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# An Automatic Sleep Spindle Detector Based on Wavelets and the Teager Energy Operator

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***Abstract*—Sleep spindles are one of the most important short-lasting rhythmic events occurring in the EEG during Non-Rapid Eye Movement sleep. Their accurate identification in a polysomnographic signal is essential for sleep professionals to help them mark Stage 2 sleep. Visual spindle scoring however is a tedious workload, as there are often a thousand spindles in an all-night recording. In this paper a novel approach for the automatic detection of sleep spindles based upon the Teager Energy Operator and wavelet packets has been presented. The Teager operator was found to accurately enhance periodic activity in epochs of the EEG containing spindles. The wavelet packet transform proved effective in accurately locating spindles in the time-frequency domain. The autocorrelation function of the resultant Teager signal and the wavelet packet energy ratio were used to identify epochs with spindles. These two features were integrated into a spindle detection algorithm which achieved an accuracy of 93.7%.**

## I. INTRODUCTION

SLEEP spindles are rhythmic transients present in the electroencephalogram (EEG) during non-rapid eye movement (non-REM) sleep. As shown in Fig. 1, they are of sinusoidal nature, characterized by progressively increasing, then gradually decreasing amplitude, with frequencies ranging approximately from 11-16 Hz and a typical duration of 0.5-2.0 s [1]. The density of spindles is typically highest in stage 2 sleep and lower in stage 3. Spindle activity is always accompanied by some level of background EEG waveforms.

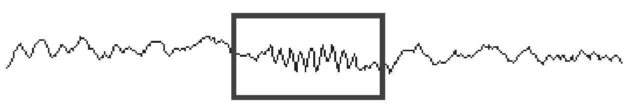

Fig. 1. An example of a sleep spindle in stage 2 sleep EEG

Spindles are an important sleep micro-event as they are considered sleep maintaining events, blocking the transfer of sensory information into the cerebral cortex at the level of the thalamus. It is in this state of reduced sensory activation that sleep related brain processes occur. They are also essential for sleep stage classification as together with K-complexes, they are hallmarks of stage 2 sleep. They also play an important role in understanding the effect of drugs on brain function, localization in the brain and memory.

As typically there can be up to 1000 spindles in a full night recording, visual analysis is time-consuming and tedious. Furthermore some spindles are hard to identify as they are borderline in frequency or duration, or superimposed on other waveforms. Automatic sleep spindle detection is hindered due to fluctuations in the frequency patterns and large inter-individual variability in spindle amplitudes.

Spectral analysis based on the frequency spectrum and linear autoregressive models of the sleep EEG has been popular in the characterization of sleep spindles because of their specific frequency range of sleep spindles [2]. In recent years advanced time-frequency analysis tools like the Gabor transform and matching pursuit algorithm [3, 4] as well as subspace methods and higher order statistics [5, 6] have been applied to the sleep EEG to derive improved feature vectors for sleep spindles.

## II. FEATURE EXCTRACTION

### A. The Teager Energy Operator (TEO)

The Teager operator is a versatile tool that measures the instantaneous changes in sinusoidal energy. It represents the energy of the input signal within a specific frequency band [9]. The Teager operator amplifies the discontinuities and sudden amplitude changes in the signal while the soft transitions between samples are reduced.

In continuous time the TEO is defined as

$$\psi[s(t)] = \left[\frac{ds(t)}{dt}\right]^2 - s(t)\frac{ds(t)}{dt} \tag{1}$$

where $s(t)$ is a continuous-time signal. If $s(n)$ is a discrete-time, random signal the TEO can be approximated by

$$\psi[s(n)] = s(n)^2 - s(n-1)s(n+1) \tag{2}$$

Epochs with spindles also have a residual background EEG component predominately in the delta range. Therefore the recorded EEG can be given by $x(n) = s(n) + v(n)$ where $s(n)$ is the sleep spindle and $v(n)$ is the residual delta EEG. The Teager energy of the recorded EEG [11] would thus be

$$\psi[x(n)] = \psi[s(n)] + \psi[v(n)] + 2\psi[s(n)v(n)] \tag{3}$$

where

$$\psi[s(n)v(n)] = s(n)v(n) - \frac{1}{2}s(n-1)v(n+1) - \frac{1}{2}s(n+1)v(n-1) \tag{4}$$

is the cross-term energy of $s(n)$ and $v(n)$. Assuming that both terms are uncorrelated, their cross-term energy will be zero, thus

$$E\{\psi[x(n)]\} = E\{\psi[s(n)]\} + E\{\psi[v(n)]\} \tag{5}$$

As there are less transitions in the background slow wave in which sleep spindles are generally found, the Teager energy of these non-spindle epochs will be less than that epochs

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with the sharp transitions of sleep spindles. Therefore it can be assumed that $E\{\psi[v(n)]\} << E\{\psi[s(n)]\}$ and thus

$$E\{\psi[x(n)]\} \approx E\{\psi[s(n)]\} \tag{6}$$

Feature vectors calculated from the Teager energy of the sleep EEG should thus provide efficient spindle detection capability after signal detrending.

### B. The Wavelet Packet Transform

The wavelet transform is an efficient analytical tool that decomposes the signal into the time and frequency domain, which is increasingly being used in pattern recognition and signal classification in the EEG.

The standard wavelet technique decomposes the frequency axis in dyadic intervals where the length of the bandwidth increases exponentially. Wavelet packet decomposition [7] generalizes the dyadic construction by decomposing the frequency axis into separate intervals of varying length, thus increasing signal analysis possibilities.


Fig. 2: Decomposition tree in a wavelet packet

A wavelet packet tree is recognized by the triplet index $(j,k,m)$ and represents level, frequency band, and time translation [8]. Fig. 2 above shows a two-level decomposition of the wavelet packet tree. $\Omega_{j,k}$, is the space of the basis vectors defined for the node $j,k$ of the binary tree, for $j = 0,1,...,J$ and $k = 0,1,...,2j-1$ where $n_0 = \log 2n \geq J$, $n$ is the signal dimensionality, $n_0$ is the maximum level of signal decomposition, and $J$ is the maximum decomposition level desired.

In this paper, wavelet packet decomposition was performed with the cross data entropy algorithm (CDE) [8] to extract an efficient feature vector for use in the accurate detection of sleep spindles. The CDE uses the sum of coefficient energies in each class and at each node to decompose the signal and construct the relative entropy measure to provide a measure of discrepancy between different classes of data to reveal the bases of a wavelet packet that distinguish one class of data from another as shown in the Fig. 3.

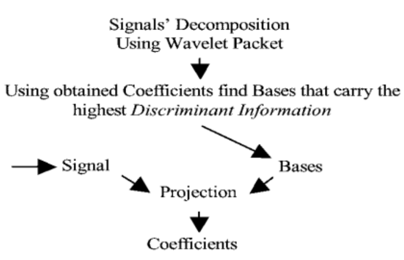


Fig. 3: Main stages of the CDE algorithm

### C. Autocorrelation Function (ACF)

The autocorrelation function (ACF) is used to identify the periodicity in an observed signal which may be corrupted by additive background signals [10]. The autocorrelation of a function measures the similarity of a signal with a delayed version of itself, thus providing information about the periodicity of the signal. The normalized autocorrelation function is given by

$$r(\tau) = \frac{1}{N}\sum_{t=0}^{N-\tau-1} x(t+\tau)x(t) \tag{7}$$

where $N$ is the total sampling number, $x$ is the signal value, $t$ is the time, $\tau$ is the shifted time, and $r$ is the ACF value.

As sleep spindles and their Teager energy are highly periodic, the autocorrelation function, normalized with respect to the value at the zero lag was applied to the Teager energy operator and its mean in each epoch calculated. The mean ACF of epochs with spindles will thus be higher than those with non-spindles.

## III. Methods

Sleep EEG data downloaded from the online Sleep-EDF database available in the Physiobank archive was used in this study. The recordings were obtained from Caucasians (21 - 35 years old) without any medication, containing horizontal EOG, submental EMG, FpzCz and PzOz EEG, each sampled at 100 Hz. They were obtained from subjects with mild difficulty falling asleep but were otherwise healthy, collected overnight in the hospital. The EEG data was examined by a neurologist with EEG fellowship training and 95 sleep spindles were marked in the selected segment. Then, the data was segmented into 1.28 second running windows with no overlap.

### A. Wavelet packet Ratio Energy

The wavelet packet energy ratio (WPER) is defined as the ratio of energies in two dominant frequency bands in the wavelet packet domain. The CDE algorithm [7] was first used to identify the most discriminant bases (i.e., bases that can distinguish one class of data from another) from a wavelet packet dictionary. Applied to sleep analysis, these classes can identify transient events occurring in the sleep signal. To obtain wavelet packet coefficients, we then projected the segmented data onto wavelet packet bases in the selected bands. The signal energies in these bands were then obtained by summing the squared coefficients. Based on the frequency characteristics of sleep spindles, we investigated different bands and found the 9 to 12 Hz and 1 to 4 Hz bands to be most discriminating.

The WPER of the epochs of the sleep EEG signal was determined by calculating the ratio of energy of the 9 to 12 Hz band over energy of 1 to 4 Hz in the wavelet packet domain. Each epoch of the data was first decomposed into a wavelet packet tree. The Daubechies-4 filter was found to give the best decomposition. Then, the sum energies of the above mentioned bands were calculated to obtain their ratio in each epoch.

## B. Teager Energy Operator

The Teager energy operator was applied to the whole marked sleep EEG recording. As shown in Fig. 4, given the nature of the TEO, the dominant frequency content of the resultant signal was not different from the original. The only variation was an increase in the periodic frequency components of the resultant TEO signal as visible in Fig. 4. Therefore the frequency bands under investigation for the identification of spindles were not altered. Given the ability of the TEO to amplify instantaneous changes in energy, the autocorrelation function of the resultant signal in each epoch was used to identify the presence of spindles in an epoch.

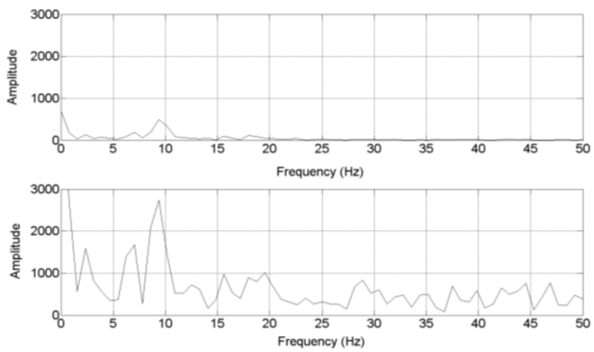


Fig. 4: a) The frequency content of an EEG epoch with a marked spindle and b) The frequency content of an EEG epoch with a marked spindle after application of the Teager Energy Operator

# IV. Results

## A. Wavelet packet Ratio Energy

The WPER of epochs with sleep spindles was compared to that of adjacent epochs with no spindles. It was found that the WPER of a significant number of epochs with spindles was larger than that of adjacent epochs with no spindles. Fig. 5 shows the WPER of a segment of EEG with a marked spindle and its adjoining non-spindle epochs. Note the sharp increase in WPER value in the epoch with the marked spindle.

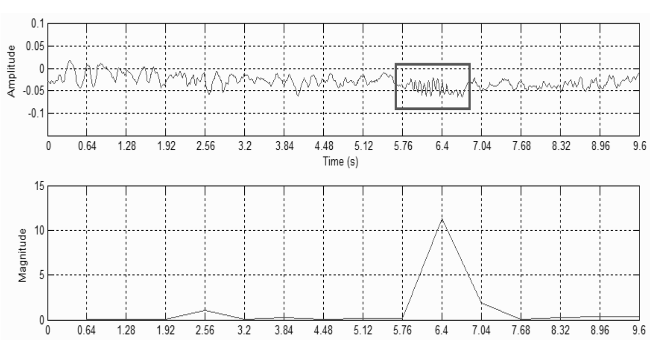


Fig. 5: a) A EEG segment with a marked spindle and b) the WPER in a segment of EEG

Table 1 gives the maximum and mean value of the WPER in epochs with spindles and the adjacent non-spindle epochs.

TABLE I
Comparison of feature values of spindles and non-spindles

| | WPER | Teager mean autocorrelation |
|---|---|---|
| **Spindles** | | |
| Maximum | 31.28 | 0.6438 |
| Mean | 2.07 | 0.1782 |
| Median | 1.05 | 0.16 |
| 70%> | 0.54 | 0.112 |
| **Non-spindles** | | |
| Maximum | 30.29 | 0.46 |
| Mean | 0.945 | 0.100 |
| Median | 0.282 | 0.0619 |
| 70%< | 0.588 | 0.126 |

The mean WPER of spindle epochs is higher than that of non-spindle epochs. As shown in Table 1, 70% of the spindle epochs had a WPER greater than 0.54, whereas 70% of non-spindle epochs had WPER less than 0.588, indicating the potential spindle discriminating ability of the WPER.

## B. Teager Energy Operator

On application of the TEO, the spindles in the sleep EEG were found to become more prominent as compared to the epochs with non-spindles as shown in Fig. 6. In the original sleep EEG, the amplitude of the marked spindle is lower than the rest of the signal, but after the TEO is applied, the spindle is amplified and become more prominent.

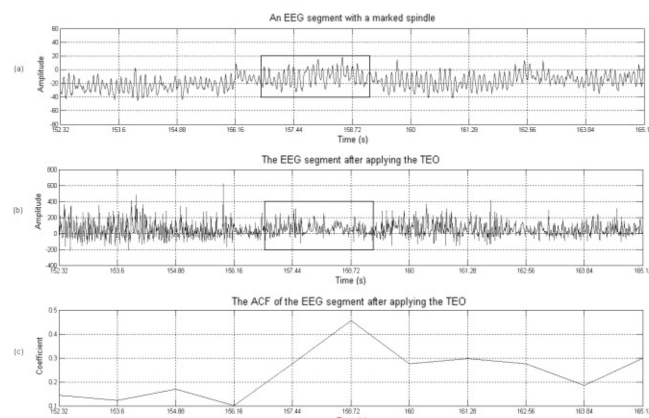


Fig.6: a) A EEG segment with a marked spindle b) The Teager Energy Operator of the EEG with the marked spindle c) the ACF of the EEG segment after applying the TEO

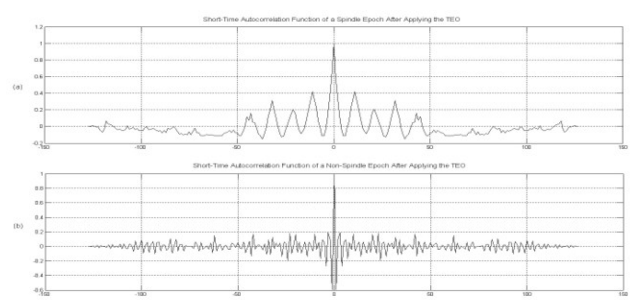

Fig.7: a) The autocorrelation function of the Teager Energy Operator of an epoch with a marked spindle b) the autocorrelation function of Teager Energy Operator of an adjacent epoch with a non-spindle

As seen in Fig. 7, the autocorrelation function of the resultant TEO signal also shows substantially higher periodicity than that of the adjacent non-spindle epoch. The mean ACF of the spindle epochs after application of the Teager was also found to be higher than that of adjacent non-spindle epochs.

Table 1 gives the maximum and mean value of the WPER and the mean ACF of the Teager energy in epochs with spindles and the adjacent non-spindle epochs. The mean and median ACF of the spindle epochs resulting from the TEO are significantly higher than that of non-spindle epochs, approximately twice the mean of the non-spindle epochs. Table 1 shows that 70% of the spindle epochs had an ACF of the resultant TEO signal higher than 0.112, whereas 70% of non-spindle epochs had an ACF less than 0.126, indicating that it can be used as a potential spindle discriminating feature.

### *C. Automatic Spindle Detection*

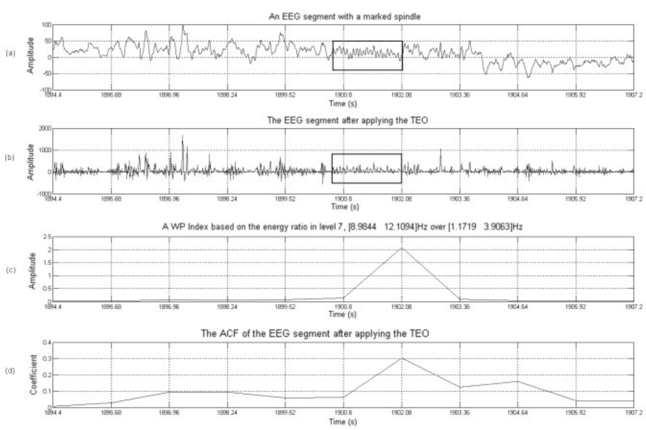


Fig.8: a) A EEG segment with a marked spindle with adjacent non-spindles, b) The Teager Energy Operator of the EEG with the marked spindle, c) the WPER of the signal d) the mean ACF of the Teager Energy Operator

Based on results obtained form the above analysis an automatic spindle detector was implemented. The inputs to the detector were the ACF of the Teager Energy Operator and the WPER each epoch of the signal. In each epoch the value of the WPER in each epoch was compared to that of the previous epoch to identify candidate spindle epochs. The WPER and mean ACF of the Teager of these candidate spindles were then compared to thresholds. The thresholds for the two parameters were determined from the first 10 spindle epochs and the adjoining non-spindle epochs in the signal. These thresholds were then used in a logic based spindle detector to test the overall signal. Of the 1519 epochs, the detector correctly identified 89 of the 95 spindles present, resulting in an accuracy rate of 93.9%. Fig 8 shows one of the identified spindles and its WPER and mean ACF compared to the adjacent epochs.

## V. CONCLUSION

In this paper a novel sleep spindle detector has been proposed based upon the Teager Energy Operator and Wavelet Packet Energy Ratio. Initial experiments conducted to test these methods showed that TEO was effective in enhancing the periodicity introduced in the signal due to the presence of sleep spindles in background EEG. The mean ACF of the Teager together with the WPER proved to be an effective technique for the detecting sleep spindles present in the EEG. An automatic sleep spindle detector based upon these measures was found to have a true accuracy of 93.9%. Further work needs to be done to enhance the classification methodology utilized in the detector and improve its efficiency, as well as testing it on a wider dataset of spindles,

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## REFERENCES

[1] M. H. Silber, S. Ancoili-Israel, M. H. Bonnet, S. Crockroverty, M. M. Grigg-Damberger, M. Hirshkowitz, S. Kapen, S. A. Keean, M. H. Kryger, T. Penzel, M. R. Pressman, C. Iber, "The Visual Scoring of Sleep in Adults," Journal of Clinical Medicine, vol. 3, 2007.

[2] E. Huupponen, G. Gomez-Herrero, A. Saastamoinen, A. Varri, J. Hasan, S. Himanen, "Development and Comparison of Four Sleep Spindle Detection Methods," Artificial Intelligence in Medicine, vol. 40, pp. 157-170, 2007.

[3] U. Malinowska, P. J. Durka, K. J. Blinowska, W. Szelenberger, A. Wakarow, "Micro- and Macrostructure of sleep EEG," IEEE Engineering in Medicine and Biology Magazine,, pp. 26-31, July 2006.

[4] S. V. Schonwald, J. L. G. Gunther, E. de Santa-Helena, and M. L. F. Chaves, "Characteristics of Human EEG Sleep Spindles Assessed by Gabor Transform," Physica, vol. 327, pp. 180-184, 2003.

[5] O. Caspary and P. Nus, "Adaptive Spectral Analysis of Sleep Spindles Based on Subspace Tracking," IEEE, 1996, pp. 976-7.

[6] T. Akgul, M. Sun, R. Sclabassi, A. E. Cetin, "Characterization of Sleep Spindles Using Higher Order Statistics and Spectra," IEEE Trans. on Biomedical Engineering, vol. 47, pp. 997-1009, 2000.

[7] R. Tafreshi, G. Dumont, D. Gross, C. R. Ries, E. Puil, B. A. Macleod, "Seizure Detection by a Novel Wavelet Packet Method," 28th IEEE EMBS Annual International Conference, New York, 2006.

[8] R. Tafreshi, F. Sassani, H. Ahmadi, G. Dumont, "An approach for the construction of entropy measure and energy map in machine fault diagnosis," ASME Journal of Vibrations and Acoustics, vol. 131, 2009.

[9] J. Kaiser, "Some Useful Properties of Teager’s Energy Operator," IEEE ICASSP, pp. 149-152, 1993.

[10] J.G. Proakis and D.G. Manolakis, ‘Digital Signal Processing’, Prentice Hall, New Jersey, 1996