ARMA Modelling for Sleep Disorders Diagnose

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Abstract. Differences in EEG sleep spindles constitute a promising indicator of sleep disorders. In this paper Sleep Spindles are extracted from real EEG data using a triple (Short Time Fourier Transform-STFT; Wavelet Transform-WT; Wave Morphology for Spindle Detection-WMSD) algorithm. After the detection, an Autoregressive–moving-average (ARMA) model is applied to each Spindle and finally the ARMA's coefficients' mean is computed in order to find a model for each patient. Regarding only the position of real poles and zeros, it is possible to distinguish normal from Parasomnia REM subjects.

Keywords: Sleep Spindles, ARMA, EEG, Parasomnia REM

1 Introduction

Sleep spindles are particular EEG patterns which occur during the sleep cycle with center frequency in the band 11.5 to 15 Hz. They are used as one of the features to classify the sleep stages [1]. Sleep spindles are promising objective indicators in sleep disorders. In order to interpret then, their structure needs to be clarified or a suitable model needs to be found. The correct detection of human sleep spindles and posterior characterization can lead to early detection of changes in brain and prevent or, at least, mitigate the influence of certain diseases [2].

In [2] automated spindle characterization by using autoregressive moving average (ARMA) was proposed by the authors to distinguish between normal, elderly and dementia patients. In this work, ARMA model for sleep spindles is used to detect meaningful differences when applied to spindles from different types of people, in this case to distinguish normal from Parasomnia REM subjects.

2 Relationship to Internet of Things

As one of the main ideas of the Internet of Things (IoT) is that all objects and people in daily life will be equipped with radio tags and they could be identified and inventoried by computers, it will bring great advantages in the bio-signal processing fields. It will come a time where people are constantly monitored in their "biological values". Signals like body heat, heart rate, ECG and EEG amongst others will be real-time monitored in order to rapidly and efficiently detect certain deceases.

3 Sleep Spindles

It is commonly referred in literature that sleep spindles are the most interesting hallmark of stage 2 sleep electroencephalograms (EEG) [1]. A sleep spindle is a burst of brain activity visible on an EEG and it consists of 11-15 Hz waves with duration between 0.5s and 2s in healthy adults, they are bilateral and synchronous in their appearance, with amplitude up to 30 µV (Fig. 1. Example of SS detection using WT. Fig. 2. Example of SS detection using WMSD.).

The spindle is characterized by progressively increasing, then gradually decreasing amplitude, which gives the waveform its characteristic name. It is now reliable that sleep spindles are originated in the thalamus and can be recorded as potential changes at the cortical surface [3].

Sleep spindles were first described in human EEG by Loomis in 1935, but the first commonly accepted definition of sleep spindle was given by [4]:

"The presence of a sleep spindle should not be defined unless it is of at least 0.5sec duration, i.e., one should be able to count 6 or 7 distinct waves within the half-second period. Because the term "sleep spindle" has been widely used in sleep research, this term will be retained. The term should be used only to describe activity between 12 and 14 cps."

4 ARMA models and Sleep Spindle detection

4.1 ARMA Model

In signal processing, autoregressive moving average (ARMA) models are typically applied to correlated time series data. Given a time series, we can consider it as the output of an ARMA system driven by white noise. The ARMA model is a tool for understanding and, whenever necessary, predicting future values in time series. The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The model is usually referred to as ARMA(p,q) where p is the order of the autoregressive part and q is the order of the moving average part .

Compared with the pure MA or AR models, ARMA models more suitable for describing the characteristics of a given process with minimum number of parameters using both poles and zeros, rather than just poles or zeros [5].

As referred, a stationary ARMA process of order (p,q) is considered as the output of a linear time-invariant(LTI) digital filter driven by white noise. The transfer function of the system is given by:

$$H(z)=\frac{\sum_{m=0}^{q} b_m z^{-m}}{\sum_{k=0}^{p} a_k z^{-k}}, \quad \mathbf{(1)}$$

with $a_0=1$. The process corresponding to this model satisfies the difference equation:

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + \sum_{m=0}^{q} b_m w(n-m)\ , \quad \textbf{(2)}$$

where w(n) is the input sequence, a zero-mean white noise and x(n) is the output sequence. The main task in the modeling can be formulated as:
Given a segment of a time series, x(n), n=0,1,2 …, L-1, estimate the p+q+1 ARMA parameters.

4.3 Sleep Spindle Detection

In this paper a combination of three different approaches is used for the automatic detection of sleep spindles: Short Time Fourier Transform, Wavelet Transform and Wave Morphology for Spindle Detection.

The individual detection algorithms are explained from section 4.3.1 trough 4.3.3. In order to improve the results, the three detectors are mixed together using the procedure presented in 4.3.4.

The best performance obtained resulted in a sensitivity and specificity of 94% when compared to human expert scorers. The algorithms were previously implemented, tested and evaluated by the authors in manual human scored signals in [6].

4.3.1 Sleep Short Time Fourier Transform (STFT)

The use of STFT is used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time and it is commonly used in signal processing [7]. The STFT of a discrete signal is:

$$\mathrm{STFT}\{x[n]\} = X(m, \omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega n}\ . \quad \textbf{(3)}$$

The magnitude squared of the STFT yields the spectrogram of the signal:

$$\mathrm{spectrogram}\{x[n]\} = |X(\tau,\omega)|^2. \quad \textbf{(4)}$$

The SS detection is based on the spectrogram. A segment is marked as SS when a peak (above a pre-specified threshold) with duration between 0.5s and 2s occurs in the SS frequency range.

In the STFT SS detection used, the threshold value used corresponds to the cumulative value of peaks in the spectrogram

4.3.2 Wavelet Transform (WT)

In this method, the detection of sleep spindles employ the continuous wavelet transform of EEG signal x(t):

$$\mathrm{CWT}_{\Psi}x(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} x(t)\ \Psi^*\left(\frac{t-b}{a}\right)dt, \quad \textbf{(5)}$$

where Ψ(t) is called the 'mother wavelet', the asterisk denotes complex conjugate, whereas a and b are scaling parameters [8]. The corresponding normalized wavelet power is defined by:

$$w(a,b) = W^2 (a,b)/\sigma^2, \tag{6}$$

and σ is the standard deviation of the EEG segment used.

Complex Morlet WT is defined as

$$\Psi(x) = \frac{1}{\sqrt{\pi fb}} e^{2\pi fcx} e^{x2/fb} dt, \tag{7}$$

where fc is the center frequency and fb the bandwidth frequency. In order to find SS using the WT, the normalized WT power was determined and when a peak (greater then a determined threshold) with a duration between 0.5s and 2s occurred a SS was marked.

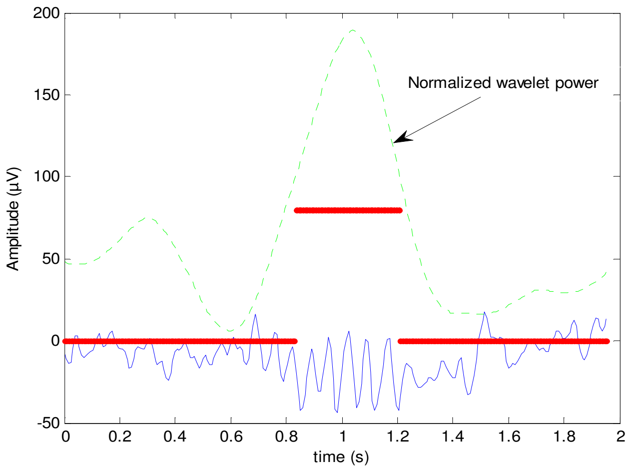

Fig. 1. Example of SS detection using WT.

4.3.3 Wave Morphology for Spindle Detection (WMSD)

The WMSD algorithm proposed in this paper is based on the definition of Sleep Spindle by Rechtschaffen and Kales [4]

The WMSD algorithm was for the first time published by the authors in [6].The implemented algorithm consists of:

a) Detection of peaks in the signal (maxima and minima), based on a defined threshold, thus, eliminating small peaks;

b) Determination of extreme to extreme time distance and conversion to frequency:

$$f = \frac{1}{T} \tag{8}$$

c) Verification if the determined frequencies lie in the SS range (11-15 Hz);

d) If there are more than 12 consecutive peaks (6 maxima and 6 minima) in the SS frequency band a spindle is marked.

The whole process mimics the visual detection mechanism.

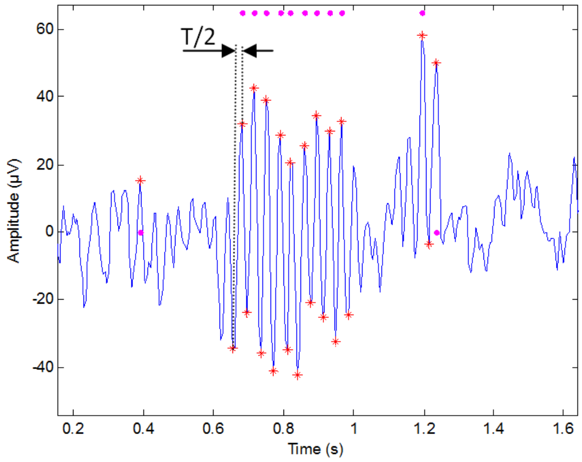

Fig. 2. Example of SS detection using WMSD.

4.3.4 Mixed Detection Using WT, STFT and WMSD

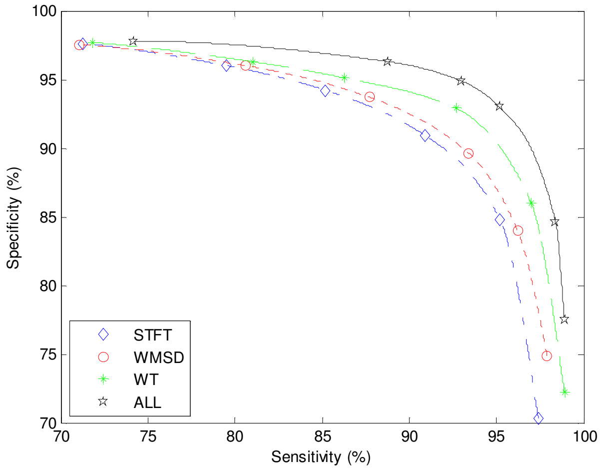

Fig. 3. Sensitivity x Specificity curves.

In this work, a mixed algorithm using WT, STFT and WMSD algorithms, was used.

In this approach, we use a vector to characterize the signal (same length as the sampled signal).This vector defines each point as belonging to a SS or not. The mixed result is computed, i.e., a point is considered belonging to a SS if it is marked as SS in WT, STFT and WMSD algorithms. Finally, if there are not enough consecutive points marked as belonging to a SS, in order to last at least 0.5 seconds, they are considered as non-spindle. The best performance obtained resulted in a sensitivity and specificity of 94% when compared to human expert scorers. In Fig. 3. Sensitivity x Specificity curves. are shown for the individual algorithms together with the combination of the 3.

5 Experimental Results

This study makes use of a sample representative of human sleep, obtained from 23 volunteers, males and females with ages between 35 and 87 years old. Briefly, all polysomnograms were obtained by a Nicolet EEG 1A97 18-channel polygraph with a sampling rate of 256Hz. From the group, 8 subjects were completely healthy and the remaining 15 had some kind of REM Parasomnia: REM sleep behavior disorder (RBD), Recurrent Isolated Sleep Paralysis or Catathrenia. The signals were unclassified and the whole night signal of C3-A2 channel was used. At this stage our objective was only to distinguish healthy from Parasomnia subjects.

The detection methods were applied with a combination of threshold parameters for the STFT, WMSD and WT algorithm. In the STFT case, the threshold value used corresponds to the cumulative value of peaks in the spectrogram. In the WMSD algorithm, a point is considered a maximum peak if it has the maximal value, and was preceded (to the left) by a value lower than the threshold defined. The Normalized Wavelet Power amplitude is used as threshold in the WT case.

After the algorithms were applied to the signals and SS identified, ARMA modelling was performed for all the SS from all subjects. After this, computation of the arithmetic means of the coefficients from the ARMA transfer functions was performed. This gave us a typical SS transfer function for each subject. 4 groups have then been created, comprising subjects with similar pole/zero distributions. Only the zero and real pole position have been taken into care. The characteristics of each group are as follows:

- Group 1: pole on the left complex plane and zero on the right complex plane (see Fig. 4. Zeros and poles from Group 1.);
- Group 2: pole on the right complex plane close to 1 and zero on the left complex plane (left from -0.1) (see Fig. 5. Zeros and poles from Group 2.);
- Group 3: pole on the right complex plane close to 1 and zero near the origin (right from -0.1 and left from +0.1) (see Fig. 6. Zeros and poles from Group 3.);
- Group 4: pole on the right complex plane close to 1 and zero on the right complex plane (right from +0.1) (see Fig. 7. Zeros and poles from Group 4.).

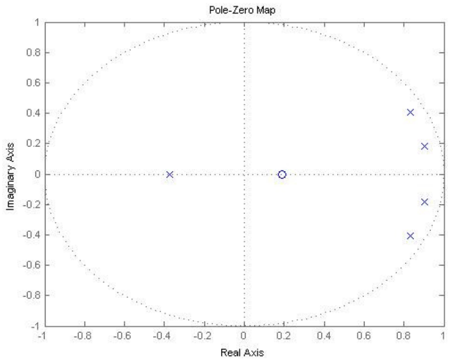

Fig. 4. Zeros and poles from Group 1.

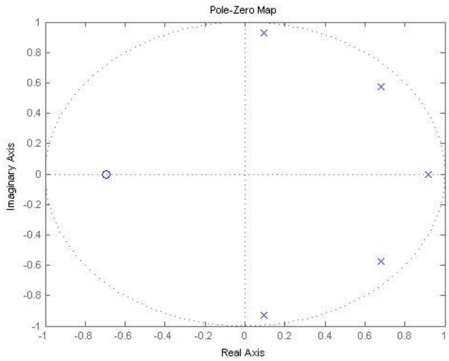

Fig. 5. Zeros and poles from Group 2.

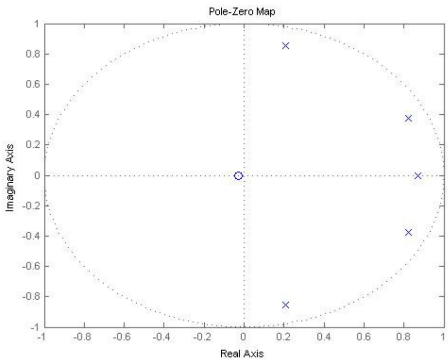

Fig. 6. Zeros and poles from Group 3.

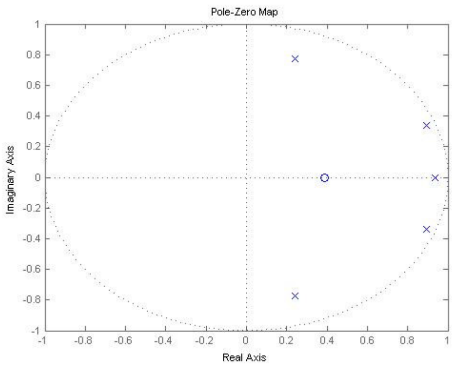

Fig. 7. Zeros and poles from Group 4.

The subjects' allocation to the groups resulted as follows:

- Group 1: 3 subjects, all suffering from REM Parasomnia;
- Group 2: 12 subjects, all suffering from REM Parasomnia;
- Group 3: 3 healthy subjects;
- Group 4: 5 healthy subjects.

It is word notice that all the healthy subjects were classified as belonging to Groups 3 or 4 and all the Parasomnia REM patients were allocated in Groups 1 or 2. A further in depth analysis of the subjects' deceases and the deceases grades should be taken into account to understand the existence of four groups instead of 2. This can also lead to the conclusion that for some reason there are significant differences between the healthy subjects.

6 Conclusions

ARMA modeling seems a promising indicator for Sleep disorders. In this work subjects suffering from several Parasomnia disorders were automatically identified based only on the zeros and poles position of their Sleep Spindle model. The work to follow will be to distinguish pathologies from each other, that is, once it is known that a patient suffers from a sleep disorder, how to automatically diagnose its condition based on the Sleep Spindle model.

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