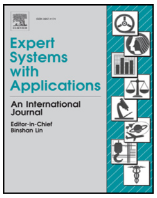
Expert Systems With Applications 67 (2017) 140–147

Contents lists available at ScienceDirect

Expert Systems With Applications

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



Electroencephalogram signal classification based on shearlet and contourlet transforms

Paulo Amorim[a], Thiago Moraes[a], Dalton Fazanaro[a], Jorge Silva[a], Helio Pedrini[b,*]

[a] Tridimensional Technology Division, Center for Information Technology Renato Archer, Campinas-SP 13069-901, Brazil
[b] Institute of Computing, University of Campinas, Campinas-SP 13083-852, Brazil

ARTICLE INFO

Article history:
Received 21 June 2016
Revised 25 September 2016
Accepted 25 September 2016
Available online 26 September 2016

Keywords:
Epilepsy
Electroencephalogram signals
Shearlets
Contourlets

ABSTRACT

Epilepsy is a disorder that affects approximately 50 million people of all ages, according to World Health Organization (2016), which makes it one of the most common neurological diseases worldwide. Electroencephalogram (EEG) signals have been widely used to detect epilepsy and other brain abnormalities. In this work, we propose and evaluate a novel methodology based on shearlet and contourlet transforms to decompose the EEG signals into frequency bands. A set of features are extracted from these time-frequency coefficients and used as input to different classifiers. Experiments are conducted on a public data set to demonstrate the effectiveness of the proposed classification method. The developed system can help neurophysiologists identify EEG patterns in epilepsy diagnostic tasks.

1. Introduction

Electroencephalograms (EEGs) are recordings of the electrical activity of the brain. The monitoring methods are typically non-invasive, where electrodes are placed along the human scalp to identify abnormalities in EEG readings, such as epilepsy, sleep disorders, coma, encephalopathies, among other brain dysfunctions (Abou-Khalil & Misulis, 2006; Bronzino, 2000; Niedermeyer & da Silva, 2005). Although EEG interpretation is traditionally performed by a neurophysiologist through visual inspection of the signals, scientific and technological advances have driven the development of reliable computer-assisted EEG analysis.

Imaging techniques, such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET) and computed tomography (CT), have high-resolution spatial capabilities, however, EEG analysis is still a valuable tool for diagnosis and research related to neurological disorders. An important characteristic of EEGs is their temporal resolution on a millisecond scale, which allows for the detection of rapid changes in brain activity. Furthermore, EEG is relatively inexpensive compared to neuroimaging techniques.

Time–frequency signal processing techniques, such as discrete wavelet transform (DWT) (Adeli, Zhou, & Dadmehr, 2003; Subasi, 2007), have been widely used to provide a quantitative measure of the frequency distribution of the EEG and detect the presence of particular patterns.

As an important tool for analyzing the human brain activity, EEG signals provide relevant information about epileptic processes. Small variations in EEG signals can show a certain type of brain abnormality. Effective signal processing methods for detecting such abrupt changes can help the diagnosis and treatment of patients with epilepsy. However, their development is still a very challenging task.

This paper describes a novel work on epileptic EEG analysis through different time–frequency transforms, such as wavelets, shearlets and contourlets. Initially, the EEG signals are decomposed into frequency bands using each transform. Then, a set of features are extracted from the transform coefficients and used as input to different classifiers. The performance of the classification process is measured according to their capacity in detecting epileptic seizures from the data. The proposed method is applied to a set of EEG signals recorded from healthy subjects and epileptic patients. Its performance is compared to other classification approaches. To the best of our knowledge, this is the first work to employ shearlet and contourlet transforms to classify EEG signals.

EEG signals contain non-stationary transient events and multiple frequency components that vary over time. Such signal characteristics motivated the use of time–frequency shearlet and contourlet transforms, which are appropriate to decompose the EEG components at different resolution levels. In contrast to the limited ability of wavelet transforms in decomposing signals only at horizontal, vertical and diagonal direction, shearlet and contourlet

---

[*] Corresponding author. Fax: +55 19 3521 5847.
E-mail addresses: paulo.amorim@cti.gov.br (P. Amorim), tfmoraes@cti.gov.br (T. Moraes), dalton.fazanaro@cti.gov.br (D. Fazanaro), jorge.silva@cti.gov.br (J. Silva), helio@ic.unicamp.br (H. Pedrini).

http://dx.doi.org/10.1016/j.eswa.2016.09.037
0957-4174/

transforms provide an effective method for overcoming such directional limitations. Therefore, features extracted from the time-frequency representation can explore variations in amplitude and frequency components of the EEG signals (such as spikes, slow and sharp waves), which are used to discriminate between epileptic and normal EEG signals.

The text is organized as follows. Section 2 briefly presents some concepts and works related to the topic under investigation. Section 3 describes the proposed methodology for EEG signal classification. Experimental results are described and discussed in Section 4. Section 5 presents the conclusions and directions for future work.

2. Background

This section briefly reviews some relevant concepts and works related to the classification of EEG signals based on time–frequency transforms.

2.1. Electroencephalography

Hans Berger (1873–1941), a German physiologist and psychiatrist, recorded the first human electroencephalogram (EEG) in 1924 (Haas, 2003). Through his device, he measured the electrical activity of the brain and conducted experiments to record the effects of drugs on EEG signal.

The brain activity is depicted as waveforms of varying amplitude and frequency measured in microvoltage. Information about amplitude, frequency and shape of recorded EEG waveforms is combined with age of the patient, state of sleep or alertness, and location on the scalp to determine abnormal rhythms.

The basic waveforms present in EEG recordings for clinical practice include alpha, beta, theta, and delta rhythms (Deuschl & Eisen, 1999; Tatum, 2014). Delta waves usually occur at a frequency from 0.5 to 4 Hz in young children or adult during sleep, theta waves at a frequency from 4 to 7 Hz in children and young adults, alpha waves are commonly recorded at 7 to 15 Hz when the person is awake but with closed eyes, beta waves occur at a frequency from 15 to 30 Hz, usually associated with depression, anxiety, or the use of sedatives, whereas gamma waves are recorded from 30 to 80 Hz related to attention, memory associations in visual discrimination tasks, among other cognitive processes.

The advances in digital technology have improved the use of EEG to include specialized techniques that provide new capabilities besides traditional practices in clinical diagnosis. Long-term EEG recordings are still used for seizure prediction in patients with epilepsy. Advanced measures of abnormal EEG signals have received attention as possible biomarkers for different brain disorders, such as Alzheimer's disease (Montez et al., 2009), Parkinson's disease, schizophrenia (Sekimoto, Kato, Watanabe, Kajimura, & Takahashi, 2011), and parasomnia (Pilon, Zadra, Joncas, & Montplaisir, 2006).

Epilepsy can be found in approximately 1% of the world population (Mormann, Andrzejak, Elger, & Lehnertz, 2007; World Health Organization, 2016). Epileptic seizures are abnormalities in EEG recordings characterized by short and episodic neuronal synchronous discharges that occur with considerably increased amplitude (Adeli et al., 2003). In general, the following terms are related to the different stages of seizures: (i) preictal refers to the state immediately before the actual seizure, which can last from minutes to days; (ii) ictal refers to the actual seizure, where physical changes occur in the person's body; (iii) postictal refers to the state shortly after the seizure; (iv) interictal refers to the period between seizures or convulsions. The diagnosis of epilepsy depends on the detection of spikes (epileptiform discharges) or other abnormalities in interictal EEG signals. The ictal pattern is generally rhythmic and often shows an increase or decrease in frequency and an increase in amplitude.

The traditional visual inspection of EEG signals requires highly trained medical professionals and is time consuming. In order to address these difficulties, automatic techniques have been proposed to analyze epileptic EEG signals.

2.2. Transforms for signal analysis

Several transforms have been proposed for signal analysis (Hramov, Koronovskii, Makarov, Pavlov, & Sitnikova, 2015; Vetterli, Kovačević, & Goyal, 2014). Some useful properties of signal transforms include their compact representation of a signal, inversibility, availability of fast versions for computer computation, capacity of analyzing signals at each frequency independently, among others.

In signal processing, time–frequency analysis consists in techniques that study a signal in both time and frequency domains simultaneously. The classical Fourier analysis assumes that signals are periodic or infinite in time, while many signals in practice have short duration and change substantially over their duration. Some examples of time–frequency transforms are the short-time Fourier transform and the wavelet transform.

A wavelet transform (Chui, 2014; Mallat, 1999; Zhai, Zhang, Liu, 2008) is a mathematical function used to decompose a continuous-time signal into different scale components. The wavelet transforms have certain advantages compared to Fourier transform since they do not require the use of fixed data windows and are localized in both time and frequency, whereas the Fourier transform is only localized in frequency. Wavelet transforms are particularly effective for representing different aspects of non-stationary, such as repeated patterns and discontinuities.

The wavelet transform of a continuous signal $f(t)$ is defined as

$$F_W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\, \psi^*\left(\frac{t-b}{a}\right) dt \tag{1}$$

where a is positive and defined a scale and b is a real number and defines a translation. $\psi(t)$ is usually referred to as the mother. The operator $*$ denotes the complex conjugate. Depending on the choice of mother wavelet, there are several wavelet families such as Haar, Daubechies, Morlet, Coiflets, Symlets, Meyer, Shannon, Gaussian, Cauchy, Gabor, among others.

Despite the advantages of wavelet transforms, a drawback is their limited capacity of representing directional features, usually determined only at horizontal, vertical and diagonal degrees. Some variations of wavelet transforms (Starck, Murtagh, & Fadili, 2010) have been proposed to overcome these limitations, such as directional wavelets, bandelets, brushlets, contourlets, curvelets, directionlets, phaselets and ridgelets.

Shearlet transforms (Lim, 2010; Schwartz, Silva, Davis, & Pedrini, 2011) possess important properties, providing a general structure for analyzing and representing data with anisotropic information at multiple levels of decomposition. Consequently, certain signal singularities, such as corners and edges, can be identified and located in images. The continuous shearlet transform for a signal in two dimensions (image) f is defined as the mapping

$$f \rightarrow \mathcal{SH}_\psi f(a, s, b) = \langle f, \psi_{a,s,b} \rangle \tag{2}$$

where ψ is a generating function, $a > 0$ is the scale parameter, $s \in \mathbb{R}$ is the shear parameter, $b \in \mathbb{R}^2$ is the translation parameter, and the analyzing elements $\psi_{a,\, s,\, b}$ (shearlet basis functions) are given by

$$\psi_{a,s,b}(x) = a^{-3/4} \psi(A^{-1} S^{-1}(x - b)) \tag{3}$$

where $A = \begin{bmatrix} a & 0 \\ 0 & \sqrt{a} \end{bmatrix}$ and $S = \begin{bmatrix} 1 & s \\ 0 & 1 \end{bmatrix}$.