Seizure 26 (2015) 56–64

Contents lists available at ScienceDirect

Seizure

journal homepage: www.elsevier.com/locate/yseiz

Review

Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis

Oliver Faust [a], U. Rajendra Acharya [b,*], Hojjat Adeli [c,d,e,f], Amir Adeli [g]

[a] School of Science and Engineering, Habib University, Karachi, Pakistan
[b] Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore 599489, Singapore
[c] Department of Neuroscience, The Ohio State University, Columbus, OH, USA
[d] Department of Biomedical Engineering, The Ohio State University, Columbus, OH, USA
[e] Department of Biomedical Informatics, The Ohio State University, Columbus, OH, USA
[f] Department Electrical and Computer Engineering, The Ohio State University, Columbus, OH, USA
[g] Department of Neurology, The Ohio State University, 470 Hitchcock Hall, 2070 Neil Avenue, Columbus, OH 43210, USA

ARTICLE INFO

Article history:
Received 25 October 2014
Received in revised form 15 January 2015
Accepted 18 January 2015

Keywords:
Continuous Wavelet Transform
Discrete Wavelet Transform
Electroencephalogram
Epilepsy

ABSTRACT

Electroencephalography (EEG) is an important tool for studying the human brain activity and epileptic processes in particular. EEG signals provide important information about epileptogenic networks that must be analyzed and understood before the initiation of therapeutic procedures. Very small variations in EEG signals depict a definite type of brain abnormality. The challenge is to design and develop signal processing algorithms which extract this subtle information and use it for diagnosis, monitoring and treatment of patients with epilepsy. This paper presents a review of wavelet techniques for computer-aided seizure detection and epilepsy diagnosis with an emphasis on research reported during the past decade. A multiparadigm approach based on the integration of wavelets, nonlinear dynamics and chaos theory, and neural networks advanced by Adeli and associates is the most effective method for automated EEG-based diagnosis of epilepsy.

1. Introduction

Scientific work on mechanizing the detection of epileptic seizures began around 1970 [1]. However, it took about 30 years to develop the algorithms to turn these ideas into physical problem solutions [2]. Various Electroencephalography (EEG) analysis and classification methods use the fact that the information processing in the brain is reflected in the EEG as dynamical changes of the electrical activity in time, frequency, and space. Various frequency and nonlinear methods have been used to understand the mechanisms behind the information processing [3,4]. Among time–frequency analysis methods the Wavelet Transform (WT) stands out in terms of algorithmic elegance and efficiency. WT captures the subtle changes in the EEG signal well. These minute variations are difficult to spot using the naked eye in the EEG signal. Therefore, this review is dedicated to WT-based EEG processing and computer-aided seizure detection and epilepsy diagnosis.

Fig. 1 shows sample normal, interictal and ictal (epileptic) EEG signals from a database hosted by the University of Bonn [5]. The signals in the database were obtained from five normal subjects and five epileptic patients. The EEG data is classified into three categories: control, interictal, and ictal/epileptic. The interictal EEG signals were obtained from the hippocampal formations during seizure free intervals. The ictal signals were recorded from the lateral and basal regions of the neocortex. The EEG signals were recorded using a 128-channel amplifier system digitized with a sampling frequency of 173.61 Hz, and filtered using a band pass filter of 0.53–40 Hz.

2. Computer aided seizure detection

A trend in healthcare is shifting from clinician-centric care to patient-centric care where the patient becomes an active participant in her care management. Automated Computer-Aided Diagnosis of epilepsy which is significantly more challenging than computer-aided seizure detection was advanced with the seminal work of Adeli et al. [6] for diagnosis of the absence seizure more than a decade ago. This review aim to summarize the research reported since then. A CAD system can help neurologists make the

* Corresponding author. Tel.: +65 64606135; fax: +65 64671730.
E-mail address: aru@np.edu.sg (U.R. Acharya).

http://dx.doi.org/10.1016/j.seizure.2015.01.012
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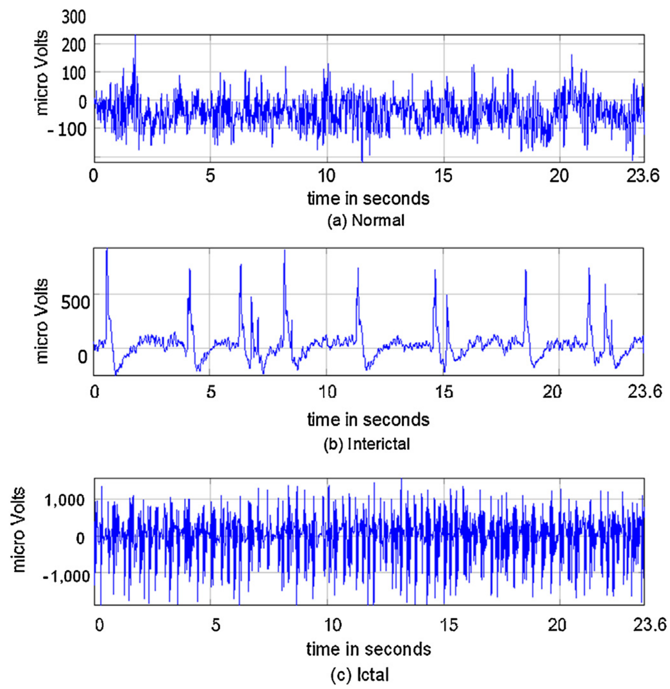

Fig. 1. Sample EEG signals.

diagnosis more efficiently and accurately. Fig. 2 presents a block diagram for a computer-aided seizure detection and epilepsy diagnosis system. It consists of an offline and an online system. The offline system consists of the design steps necessary to create and test the CAD algorithm structure. This algorithm is then used in the online system by the neurologist as a decision support system.

WT is used for signal preprocessing/denoising and for feature extraction. WT was developed in the 1980s as a powerful signal processing technique to overcome the shortcomings of other methods such as the Fourier transform [11]. Since then it has been used in a variety of signal processing applications [8,9]. WT provides a smooth representation, unlike windowed representation in the short time Fourier transform. Hence, one can capture very minute details, sudden changes and similarities in the EEG signals. WT acts like a mathematical microscope, because it has the capability to analyze EEG signals at different scales [12]. Researchers have proposed unique wavelets. Fig. 3 shows examples of mother wavelets used for EEG processing: (a) Daubechies (db), (b) Morlet, (c) Biorthog-onal (bior), (d) Orthogonal Cubic Spline (ocs), (e) Mexican Hat (MH), (f) Haar, (g) Complex Gaussian (CG), and (h) Coiflet (coif) wavelet. The following two sections introduce the application of WT in computer aided seizure detection.

3. Signal preprocessing/denoising

Raw EEG signals suffer from poor spatial resolution, low signal-to-noise ratio and artifacts [7]. Preprocessing is the denoising step which aims to improve the signal-to-noise ratio of the EEG.

The WT is now a well-known tool for removing noise from the signal. Multi-resolution analysis provides information about the signal in different frequency bands. The wavelet decomposition of a noisy signal concentrates intrinsic signal information in a few wavelet coefficients having large absolute values without modifying the random distribution of noise. Therefore, denoising can be achieved by thresholding the wavelet coefficients. The WT gives a time-variant decomposition, an advantage over techniques such as Wiener filtering. With a time-variant decomposition it is possible to choose different filtering settings (i.e. wavelet coefficients) for different time ranges. Hence, it is possible to create event-related filter responses. With time-invariant approaches, such as Wiener filtering, it is not possible to find a unique implementation that is suitable for all event related potentials [10].

4. Wavelet analysis for signal feature extraction

In addition to denoising, wavelets can be used for feature extraction. The mother wavelet is shifted by a small interval in the x-axis and correlation coefficients are computed. This procedure is repeated for various scaling factors (dilations) in the y-axis.

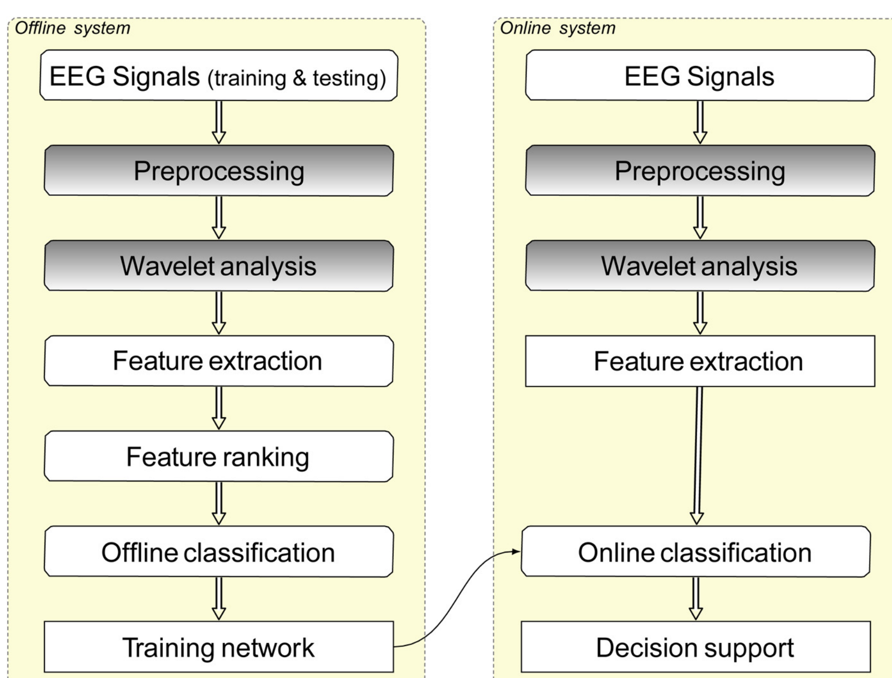

Fig. 2. Block diagram for a computer-aided seizure detection and epilepsy diagnosis system.

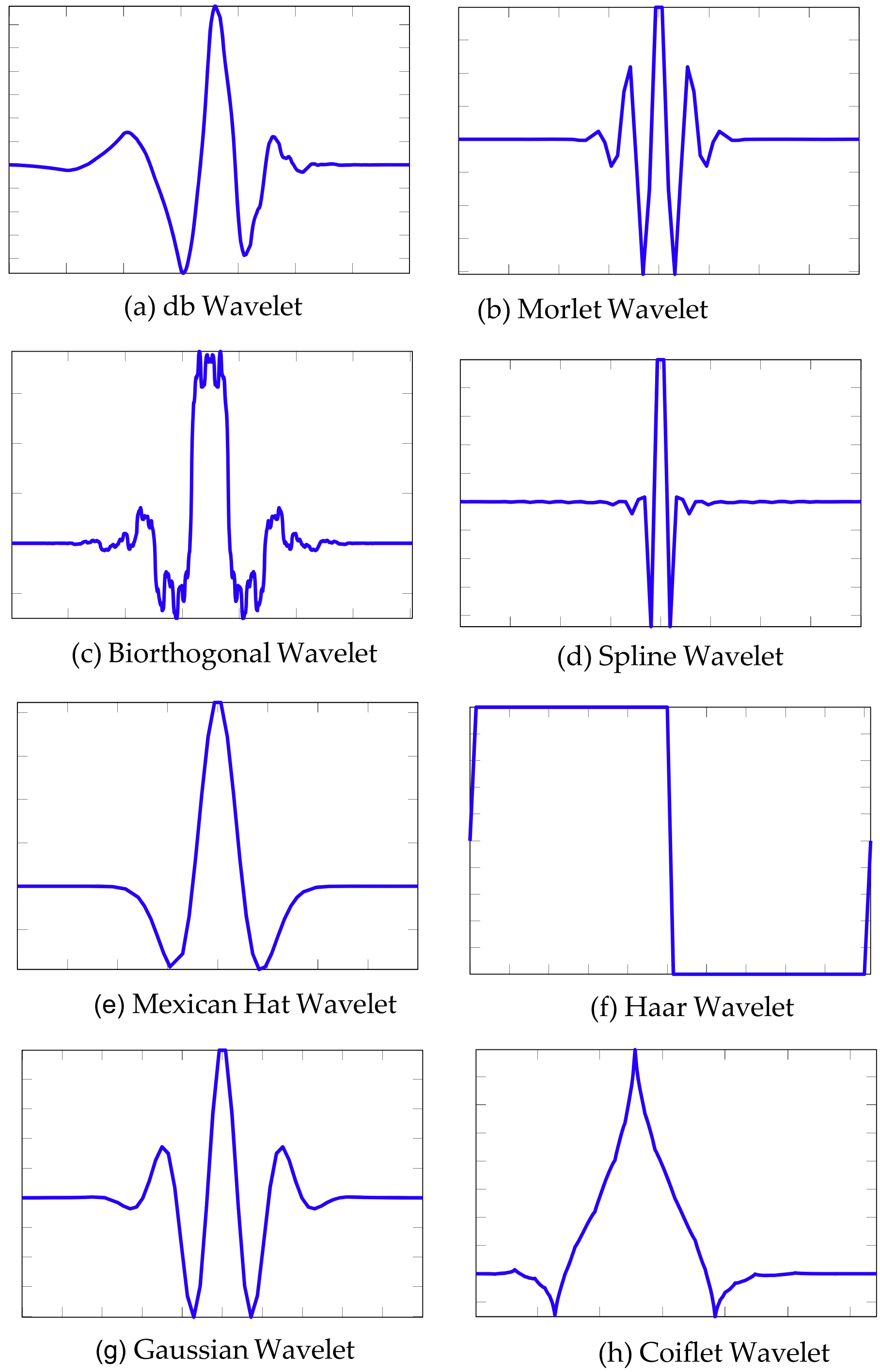

Fig. 3. Examples of wavelets used for EEG processing.

There are two types of wavelet analysis: Continuous Wavelet Transforms (CWT) and Discrete Wavelet Transform (DWT) [12]. The CWT coefficients are evaluated for a continuous variation (infinitesimal increments) of both translation and dilation factors. DWT processes the input signals with finite impulse response filters.

4.1. Continuous time wavelet analysis (CWT)

Duration and location of the abnormality can be detected using dilation and translation factors. Fig. 4 shows scalogram plots of the normal, ictal, and interictal EEG signals shown in Fig. 1, where *x*-axis represents time, *y*-axis is the scale factor (reciprocal of frequency) and pixel intensity represents the magnitude of the correlation. Scalogram plots are unique and the sudden changes in the epileptic EEG signal can be observed through changes in the color. There is continuous variation in the color in the plot depicting the randomness as well chaotic nature of the EEG signal. Fig. 4(b) shows repeating patterns compared with Fig. 4(a) which appears as random.

Table 1 summarizes published research on EEG signal feature extraction using CWT in terms of goal, wavelet used (W), number of signal classes (No) and results evaluation. The EEG data used has five subgroups Z, O, N, F, and S. Subgroups Z and O correspond to

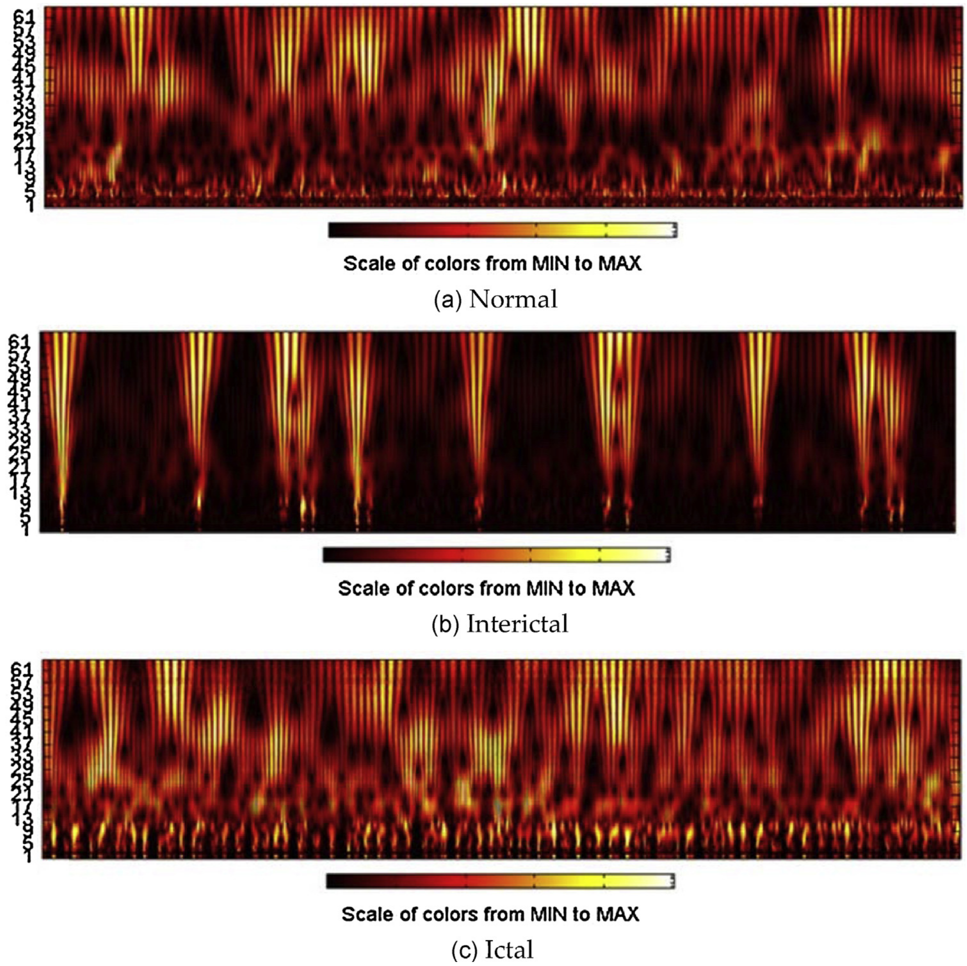

Fig. 4. Scalogram plots of the signals shown in Fig. 1 using CWT.

the EEG signal acquired from normal subjects with eyes closed and open respectively. N and F subgroups indicate the interictal (seizure free) EEG signals. S group denotes the seizure EEGs. No = 2 indicates two classes of normal (O) and seizure (S) classes; No = 3 means three classes of normal (O), interictal (F) and seizure (S) classes; No = 4 indicates four classes of normal (O), seizure-free intervals of five patients from hippocampal formation of opposite hemisphere (N), seizure-free intervals of five patients from

Table 1
Summary of published research on EEG signal feature extraction using CWT in terms of goal, wavelet used (W), number of signal classes (No), and results evaluation.

Author	Year	Goal	W	No	Result evaluation
Gadhoumi et al. [74]	2013	Seizure prediction	Morse	2	Nonstandard classifier
Acharya et al. [29]	2013	CAD of epilepsy	MH	3	Various standard classifier, accuracy sensitivity specificity
Gadhoumi et al. [75]	2012	Discrimination of pre-ictal and interictal states	Morse	2	Nonstandard classifier, sensitivity
Indic and Narayanan [76]	2011	Study of EEG before and during mesial temporal lobe seizures	Morlet	–	–
Abibullaev et al. [77]	2010	CAD of epilepsy	bior	2	ANN, accuracy
Pravin Kumar et al. [78]	2010	Seizure detection	bior4.4	3	ANN, accuracy sensitivity specificity
Arab et al. [79]	2010	Feature extraction and de-noising topographic brain mapping and epilepsy classification	bior3.3	3	ANN, accuracy
Abibullaev et al. [80]	2010	Seizure detection	bior1.5	3	ANN, accuracy
Meier et al. [81]	2008	Seizure detection	Symlet	2	SVM, accuracy
Chiu et al. [82]	2006	Online seizure detection	Nr	4	ANN, accuracy
Subasi et al. [83]	2005	CAD of epilepsy	Morlet	2	ANN, accuracy sensitivity specificity
Gigola et al. [84]	2004	Seizure prediction	db4	–	–
Rosso et al. [85]	2003	Seizure analysis	Ocs	3	–
Latka et al. [86]	2003	Seizure analysis	MH	–	

epileptogenic zone (F), and seizure (S) classes, and No = 5 indicates five classes: normal with eyes open (O), normal with eyes closed (Z), seizure-free intervals of five patients from hippocampal formation of opposite hemisphere (N), seizure-free intervals of five patients from epileptogenic zone (F), and seizure (S) classes.

4.2. Discrete Wavelet Transform (DWT)

The DWT algorithm decomposes a given signal into approximation and detail coefficients to obtain a first level of decomposition. The approximation coefficients in every level are further decomposed into next level of approximation and detail coefficients [12]. The features extracted from the detailed coefficients at various levels or different frequency bands can reveal the characteristics of the time series and can be used in automated seizure detection systems [13,14]. Leung et al. used an absolute slope method for DWT-based EEG denoising and feature extraction [16]. Işik and Sezer used DWT-based denoising and feature extraction prior to application of Artificial Neural Networks (ANN) for epilepsy diagnosis [18].

Table 2 summarizes published research on EEG signal feature extraction using CWT in terms of goal, wavelet used (W), number of signal classes (N) and results evaluation. Table 3 shows 40 studies used DWT and 21 studies used CWT. A classification accuracy of 99.7% was reported using DWT [24] and a classification accuracy of 96% was reported using CWT [28]. CWT provides a pictorial representation of the signal. However, classification algorithms often require two-dimensional (2D) feature vectors. DWT coefficients can be used directly as features. It turns out that the DWT coefficients represent the subtle changes in the EEG signal very well.

It can be seen from Tables 1 and 2 that various studies have been conducted using wavelet features for automated seizure detection. The detailed coefficients of the DWT at various levels have the signatures of the normal, interictal and ictal EEG classes. These features can be used for automated detection of seizure. In CWT, various 2D features like texture, fractal dimension, entropies,

Table 2
Summary of published research on EEG signal feature extraction using DWT in terms of goal, wavelet used (W), number of signal classes (No), and results evaluation (Var indicates that different mother wavelets were used).

Author	Year	Goal	W	No	Result evaluation
Nunes et al. [35]	2014	EEG signal classification	Var	4	OPF 10-fold stratified cross validation accuracy sensitivity PPV
Chen [87]	2013	Seizure detection with dual-tree complex DWT	Nr	4	Various standard classifier, accuracy
Xie and Krishnan [33]	2013	Seizure detection and epilepsy diagnosis	Haar	2	SVM k-NN FLD
Acharya et al. [46]	2012	Seizure diagnosis	Bior	3	Various classifiers, accuracy, sensitivity, specificity
Acharya et al. [24]	2012	CAD of epilepsy based on Wavelet packet transform (WPT)	db10	3	Various standard classifier, accuracy, sensitivity, specificity
Acharya et al. [27]	2011	CAD of epilepsy	Nr	3	Various standard classifiers, accuracy sensitivity specificity PPV
Guo et al. [31]	2011	Seizure detection	db4	3	k-NN, accuracy
Guo et al. [41]	2010	Dual tree complex DWT	db6	2	ANN, accuracy, sensitivity, specificity
Zandi et al. [38]	2010	Real-time seizure detection with WPT	db6	2	Sensitivity, specificity, ROC
Gandhi et al. [88]	2010	Expert model for epilepsy detection	db4	2	PNN, accuracy, sensitivity, specificity
Guo et al. [43]	2010	Seizure detection	db4	2	ANN, accuracy, sensitivity, specificity
Lima et al. [89]	2009	EEG signal classification	db4	2	SVM, accuracy
Übeyli [90]	2009	EEG signal classification	db2	3	ANN, accuracy, sensitivity, specificity
Magosso et al. [91]	2009	Seizure analysis	db4	–	–
Ocak [96]	2008	Seizure detection	Nr	2	Threshold
Indiradevi et al. [92]	2008	Seizure detection	db4	2	Threshold, sensitivity, specificity
Ghosh-Dastidar et al. [93]	2008	CAD of epilepsy	db4	3	Modified ANN, parametric and sensitivity analysis
Patnaik and Manyam [94]	2008	Epileptic EEG detection	Nr	3	ANN, specificity, selectivity
Übeyli [95]	2008	EEG signal classification	db2	3	ANN, sensitivity, specificity, ROC
Ocak [96]	2008	CAD of epilepsy based on WPT	db2	4	ANN, accuracy
Ghosh-Dastidar and Adeli [97]	2007	CAD of epilepsy	db4	3	Spiking neural network, accuracy
Pereyra et al. [98]	2007	Studying the dynamics of EEG	Ocs	–	–
Adeli et al. [99]	2007	CAD of epilepsy	db4	3	–
Ghosh-Dastidar et al. [23]	2007	CAD of epilepsy	db4	3	ANN, accuracy, sensitivity, specificity
Ouyang et al. [100]	2007	Seizure analysis	db4	–	–
Subasi [39]	2007	Seizure detection	db4	2	Mixture of experts, sensitivity, specificity
Subasi [101]	2007	Seizure detection	db4	2	Adaptive neuro-fuzzy inference system, sensitivity, specificity
Figliola et al. [102]	2007	Seizure analysis	Ocs	–	–
Rosso et al. [103]	2006	Seizure analysis	Ocs	–	–
Subasi [104]	2006	Seizure detection	db4	2	ANN and fuzzy logic, sensitivity, specificity
Subasi [105]	2005	Seizure detection	db4	2	ANN, sensitivity, specificity
Rosso et al. [106]	2005	Gain insights into the dynamics of neural activity	Ocs	–	–
Güler and Übeyli [107]	2005	EEG signals classification	db2	5	Adaptive neuro-fuzzy inference system, accuracy, sensitivity, specificity
Guler and Ubeyli [108]	2005	Epilepsy detection	db1	2	ANN, accuracy, specificity, sensitivity
Rosso et al. [109]	2005	Study of children with and without childhood absence epilepsy	Ocs	–	Statistical analysis
Subasi and Erçelebi [32]	2005	Seizure detection	db4	2	PNN, accuracy, sensitivity, specificity ROC
Khan and Gotman [110]	2003	Seizure detection	db4	–	Basic statistical methods
Adeli et al. [6]	2003	CAD of epilepsy	db4	–	–

Table 3
Summary of the research in terms of number of signal classes and type of wavelet transform used.

Measures	DWT	CWT	Total
Number of studies	40	21	81
Number of studies with no classes	9 (22.5%)	9 (42.8%)	19
Number of studies with 2 classes	15 (37.5%)	6 (28.5%)	22
Number of studies with 3 classes	12 (30%)	5 (23.8%)	17
Number of studies with 4 classes	3 (7.5%)	1 (4.7%)	4
Number of studies with 5 classes	1 (2.5%)	0 (0%)	1

Table 4
Summary of the research in terms of the type of wavelet used.

Wavelet	DWT	CWT	Total
db4	19	0	19
db/=4	7	1	8
Morlet	0	7	7
ocs	5	1	6
bior	0	4	4
nr	4	1	5
MH	0	3	3
Morse	0	2	2
coif	1	0	1
Haar	1	0	1
Biphasic (bip)	1	0	1
rbio6.8	1	0	1
Symlet 5	0	1	1
CG	0	1	1
ocs	0	1	1

higher order spectra features can be extracted from the scalogram and used for seizure detection.

5. Nonlinear dynamics and chaos theory

Adeli and associates advanced the idea of a multi-paradigm approach for automated EEG-based diagnosis of epilepsy through adroit integration of wavelets, a signal processing technique, nonlinear dynamics [6,14,23,54,100,102] and chaos theory [19], and neural networks, a pattern recognition and classification method [15,17,19–22,26,50].

Employing nonlinear dynamics and chaos theory researchers have extracted various nonlinear features such as entropies [24], energy [25], correlation dimension [47], fractal dimension [47,27], Lyapunov exponent [47], Higher Order Spectra (HOS) [28,25] from both detailed and approximate coefficients of the WT and used them for signal classification and seizure detection and epilepsy diagnosis [29,30,31].

6. Classification

Examples of classification algorithms used for seizure detection and epilepsy diagnosis are: *k*-Nearest Neighbor algorithm (*k*-NN) [31], Probabilistic Neural Network (PNN) [32], Fisher's linear discriminant (FLD) [33], Support Vector Machine (SVM) [34], Optimum Path Forest (OPF) [35], Principal Component Analysis (PCA) [36], and Enhanced Probabilistic Neural Network (EPNN) [37]. The offline classification results are assessed by accuracy, sensitivity specificity, Positive Predictive Value (PPV) and Receiver Operating Characteristic (ROC) [38]. This assessment is used to select the best classification algorithm.

The following features are used for the two class classification of epilepsy:

Approximate Entropy (ApEn) on DWT coefficients [40,41], relative wavelet energy [42], line length feature [43], Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA) on DWT coefficients [44] and wavelet packet entropy [45].

In the three class classification of epilepsy the following features are used: nonlinear features extracted from DWT coefficients [23,24], HOS cumulants extracted from Wavelet Packet Decomposition (WPD) coefficients [27], wavelet coefficients using WPT, and extracted eigenvalues from the resultant wavelet coefficients using PCA [46], ICA on the DWT coefficients [29] and HOS and texture features from scalogram plots [28].

7. Discussion

Table 3 summarizes the research in terms of number of signal classes and type of wavelet transform used. It shows that DWT has been used in research more often than CWT. Table 4 summarizes the research in terms of the type of wavelet used. When the researchers did not report the type of wavelet used it is noted as Not Reported (nr). Table 4 shows that db is the most commonly used wavelet for DWT research. In previous papers authors [43–49] explored various types of wavelet functions for automated classification. The highest classification accuracy was obtained using db4. Table 4 shows a summary of the research in terms of the type of wavelet used. It indicates that db4 is the most widely used wavelet for seizure detection. It appears that db4 is the most suitable wavelet for seizure detection.

Physiological signal analysis is challenging because the origins of the observable physical quantities are largely unknown [24]. Nowhere is this statement more true than for EEG signal processing. The analysis of EEG signals can lead toward a better understanding of the electrical activity of the brain. The research has moved from automated seizure detection toward automated epileptic background detection and epilepsy diagnosis. This was only possible through the development of increasingly sophisticated algorithms. Following this trend, our understanding will grow and we will have the ability to diagnose epilepsy even when there is no epileptic background.

The work on epilepsy has opened the door for new and exciting research on other brain disorders [51–53]. Recently, Adeli and associates have developed novel algorithms for automated EEG-based diagnosis of other neurological and psychiatric disorders such as the Alzheimer's disease [54–59], Autism Spectrum Disorder [60–62], Attention Deficit Hyperactivity Disorder (ADHD) [63–65] and Major Depressive Disorder [66,67]. Further, EEG signal analysis has been used to detect alcohol related changes in the electrical activity of the brain [68,69]. Similar EEG signal analysis techniques have been used to study drug abuse-induced changes on the electrical activity of the brain [67].

Research also will advance in other types of brain signals. Recently, using Magneto-Encephalogram (MEG) signals, Ahmadlou et al. studied the differences of complexity of functional connectivity network, a global property of the brain, between Mild Cognitive Impairment (MCI) and normal elderly subjects during a working memory task. They measured the brain networks' complexities by Graph Index Complexity and Efficiency Complexity computed in theta and alpha bands. Their results show Efficiency Complexity at theta band can be used as an index for assessing working memory deficits and potentially as a biomarker for the diagnosis of MCI [68].

Another promising application of automated EEG processing is brain computer interfaces [72,73]. This technology can be used for rehabilitation and mobility improvements for paralyzed patients. All the aforementioned approaches and systems were based on only one physiological measurement, i.e. EEG. However, a single source of physiological information may not deliver a clear picture of the patient health. Therefore, future CAD systems will be based

on a range of physiological measurements, such as Electrocardiogram (ECG) [74–76].

8. Conclusion

In this review authors explored the importance of WT for EEG-based computer aided seizure detection and epilepsy diagnosis. The paper began by investigating the rational behind computerized EEG processing. Relevant information about diseases, such as epilepsy, is hidden within the main structure of the EEG signal. For seizure detection and prediction a good understanding of both time and frequency location of the abnormalities is necessary. While WT makes this information more accessible, additional feature extraction steps are necessary to refine and distil information from the wavelet coefficients. Only with this refinement it is possible to build reliable CAD systems.

Extensive review of the literature established that WT is the method of choice for EEG-based seizure detection, no other signal processing method featured so prominently. It was found more scientific work has been carried out using the DWT than the CWT. This review also discussed the measurements used to assess the quality of wavelet-based EEG analysis systems. The rationale behind this interest comes from the fact that only rigorously assessed methods will continue to be relevant in future.

Conflict of interest

We declare that we have no conflict of interest.

Appendix A. Acronyms

ADHD	Attention Deficit Hyperactivity Disorder
ApEn	Approximate Entropy
ANN	Artificial Neural Network
ApEn	Approximate Entropy
bior	Biorthogonal
bip	Biphasic
CAD	Computer-Aided Diagnosis
CG	Complex Gaussian
coif	Coiflet Wavelet
CWT	Continuous Wavelet Transforms
db	Daubechies
DBS	Deep Brain Stimulation
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EEG	Electroencephalography
FLD	Fisher's linear discriminant
FT	Fourier Transform
HOS	Higher Order Spectra
ICA	Independent Component Analysis
***k*-NN**	*k*-Nearest Neighbor algorithm
LDA	Linear Discriminant Analysis
MCI	Mild Cognitive Impairment
MEG	Magneto-Encephalogram
MH	Mexican Hat
nr	Not Reported
ocs	Orthogonal Cubic Spline
OPF	Optimum Path Forest
PCA	Principal Component Analysis
PPV	Positive Predictive Value
PNN	Probabilistic Neural Network
ROC	Receiver Operating Characteristic
SVM	Support Vector Machine
TMS	Transcranial Magnetic Stimulation
WPD	Wavelet Packet Decomposition
WPT	Wavelet Packet Transform
WT	Wavelet Transform

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