PARAMETRIZATION OF THE INTRACRANIAL ELECTROENCEPHALOGRAPHY VIA WAVELET TRANSFORMATION

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Abstract

This paper describes a methodology for finding appropriate wavelets to parameterizing of intracranial electroencephalography (iEEG) records. Suitable wavelets were calculated according to mutual energy in defined frequency ranges that correspond with standard distributions of EEG bands. The appropriate wavelets were selecting from 84 types of wavelets. The wavelets will be used to parameterizing iEEG records for classifier that will be localizing the seizure onset zone (SOZ) in the epileptology.

1 Introduction

Patients with pharmacoresistant epilepsy diagnosis are treated by neurosurgery, with the part of the brain that is responsible for paroxysmal states being removed during surgical treatment. Currently, non-invasive diagnostic procedures do not allow for precise localization of the seizure onset zone (SOZ) in some cases. Therefore, intracranial electroencephalography monitoring (iEEG) is performed to find the epileptic bearings. The example of implanted electrodes is given in Figure 1 as x-ray radiography. The surgeon extracts the bearings, but inevitably as well removes part of the healthy nervous tissue.

The goal of the iEEG signal analysis is the most precise localization of the epileptiform area. Finding of bearings and the early propagation areas, which respond primarily for epileptic seizures, leads to successful treatment in the ideal case.

Wide spectrums of methods exist that can be used to trace the signal through the promotion of the brain structures. A combination of these analytical methods is necessary for refinement of the final conclusion. Epileptic seizures are manifested through the sudden presence of abnormal and often synchronized periodically EEG activity. The sudden changes can be accurately described using wavelet transformation [1], which provides a description of the signal in time-frequency domain. Its graphical output is called the scalogram, which shows the density of the mutual energy between the signal and wavelet in the time and frequency scale, see Figure 2 – below.

When the appropriate shape of the wavelets is selected, changes in the signal can be seen with good time-frequency resolution. From each transformed channel (single electrode), features can be extracted in different bandwidths. Through energy density, the features describe signal parameters such as frequency changes, length of oscillations, instant energy, etc. The extracted features of the signal can be used as input vectors for the Support Vector Machine classifier (SVM) [2]. Chronology of the seizure onset at the individual electrodes is used for the backward tracing of the initial location. The SVM classifies features of segmented iEEG into the classes “seizure” and “seizure-free”. The result of the classification process will be shown in the SOZ.

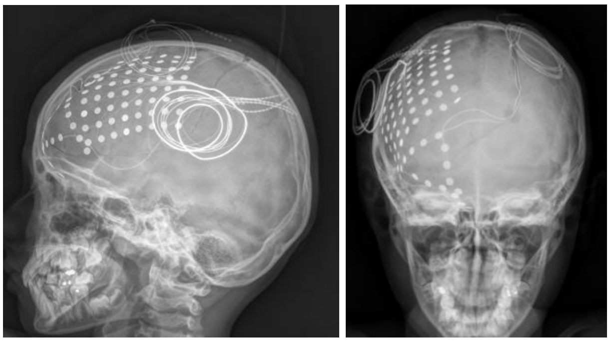

Figure 1: X-ray radiography with implanted ECoG electrodes.

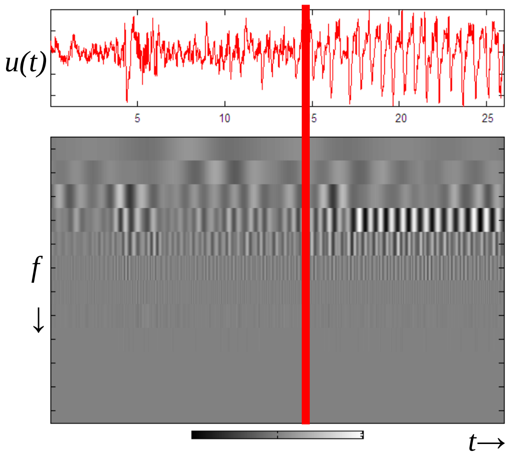

Figure 2: The scalogram of the iEEG signal with the seizure onset marked.

2 Searching for the appropriate wavelet

The most suitable shape of the wavelet cannot be found via optical comparisons of signals and waveforms. The signal is too complex, because it composed of many components, each of which has a different similarity with another wavelet. The EEG is divided into the standardized frequency bandwidth, see Table 1. Non-pathological activity in the bandwidth has a characteristic waveform marked by Greek letters. Consequently, some shapes of wavelet are suitable for certain bandwidths and others are not; in other words, it necessary to find the appropriate wavelet for each frequency band.

Table 1: SUB-BANDS OF THE IEEG SIGNAL

Bandwidth	δ	θ	α_1	α_2	β_1	β_2	γ_1	γ_2
Frequency [Hz]	2 - 4	4 - 8	8 - 10	10 - 12	12 - 18	18 - 25	25 - 48	52 - 85

Eighty-four wavelets of 15 families were tested using the Matlab Wavelet Toolbox. The names of the wavelet families with their abbreviated expressions are given in Table 2. A detailed description of the complete list of all wavelets is offered by Matlab help [3].

Table 2: LIST OF ALL WAVELETS FAMILY NAMES

All Wavelets Family Names	***Abbreviated Expressions***
Haar	haar
Daubechies	db
Symlets	sym
Coiflets	coif
BiorSplines	bior
ReverseBior	rbio
Meyer	meyr
Dmeyer	dmey
Gaussian	gaus
Mexican Hat	mexh
Morlet	morl
Complex Gaussian	cgau
Shannon	shan
Frequency B-Spline	fbsp
Complex Morlet	cmor

2.1 Testing methodology

The signal selected as the representative testing signal was the electrocorticography (ECoG) record of a patient with known diagnosis and with a marked time of the seizure onset. The record was captured through a medical measurement system with a 1 kHz sample rate for 3 minutes. One channel of the testing signal directly corresponded with an epileptic lesion. Parameterization of the signal using the wavelet transformation will be used for classification into seizure and seizure-free classes, so the suitable wavelet has to describe both states accurately.

Each variant of the wavelet was cyclically tested for the described frequency range, as in Table 1. The scalogram described the mutual energy of tested wavelet and the signal in the time and frequency range. The similarity of the wavelet and the waveform of signal defined the mean energy. The mean energy is calculated as the sum of all absolute values of the scalogram in defined frequency range. The result of the test was a matrix which assigns to each wavelet values of energy of the frequency range. The scalogram was computed through continuous wavelet transformation (CWT).

The same cyclical test was applied to both parts of the signal, without seizure and with seizure. The suitability of the wavelet for parameterizing corresponds with the difference of the mean energy that is present between both parts. Because different types of the wavelet have distinct characteristic energy, the mean energy is relative, and thus the division of the mean energy between parts must be expressed as percentages. The divide is normalized by the maximal energy value of both parts. The shape of wavelet with the maximal absolute normalized difference in frequency was determined as the best for parameterizing.

3 Results

The difference between mean energy in frequency bands is revealed in a few types of wavelets, which are the most appropriate for parameterizing iEEG signals. The descending type of the absolute difference of energy determines the wavelet's ability which follows the waveform changes in iEEG. Table 3 describes the five best combinations of the wavelet.

Table 3: THE ORDER OF WAVELETS AS APPROPRIATE TO THE CLASSIFICATION FOR EACH BANDWIDTH

	Bandwidth [Hz]							
Order	***δ*** 2-4	***θ*** 4-8	α_1 8-10	α_2 10-12	β_1 12-18	β_2 18 - 25	γ_1 25 - 48	γ_2 52 - 85
1st	gaus2	gaus1	cmor1-0.1	cmor1-0.1	cmor1-0.1	cmor1-0.1	fbsp2-1-0.1	fbsp2-1-0.1
2nd	cgau1	mexh	gaus1	fbsp2-1-0.1	gaus1	fbsp2-1-0.1	shan1-0.1	shan1-0.1
3rd	gaus3	cgau1	fbsp2-1-0.1	shan1-0.1	shan1-0.5	shan1-0.1	shan1-0.5	shan1-0.5
4th	mexh	rbio3.1	shan1-0.1	shan1-0.5	fbsp1-1-0.5	shan1-0.5	fbsp1-1-0.5	fbsp1-1-0.5
5th	cgau2	gaus2	shan1-0.5	fbsp1-1-0.5	fbsp2-1-0.1	fbsp1-1-0.5	cmor1-0.1	cmor1-0.1

4 Conclusion

Wavelets were found that were suitable for parameterization of the iEEG signal. Each standardized frequency bandwidth has a specific type of wavelet that follows changes in the iEEG waveform. The parts of signal with and without seizure occurrence can be optimally parameterized regarding significant features, features that will be used as a classifier, which is the basis of the method for SOZ localization [2].

Finding of the optimal shape of the wavelet using only one representative signal is insufficient for general conclusions. However, the method described shows a possible way to find the appropriate wavelet types for wavelet transformation. Each new patient can by tested using a signal with defined parts of seizure and seizure-free signals for determining the optimal wavelet.

Acknowledgments

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