	51.42	55.68	62.89
	SZ-Po	**81.60**	77.76	70.83	56.86	73.79	75.72

The best performance for each classification is individually written in bold

Performance of epileptic scalp EEG classifications

The products of sensitivity and specificity obtained from the scalp EEG classifications using the wavelet-based features, i.e., λ_1, λ_2, λ_3, λ_4, λ_5, and λ_6, are summarized in Table 4. The best performance for each classification is individually written in bold. The wavelet-based features λ_1, λ_2, λ_4, λ_5, and λ_6 are the quantitative features that provide the best classification performance in terms of product of sensitivity and specificity. The products of sensitivity and specificity of the classification between scalp EEG epochs associated with SZ and NS classes, the classification between scalp EEG epochs associated with SZ and Pr classes, and the classification between scalp EEG epochs associated with SZ and Po classes range between 35.67% and 94.08%, between 36.73% and 93.19%, and between 39.94% and 94.68%. The best products of sensitivity and specificity for the classification between scalp EEG epochs associated with SZ and NS classes, the classification between scalp EEG epochs associated with SZ and Pr

Table 5 The best individual performance on epileptic seizure classification

Subject	Class.	Feature	Accuracy (*Ac*)	Sensitivity (*Se*)	Specificity (*Sp*)	$Se \times Sp$
chb01	SZ-NS	λ_5	97.28	96.67	97.31	94.08
	SZ-Pr	λ_5	96.18	96.91	96.11	93.15
	SZ-Po	λ_5	97.63	96.91	97.70	94.68
chb02	SZ-NS	λ_5	88.72	66.26	89.92	59.58
	SZ-Pr	λ_5	86.84	71.78	88.41	63.46
	SZ-Po	λ_5	86.58	66.87	88.75	59.35
chb05	SZ-NS	λ_4	96.30	97.61	96.19	93.89
	SZ-Pr	λ_4	95.25	96.32	95.07	91.57
	SZ-Po	λ_4	95.89	97.97	95.58	93.64
chb08	SZ-NS	λ_6	88.29	85.84	88.62	76.07
	SZ-Pr	λ_6	90.83	88.72	91.36	81.06
	SZ-Po	λ_6	83.52	85.84	82.86	71.13
chb09	SZ-NS	λ_2	94.17	94.68	94.15	89.14
	SZ-Pr	λ_2	90.75	94.68	90.39	85.58
	SZ-Po	λ_3	96.30	99.24	95.99	95.26
chb10	SZ-NS	λ_4	86.41	98.35	85.88	84.47
	SZ-Pr	λ_4	87.89	98.58	86.99	85.76
	SZ-Po	λ_4	85.21	98.58	83.97	82.78
chb13	SZ-NS	λ_6	91.48	38.28	93.18	35.67
	SZ-Pr	λ_6	91.46	38.68	94.97	36.73
	SZ-Po	λ_6	86.78	44.69	89.37	39.94
chb14	SZ-NS	λ_5	95.10	91.03	95.15	86.62
	SZ-Pr	λ_5	93.84	91.03	93.91	85.49
	SZ-Po	λ_5	95.65	91.72	95.76	87.83
chb16	SZ-NS	λ_4	93.82	61.11	93.95	57.42
	SZ-Pr	λ_4	93.70	62.96	93.95	59.15
	SZ-Po	λ_4	93.47	64.81	93.69	60.73
chb20	SZ-NS	λ_1	97.45	89.26	97.66	87.17
	SZ-Pr	λ_1	99.17	92.22	99.56	91.82
	SZ-Po	λ_1	95.78	89.26	96.09	85.77
chb22	SZ-NS	λ_5	99.01	93.85	99.30	93.19
	SZ-Pr	λ_5	99.36	95.90	99.68	95.59
	SZ-Po	λ_5	97.76	93.85	98.36	92.30
chb23	SZ-NS	λ_1	90.89	87.10	91.05	79.30
	SZ-Pr	λ_1	90.03	87.10	90.28	78.63
	SZ-Po	λ_1	90.77	89.83	90.84	81.60
Average	SZ-NS		93.24	83.34	93.53	78.05
	SZ-Pr		92.94	84.57	93.39	79.00
	SZ-Po		92.11	84.97	92.41	78.75

classes, and the classification between scalp EEG epochs associated with SZ and Po classes are 94.08% (chb01), 95.59% (chb22), and 94.68% (chb01), respectively.

The accuracy, the sensitivity, and the specificity corresponding to the best classification performances in terms of products of sensitivity and specificity shown in Table 4 are further shown in Table 5. The accuracies of the classification between scalp EEG epochs associated with SZ and NS classes, the classification between scalp EEG epochs associated with SZ and Pr classes, and the classification between scalp EEG epochs associated with SZ and Po classes range between 86.41% and 99.21%, between 86.84% and 99.36%, and between 83.52% and 97.76%. The sensitivities of the classification between scalp EEG epochs associated with SZ and NS classes, the classification between scalp EEG epochs associated with SZ and Pr classes, and the classification between scalp EEG epochs associated with SZ and Po classes range between 38.28% and 98.35%, between 38.68% and 98.58%, and between 44.69% and 99.24%.

The specificities of the classification between scalp EEG epochs associated with SZ and NS classes, the classification between scalp EEG epochs associated with SZ and Pr classes, and the classification between scalp EEG epochs associated with SZ and Po classes range between 35.67% and 94.08%, between 36.73% and 95.59%, and between 39.94% and 95.26%.

Discussion

The wavelet-based features λ_5 and λ_4 are the two quantitative features that provide the best performance of epileptic seizure classification in terms of the product of sensitivity and specificity in most subjects. The wavelet-based features λ_5 and λ_4 correspond to the θ (4–8-Hz spectral subband) and α (8–16-Hz spectral subband) bands. The feature λ_3 corresponding to the β (16–32-Hz spectral subband) band is the only wavelet-based feature that does not provide the best performance of epileptic seizure classification. The best performance on classification between scalp EEG epochs associated with epileptic seizure event and those associated with pre-ictal state is obtained in the subject chb22 with the product of sensitivity and specificity of 95.59%. The best performance on classification between scalp EEG epochs associated with epileptic seizure event and those associated with post-ictal state is obtained in the subject chb09 with the product of sensitivity and specificity of 95.26%. The best performance on classification between scalp EEG epochs associated with epileptic seizure event and those associated with non-seizure period is obtained in the subject chb01 with the product of sensitivity and specificity of 94.08%.

The average accuracy and specificity of all three classifications are higher than 90%. In general, the accuracy of epileptic seizure classifications correlates with the corresponding specificity because the number of scalp EEG epochs associated with non-seizure period, i.e., pre-ictal or post-ictal states, dominates the number of scalp EEG epochs associated with epileptic seizure event. The average sensitivity of all three classifications are higher than 80%. Interestingly, the average performance on epileptic seizure classifications between scalp EEG epochs associated with epileptic seizure event and those associated with pre-ictal state is comparable to the average performance on epileptic seizure classifications between scalp EEG epochs associated with epileptic seizure event and those associated with post-ictal state. However, there are some significant differences between those two classifications in some subjects.

To provide some general picture on the performance on epileptic seizure classifications obtained using single wavelet-based features of scalp EEGs, the performances on epileptic seizure classifications and detections examined using the same source of epileptic scalp EEG data, i.e., the CHB-MIT Scalp EEG Database, are summarized as follows. The sensitivity of epileptic seizure classification and detection reported in literature ranges between 95.2% and 71.3% (95.2% [13], 94.91% [8], 87.3% [11], 71.32% [7]) while the specificity of epileptic seizure classification and detection was reported to be higher than 93% [9] and 79.7% [7]. In addition, the false detection rate ranges between 0.11 and 1.53 per hour (0.11 per hour [10], 0.59 per hour [13], 0.83 per hour [12, 14], 1.52 per hour [15], 1.53 per hour [8]). The latency of seizure detection ranges between 3 and 9.3 s (3 [12, 14], 6.43 [13], 7.8 [10], 9.3 [15]). However, it needs to be remarked that the experimental setups vary from study to study.

Conclusions

In this study, the logarithm of variance of detail and approximation coefficients of epochs of single-channel scalp EEGs are used as quantitative features for patient-dependent based epileptic seizure classification. The performance on patient-dependent based epileptic seizure classification using single wavelet-based features in a group of children subjects with age ranging between 2 and 11 years old are examined. Rather than aiming to achieve the best classification performance using computationally complicated algorithms as other studies, this study aims to provide a baseline of performance on patient-dependent based epileptic seizure classification, in particular, using single wavelet-based feature of single-channel scalp EEGs with the thresholding technique. The computational results evaluated using 4-fold cross validations show that an excellent performance on epileptic seizure classification can be obtained using only a single wavelet-based feature λ_k in a number of subjects. Such promising results suggest that a single wavelet-based feature λ_k of single-channel scalp EEGs can be further applied for epileptic seizure detection.

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Compliance with Ethical Standards

Conflicts of interest The authors declare that they have no conflicts of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. National Institute of Neurological Disorders and Stroke (2016) The epilepsies and seizures: hope through research. National Institute of Neurological Disorders and Stroke, Bethesda
2. World Health Organization (2016) Epilepsy. World Health Organization, Geneva
3. Clinical Practice Guidelines for Epilepsy (2012) http://www.neurothai.org/images/2012/download/epilepsy.pdf
4. Shoeb A, Edwards H, Connolly J, Bourgeois B, Treves S, Guttag J (2004) Patient-specific seizure onset detection. Epilepsy Behav 5:483–498
5. Tyner FS. Knott JR, Mayer WB (1983) Fundamentals of EEG technology: basic concepts and methods. Lippincott Wiliams & Wilkins, Philadelphia
6. Klass D, Daly D (1979) Current practice of clinical electroencephalography. Raven Press, New York
7. Logesparan L, Casson AJ, Rodriguez-Villegas E (2012) Optimal features for online seizure detection. Med Biol Eng Comput 50:659–669
8. Chiang J, Ward RK (2014) Energy-efficient data reduction techniques for wireless seizure detection systems. Sensors 14:2036–2051
9. Kiranyaz S, Ince T, Zabihi M, Ince D (2014) Automated patient-specific classification of long-term electroencephalography. J Biomed Inform 49:16–31
10. Hunyadi B, Signoretto M, van Paesschen W, Suykens JAK, van Huffel S, de Vos M (2012) Incorporating structural information from the multichannel EEG improves patient-specific seizure detection. Clin Neurophysiol 123:2352–2361
11. Hopfengärtner R, Kasper BS, Graf W, Gollwitzer S, Kreiselmeyer G, Stefan H, Hamer H (2014) Automatic seizure detection in long-term scalp EEG using an adaptive thresholding technique: a validation study for clinical routine. Clin Neurophysiol 125:1346–1352
12. Shoeb AH (2009) Application of machine learning to epileptic seizure onset detection and treatment. PhD thesis, Massachusetts Institute of Technology, Cambridge.
13. Qaraqe M, Ismail M, Serpendin E (2015) Band-sensitive seizure onset detection via CSP-enhanced EEG features. Epilepsy Behav 50:77–87
14. Shoeb H, Guttag J (2010) Application of machine learning to epileptic seizure detection. In: Proceedings of the 27th International Conference on Machine Learning, 2010
15. van Esbroeck A, Smith L, Syed Z, Singh S, Karam Z (2016) Multi-task seizure detection: addressing intra-patient variation in seizure morphologies. Mach Learn 102:309–321
16. Abry P, Goncalves P, Flandrin P (1993) Wavelet-based spectral analysis of $1/f$ processes. In: IEEE International Conference on Acoustics, Speech, and Signal Processing, pp III-237–III-240
17. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE (2000) Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. Circulation 101(23):e215–e220
18. Mallat S (1998) A wavelet tour of signal processing. Academic Press, San Diego
19. Wornell GW (1993) Wavelet-based representations for the $1/f$ family of fractal processes. Proc. IEEE 81:1428–1450
20. Mallat SG (1989) A theory for multiresolution signal decomposition: the wavelet representation. IEEE Trans Pattern Anal Mach Intell 11:674–693
21. Daubechies I (1992) Ten lectures on wavelets. SIAM, Philadelphia