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Sleep Spindles Detection: a Mixed Method using STFT and WMSD

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Abstract. Sleep spindles are a hallmark of stage 2 sleep and are promising indicators of neurodegenerative disorders such as schizophrenia and dementia. In this paper two sleep spindle detectors are presented. The first is based on the Short Time Fourier Transform (STFT), the second is a novel algorithm and is based in the wave morphology of sleep spindles. Finally, a combination of the previous is proposed in a novel mixed algorithm. Performance results are presented applying the algorithms to a signal scored by two human experts. It is showed in that the combination of two algorithms, which separately provided seasonable results (around 91% sensibility), improves when they are mixed using the approach proposed (93%sensibility).

Keywords: Sleep Spindles, EEG, Short Time Fourier Transform, Wave Morphology for Spindle Detection, Statistical Measures

1. Introduction

Sleep spindles (SS) are particular EEG patterns which occur during the sleep cycle. They resemble an AM/FM sinusoid with center frequency in the band 11 to 15 Hz and they are used as one of the features to classify the sleep stages [De Gennaro L., 2000]. Sleep spindles are promising objective indicators for neurodegenerative disorders [Ktonas PY, 2009]. In this work, two methods are used to find SS, Short Time Fourier Transform (STFT) and Wave Morphology for Spindle Detection (WMSD). These methods are then combined in the pursuit of a better SS detector.

After the methods are explained, threshold values were chosen in order to maximize relationship between sensitivity and specificity for the specific detector.

The algorithms were then applied to a EEG signal, previously scored by two human. Conclusions are made about differences in performance from the three algorithms.

1.1 State of the art

There are several publications related to sleep spindle automatic detection. Most of them make use of two or more detection algorithms, which combined provide best results. It is not easy to compare results, as authors tend to publish different statistical measures of the performances. The use of sensitivity, specificity and accuracy are however the most common, but, rarely the authors publish all these statistical measures.

An approach for the automatic detection of SS based upon the Teager Energy Operator and Wavelet Transform was presented in [Ahmed B, 2009]. These two features were integrated into a spindle detection algorithm with a reported accuracy of 93.7%, without reference to sensibility or specificity.

In [Duman F, 2005], STFT and Wavelet Transform were used. After the detection, Teager Operator is applied to determine the duration of the spindle. True localization is reported to be 92%, without references to other statistical measures of the performance.

An automated spindle detection using AR modeling for feature extraction was proposed in [Görür D, 2003]. Multilayer Perceptron and Support Vector Machine are used as classifiers for comparison. Performances were reported as 93.6% for the MLP and 94.4% for the SVM classifiers.

In [Ventouras E, 2005] an artificial neural network based on the Multi-Layer Perceptron architecture was used for detecting SS in band-pass filtered EEG's. Following optimum classification schemes, the sensitivity of the network ranges from 79.2% to 87.5% and false positive rate ranges from 3.8% to 15.5%.

A SS detection algorithm based on decision tree was proposed in [Duman F., 2009]. After analyzing the EEG waveform, the decision algorithm determines the location of sleep spindle by evaluating the outputs of three different methods namely: STFT, Multiple Signal Classification algorithm and Teager Energy Operator. A 96.17% sensitivity and 95.54% specificity is reported.

Results from 7 studies are compiled in [Causa L, 2010], sensitivity rates range from 62.9% to 92.9% (7 studies), specificity ranges from 81.2% to 89.7% (2 studies) and false positive rate (FPR=1-specificity) ranges from 3.4% to 58.4% (5 studies). The best results were obtained by the authors, using Empirical-Mode Decomposition (EMD), Hilbert–Huang transform, and application of fuzzy logic. They claim a sensitivity of 88.2%, a specificity of 89.7%.

1.2 Sleep Spindles (SS)

It is commonly referred in literature that sleep spindles are the most interesting hallmark of stage 2 sleep electroencephalograms (EEG) [De Gennaro L., 2000]. 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 (Figs.1 and 2).

The spindle is characterized by progressively increasing, then gradually decreasing amplitude, which gives the waveform its characteristic name [Rechtschaffen A., 1968]. It is now reliable that sleep spindles are originated in the thalamus and can be recorded as potential changes at the cortical surface [Steriade M, 1990].

Sleep EEG measures seem promising as objective indicators in neurodegenerative disorders, including dementia, where sleep changes appear to be an exaggeration of changes that come normally with aging.

2. Methods

2.1 Short Time Fourier Transform (STFT) for Spindle Detection

The use of STFT is commonly used in signal processing [Proakis, 2006]. The STFT of a discrete signal is defined as:

$$STFT\{x[n]\} = X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n] \cdot \omega[n-m] \cdot e^{-j\omega n} \qquad (1)$$

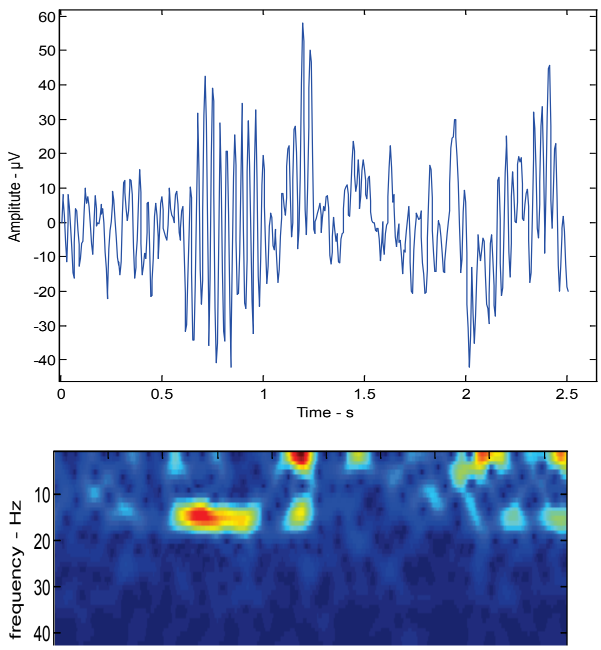

Figure 1. *Example of SS detection using STFT.*

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

$$spectrogram\{x[n]\} = \left|X(\tau,\omega)\right|^2 \tag{2}$$

An example of detection of SS using STFT and corresponding spectrogram can be seen in (Fig. 1). It is clear the presence of peak in the spectrogram (t=0.5s and f=15Hz), corresponding to a SS.

2.2 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 [Rechtschaffen A., 1968] which states:

"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."

The WMSD 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:

$$f = 1/T \tag{3}$$

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.

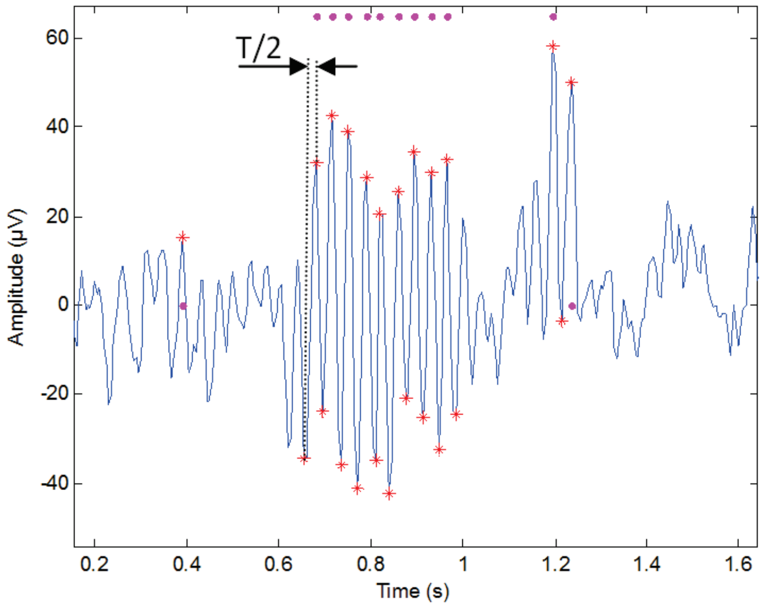

Figure 2. *Example of SS detection using WMSD.*

The whole process mimics the visual detection mechanism. An example of a SS detected using this algorithm can be seen in Fig. 2, where the SS is marked between t=0.6s and t=1.1s. The peaks above the threshold limit are marked with a '*', the ones which also satisfy the frequency criteria are marked with a '•'.

2.3 Mixed detection using STFT and WMSD, the AND algorithm

In this work, after the SS has been detected using both STFT and WMSD algorithms, mixed results were computed. It was expected that the mixed combination of algorithms would produce enhanced results.

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 between STFT and WMSD algorithm is computed, i.e., a point is considered belonging to a SS if it is marked as SS in both 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. We now address it as the AND algorithm.

In Fig. 3, a SS is marked by STFT between 6s and 6.7s (x), by the WMSD algorithm between 6.25s and 6.8s (•). Finally the SS is identified by the AND algorithm between 6.25s and 6.75s (*).

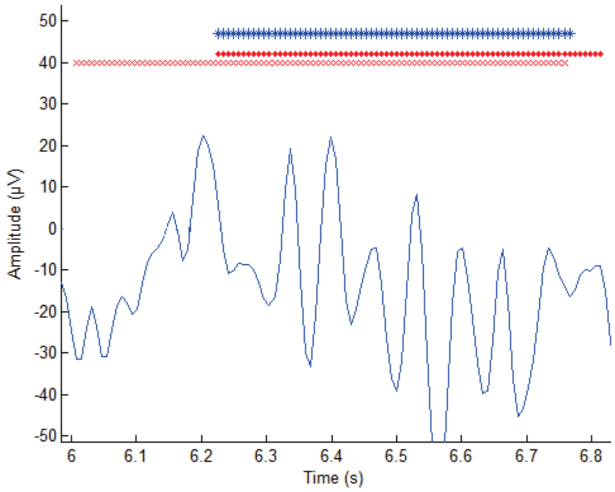

Figure 3. *SS marked by the AND algorithm.*

2.4 Statistical Measures

In order to assess the validity of results, the algorithm was applied to the data and results compared with visually scored signal. Measures were taken, namely true positive (TP), false positive (FP), true negative (TN) and false negative (FN) events.

A TP result is counted when a sample was scored as a spindle by the automatic method and the expert simultaneously. A TN result is set when a correct decision of absence of spindle was made. If the automatic result indicated a presence of spindle and there was no spindle visual scoring, a FP result was counted. On the opposite, if the output indicated no spindle while the expert scored some, a FN result was counted. [Devuyst S., 2006]

Sensitivity, specificity and accuracy are defined respectively as:

$$Sesitivity = SEN = \frac{TP}{TP + FN} \tag{4}$$

$$Specificity = SPE = \frac{TN}{FP + TN} \tag{5}$$

$$Accuracy = ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

In [Costa J, 2012] a comparison of the threshold choice is presented based on a EEG signal partly scored by a human expert. In this work, however, several values have been used in order to obtain representative curves of the sensitivity vs specificity relationship.

3. Results

This study makes use of a sample representative of human sleep, obtained from healthy male volunteers: 18 sets comprising 3 minutes each. Briefly, all polysomnograms were performed in an 18-channel analog NIHON-KOHDEN polygraph with 12 bit digital conversion (STELLATEs RHYTHM V10.0), recorded with 128Hz resolution, with manufacturers 0.5Hz high-pass filter, 0.3s time constant and -3dB IIR32 digital filter conditions applied to the signal. Sleep was visually scored according to RK [(Rechtschaffen A., 1968)]. From a screen display of C3-A2 channel, two specialists scored all concordant spindles, using the RK68 spindle definition.

The detection methods were applied with a combination of threshold parameters for the STFT and WMSD algorithm. In the STFT case, the threshold value 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.

In Fig. 4, Sensitivity x Specificity curves are shown for the STFT, WMSD and AND algorithms. It can be seen that there is a trade-off between these two measures, the higher the sensibility, the lower the specificity and vice-versa.

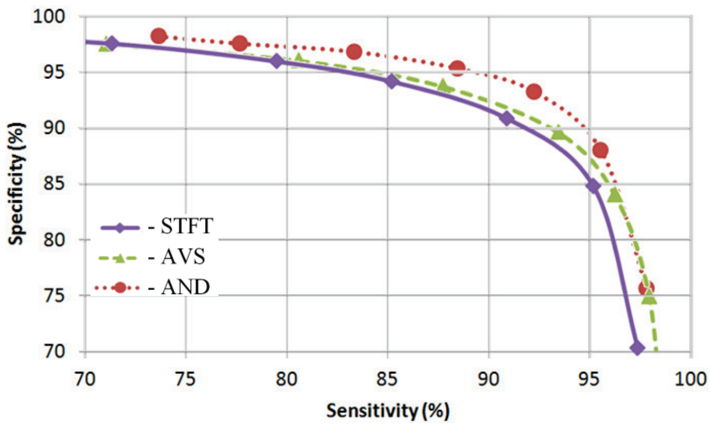

Figure 4. *Sensitivity x Specificity curve for the proposed algorithms.*

For the STFT algorithm a sensibility of 90.9% and a specificity of 90.9% were achieved. Using the wave morphology for spindle detection a sensibility of 91.3% and a specificity of 91.3% were achieved. Accuracy for the AND algorithm ranges from 86.4% (sensibility=96.1%) to 97.5% (sensibility=63.7%) within the threshold values tested. The more balanced result obtained is a sensibility of 92.9%, a specificity of 92.9% and an accuracy of 93%.

4. Conclusions

Both STFT and WMSD produced good results in sleep spindle detection. Sensibility and specificity for these algorithms is around 91%. Using a combination of both, the AND algorithm, the results improved to sensibility and specificity around 93%. The introduction of one or more supplementary detection methods can also improve the results and will be tested in future work.

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