ESTIMATION OF THE ANESTHETIC DEPTH USING WAVELET ANALYSIS OF ELECTROENCEPHALOGRAM

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Abstract – **This paper investigates the use of wavelet decomposition of the electroencephalogram (EEG) to assess the hypnotic state of anesthetized patients undergoing surgery. A single case study and a comparison with an existing monitor of hypnosis are presented. The proposed technique can differentiate clearly between the anesthetized state and the awake "baseline" state.**

I. INTRODUCTION

Prys-Roberts has defined the state of anesthesia as "*the state in which, as a result of drug-induced unconsciousness, the patient neither perceives nor recalls noxious stimuli*" [1]. Loss of cognition and awareness characterizes the sleep-like state of unconsciousness. Although the mechanisms of hypnosis and anesthesia are different [2], hypnosis is a major component of anesthesia. The need for a monitor of anesthesia has arisen with the use of neuromuscular blocking agents and vasoactive drugs. Such a monitor may provide anesthetists with a guide for titration of anesthetic drugs, avoiding overdosing and intraoperative awareness. Numerous studies have explored this field (refer to [3] for a complete review) since the first observation in the late 1930's of the effect of "narcotics" or general depressant drugs on the EEG [4]. EEG-based indices that correlate with the anesthetic state have received a great deal of attention [5].

In the early 1990's, a research team observed that the phase information usually discarded in classical power spectral analysis, might contain relevant information concerning the patient's hypnotic state. Using bispectral analysis to quantify the phase coupling of specific frequency components, they accurately characterize the hypnotic depth [6]. The Bispectral Index Scale (BIS™, Aspect Medical Inc.) is a commercially available monitor used for assessing anesthesia since 1996. This monitor measures the patient's EEG and displays a number scaled from 100 to 0 representing the hypnotic state. A value of 100 represents the awake state, whereas an index between 40 and 60 signifies general anesthesia [7].

While bispectral analysis provides the most accurate and reliable index, clinical practice has shown that some lag exists between the change of the anesthetic state and the changes in the BIS™. Although the BIS™ monitor is already being used with success in the operating room, an index reacting faster to clinical changes is desirable.

Wavelets have generated great interest in the biomedical field [8]. Their very low computational complexity [9] associated with time-frequency localization properties, make them particularly well suited for the analysis of non-stationary signals such as the EEG. Also, they have been successfully used as a diagnostic tool to discriminate between different states [10] and for the detection of particular patterns in a given signal [11]. Hence, it appears that wavelets can provide a suitable instrument in deriving an index of hypnosis from EEG signals.

In the following section, we present a brief account of standard dyadic wavelet decomposition and wavelet packets. We refer interested readers to [12-14] for a thorough introduction to wavelet theory and filter banks. The third section focuses on the methodology used to analyze and classify EEG epochs. Based on this analysis, we have derived an index – referred to as WAV index. Finally, we present a single case study and compare the proposed wavelet index to the BIS™, emphasizing the faster response of the WAV index.

II. OVERVIEW OF WAVELET DECOMPOSITION

Wavelets are classes of functions with properties suitable for the analysis of a wide spectrum of signals often found in engineering and biomedical applications. They can be viewed as a generalization of Fourier analysis that introduces time localization in addition to frequency properties of a signal. Thus, wavelets are capable of capturing signal features like breakpoints, discontinuities as well as general trends and self-similarity, unmeasured by other techniques.

Non-stationary or transitory features characterize most signals of interest. Fourier analysis is not suitable for capturing these features because it discards all time information. To alleviate this problem, Gabor (1946) introduced Fourier signal analysis through a time window of fixed size (*Short-Time Fourier Transform* - STFT). Wavelet analysis goes further and uses a variable-sized *windowing*, hence achieving time-frequency localization. Wavelets are

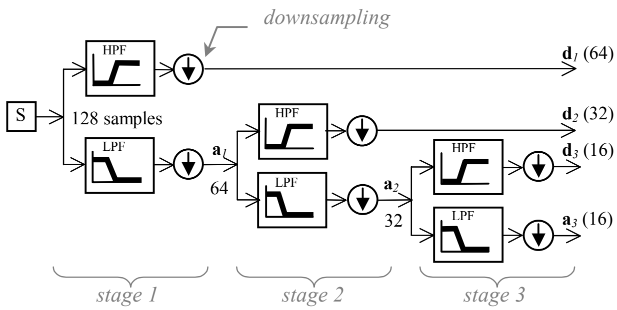

Fig. 1. 3-level DWT
($\mathbf{a}_j$ – the vector of approximation coefficients at level j,
$\mathbf{d}_j$ – the vector of detail coefficients at level j)

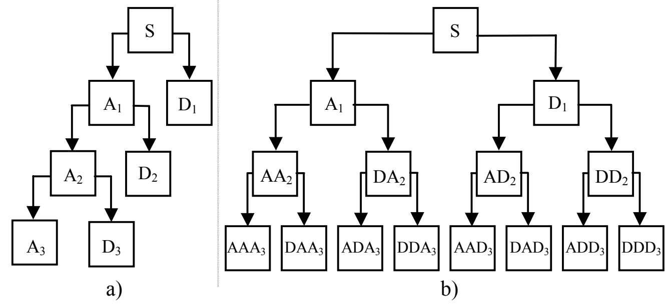

Fig. 2. Analysis tree (approximations and details)
a) 3-level dyadic decomposition
b) 3-level wavelet packet decomposition

classes of wave-like functions with a finite number of oscillations, an effective length of finite duration and no DC component. They tend to be irregular and asymmetric, and facilitate better analysis of signals composed of fast changes.

A. Standard Wavelet Dyadic Decomposition

Wavelet analysis represents a signal as a weighted sum of shifted and scaled versions of the original wavelet, without any loss of information. For efficient analysis, scales and shifts take discrete values based on powers of two (*dyadic* decomposition). This leads to octave band signal decomposition (Fig. 3a). For implementation, filter bank and quadrature mirror filters are utilized for a hierarchical signal decomposition, in which a given signal is decomposed by a series of low- and high-pass filters followed by *downsampling* at each stage (Fig. 1). This analysis is referred to as *discrete wavelet transform* (DWT).

The particular structure of the filters is determined by the wavelet used for data analysis and by the conditions imposed for a perfect reconstruction of the original signal. The approximation is the output of the low-pass filter, while the detail is the output of the high-pass filter. In a dyadic multiresolution analysis, the decomposition process is iterated such that the approximations are successively decomposed. The original signal can be reconstructed from its details and approximation at each stage, e.g., for a 3-level signal decomposition, a signal S can be written as $S=A_3+D_3+D_2+D_1$ (Fig. 2a). The decomposition proceeds until the individual details consist of a single sample.

The nature of the process generates a set of vectors $\mathbf{a}_3$, $\mathbf{d}_3$, $\mathbf{d}_2$, and $\mathbf{d}_1$, containing the corresponding coefficients. These vectors are of different lengths, based on powers of two (see Fig. 1). These coefficients are the projection of the signal onto the wavelet at a given scale; they contain signal information at different frequency bands (a_3, d_3, d_2, and d_1) determined by the filter bank frequency response. As expected, these bands are of unequal widths (see Figs. 1 and 3.a).

B. Wavelet packet analysis

Despite its high efficiency for signal analysis, standard discrete wavelet decomposition does not provide sufficient flexibility for a narrow frequency bandwidth data analysis (Fig. 3a). Wavelet packets, as a generalization of standard DWT, alleviate this problem. At each stage, details as well as approximations are further decomposed into low and high frequency signal components. Figure 2.b shows the wavelet packet decomposition tree. Accordingly, a given signal can be written in a more flexible way than provided by the standard dyadic decomposition; e.g., at level 3 we have $S=A_1+AD_2+ADD_3+DDD_3$, where DDD_3 is the signal component of the narrow high frequency band ddd_3. Wavelet packet analysis results in signal decomposition with equal frequency bandwidths at each level of decomposition. This also leads to an equal number of the approximation and details coefficients, a desirable feature for data analysis and information extraction. Figure 3.b illustrates frequency bands for the 3-level wavelet packet decomposition.

III. METHODOLOGY

This section presents the methodology used to classify the EEG according to the hypnotic state of the patient. The proposed technique is based on the wavelet decomposition of the EEG. Statistical information correlated to the hypnotic state is derived from the wavelet coefficients and integrated into an index of hypnosis. We first discuss the selection of the wavelet filter, which brings the highest degree of discrimination between the awake baseline state and the anesthetized state.

In order to focus more exactly on the phase and frequency content of the EEG, rather than its amplitude, each EEG epoch is normalized prior to analysis.

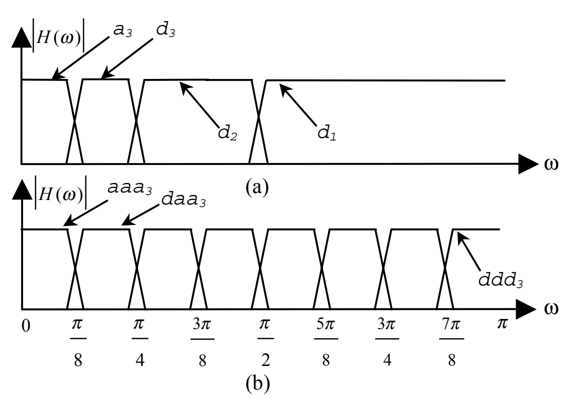

Fig. 3. Frequency bands for the analysis tree
a) 3-level dyadic decomposition b) 3-level wavelet packet decomposition

A. A Mathematical Approach to Feature Extraction

Our feature extraction technique is based on the analysis of two distinct EEG signals. The first signal was obtained from a healthy awake subject, while the second signal was recorded after induction and during surgery from a different subject. The signals were sampled at 128 Hz and low-pass filtered. They both contained $M = 60$ epochs of 128 samples with no apparent artifacts. These two signals form two training data sets that have sufficient information allowing us to discriminate the awake baseline state from the anesthetized state. These data sets can be written as:

$$\begin{cases} T_w = \left\{ \mathbf{x}_{w,k},\ k = 1,2 \ldots M \right\} & \text{(awake)} \\ T_a = \left\{ \mathbf{x}_{a,k},\ k = 1,2 \ldots M \right\} & \text{(anesthetized)} \end{cases} \tag{1}$$

where the vectors $\mathbf{x}_{\bullet,k}$ contain $N = 128$ samples representing the k^{th} epoch of either the awake or anesthetized data set.

To characterize the data sets, we then can extract a particular feature from each epoch. Let us define the feature extraction function, f as:

$$f : \mathbf{x}_{\bullet,k} \rightarrow f(\mathbf{x}_{\bullet,k}) = \mathbf{f}_{\bullet,k} \tag{2}$$

For each epoch $\mathbf{x}_{\bullet,k}$ we associate a feature $\mathbf{f}_{\bullet,k}$, which can be either a scalar or a vector. We then characterize a particular state by averaging the set $\{\mathbf{f}_{\bullet,k}\}$ over the corresponding training data set. This sires two averaged features $\overline{\mathbf{f}_w}$ and $\overline{\mathbf{f}_a}$ defined as:

$$\begin{cases} \overline{\mathbf{f}_w} = \dfrac{1}{M} \cdot \displaystyle\sum_{k=1}^{M} \mathbf{f}_{w,k} \\ \overline{\mathbf{f}_a} = \dfrac{1}{M} \cdot \displaystyle\sum_{k=1}^{M} \mathbf{f}_{a,k} \end{cases} \tag{3}$$

These are representatives of the awake and the anesthetized state. In order to assess the hypnotic state of a patient, it is sufficient to record the patient's EEG and calculate the feature $\mathbf{f}$ for each epoch. Comparing this value to $\overline{\mathbf{f}_w}$ and $\overline{\mathbf{f}_a}$, we can then determine the likelihood for the patient to be either awake or anesthetized. Hence, we define two indexes i_w (awake) and i_a (anesthetized) such that:

$$\begin{cases} i_w = \left\| \mathbf{f} - \overline{\mathbf{f}_w} \right\|_1 \\ i_a = \left\| \mathbf{f} - \overline{\mathbf{f}_a} \right\|_1 \end{cases} \tag{4}$$

where the norm $\| . \|_1$ is defined as:

$$\|\mathbf{x}\|_1 = \sum_{j=1}^{N} \left| x_j \right| \tag{5}$$

The norm $\| . \|_1$ accurately quantifies the difference between $\mathbf{f}$ and $\overline{\mathbf{f}_\bullet}$ by integrating the distance between the two vectors. Higher degree norms can be used for this analysis. However, they would emphasize large differences and lead to a noisier index. Note that due to the definition of the norm, i_w and i_a are not complementary.

B. Selected Feature

The main difficulty is obviously the selection of an appropriate function *f*. As mentioned in the previous section, each EEG epoch can be decomposed using dyadic DWT into a set of coefficients $\mathbf{a}$ and $\mathbf{d}_j$:

$$\mathbf{x} \rightarrow \left\{ \{\mathbf{a}; \mathbf{d}_j\},\ j = 1,2 \cdots L \right\} \tag{6}$$

where L is the level of decomposition. Each vector $\mathbf{d}_j$ represents the detail of the signal in a specific frequency band, d_j, and $\mathbf{a}$ is the signal approximation at the highest level of decomposition. As for the feature used to characterize each EEG epoch, we selected the *Probability Density Function* (PDF) of a chosen wavelet detail band d_j:

$$f : \mathbf{x} \rightarrow f(\mathbf{x}) = \mathbf{f} = \mathrm{PDF}(\mathbf{d}_j) \tag{7}$$

This choice is motivated by the fact that PDF does not emphasize large nor small coefficients and, conversely, tends to focus more on the general content of each wavelet decomposition band. This property is indeed interesting when dealing with noise-like signals such as EEG. Other statistical functions, such as the variance or standard deviation of the wavelet coefficients, can also be considered.

C. Best Wavelet Selection

Another difficulty arises when selecting an appropriate wavelet filter and choosing the best detail coefficient vector $\mathbf{d}_j$ for carrying out the analysis. To compare the effectiveness of different wavelets, we then introduce the *discrimination parameter D*:

$$D = \left\| \overline{\mathbf{f}_a} - \overline{\mathbf{f}_w} \right\|_1 \tag{8}$$

The discrimination parameter, *D*, quantifies the difference between $\overline{\mathbf{f}_w}$ and $\overline{\mathbf{f}_a}$. Obviously, to better distinguish between the awake and anesthetized states, *we need to maximize* D, i.e., select the wavelet filter and coefficient band that gives the highest value for *D*.

D. Application and Results

The best wavelet selection method has been applied to the training data sets. The sets have been processed to derive the averaged features $\overline{\mathbf{f}_w}$ and $\overline{\mathbf{f}_a}$ and D. The search spanned different wavelet filters, wavelet families (Daubechies, Coiflets, Symmlets, biorthogonal and reverse biorthogonal), and levels of decomposition.

This analysis using standard dyadic decomposition and the Daubechies wavelet family has clearly singled out the PDF of the band d_1 as the most discriminating. This result is interesting since the d_1 band corresponds to the detail in the 32-64 Hz frequency range.

In neurophysiology, this particular frequency band, referred to as the γ-band, often is discarded in classical power

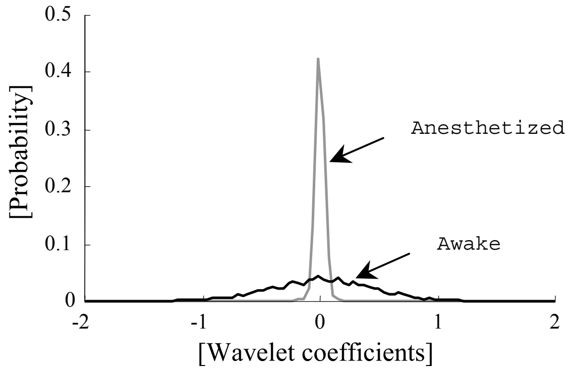

Fig. 4. Probability Density Function of wavelet coefficients (Daubechies #14, band d_1)

spectral analysis since it carries a very small amount of the EEG energy. However, recent findings in brain research imply that sensory information transits mostly in this particular band [15]. Our results tend to confirm this observation. Figure 4 illustrates the probability density functions characterizing the awake and anesthetized states.

We have reached a similar conclusion from results using wavelet packets. Using a 3-level decomposition, the best wavelet selection algorithm selected the band dda_3 (48-56 Hz) as the most discriminating, in conjunction with the wavelet filter Daubechies #8.

IV – Case Study

This section illustrates the BIS™ (version 3.4) and the EEG-based wavelet monitoring of a single case study of a patient subjected to anesthetic procedures. Anesthesia was induced using an intravenous anesthetic and maintained using inhalational anesthetics. The proposed wavelet-based technique for assessing the hypnotic depth was applied using the wavelet filters selected in the previous section.

A. Dyadic Wavelet Decomposition

Each epoch extracted from the EEG was first filtered through the high-pass wavelet filter. Once the coefficients were obtained, the probability density function was calculated and compared to the average PDFs of the awake and anesthetized state, obtained in the previous section. The comparison yielded the indices i_w and i_a, which were smoothed by averaging over a period of 15s and further combined to derive the wavelet index as follows:

$$\mathrm{WAV} = a \cdot \left(i_a - i_w\right) + b \tag{9}$$

where *a* and *b* are scaling and stretching factors calculated so that $\mathrm{WAV} = 1$ represents the awake baseline state, and $\mathrm{WAV} = 0.5$ represents the anesthetized state.

Results using standard dyadic decomposition are presented in Fig. 5. The wavelet filter Daubechies #14 and the detail band d_1 were selected for the analysis. There is a strong correlation between the bispectral and the wavelet index. However, some deviation between the indices is also evident. For instance, the deep hypnotic state induced prior to intubation and surgery is poorly estimated by the wavelet analysis. Furthermore, the WAV index is noisier, compared to the BIS™.

As shown in Fig. 6, the main advantage of the WAV index is an ability to better predict large hypnotic changes such as the emergence from the anesthetized state. With dyadic wavelet decomposition, the WAV index detected

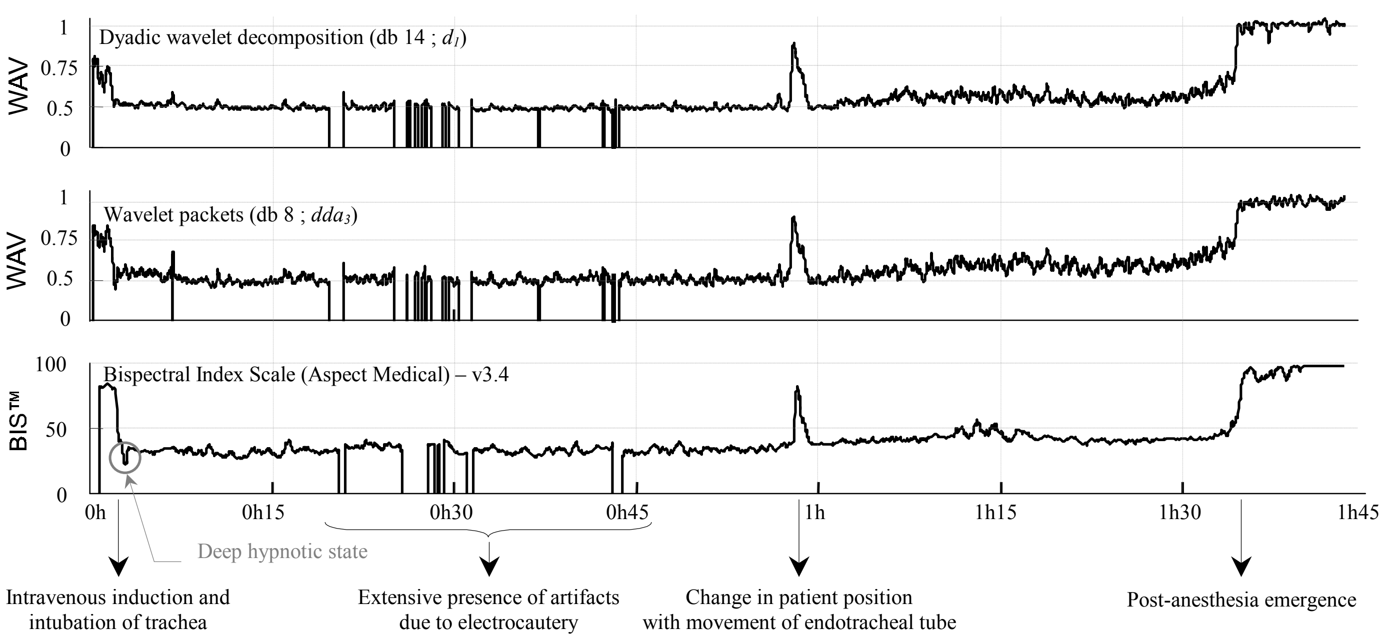

Fig. 5. WAV index for standard dyadic decomposition and wavelet packets. Comparison with BIS™ index. Note that large negative values indicate extensive presence of artifacts, i.e. no accurate measurement could be achieved.

events that were approximately 30s ahead of the BIS™. Another advantage of using wavelet analysis lies in the very low computational complexity of the wavelet decomposition algorithm [9]; the processing of one EEG epoch of 1s takes about 0.03 seconds using Matlab (Mathworks Inc.) programming and a modern computer (Pentium III – 850 MHz).

B. Wavelet Packets

Using wavelet packet analysis, we selected the wavelet filter Daubechies #8 as well as the detail band dda_3. The results presented in Fig. 5 show that wavelet packets seem to have better potential for representing the intermediate states, as well as the deep hypnotic state. There is also a large lead of 25s (see Fig. 6).

CONCLUSION

In this work, we have clearly demonstrated the usefulness of wavelet decomposition of EEG for estimating the hypnotic depth. Results have shown that the WAV index correlates closely to the BIS™ index while providing a lead time of approximately 30s. Also, the WAV index requires a very low algorithmic complexity. Further, neither large subject pool nor extensive training data sets were needed for its tuning.

However, the wavelet index was designed as an on/off index, and as such failed to capture precisely intermediate states of sedation and deeper hypnotic states. The wavelet index obtained using wavelet packets seems to be more promising but at the cost of a slight increase in computational complexity.

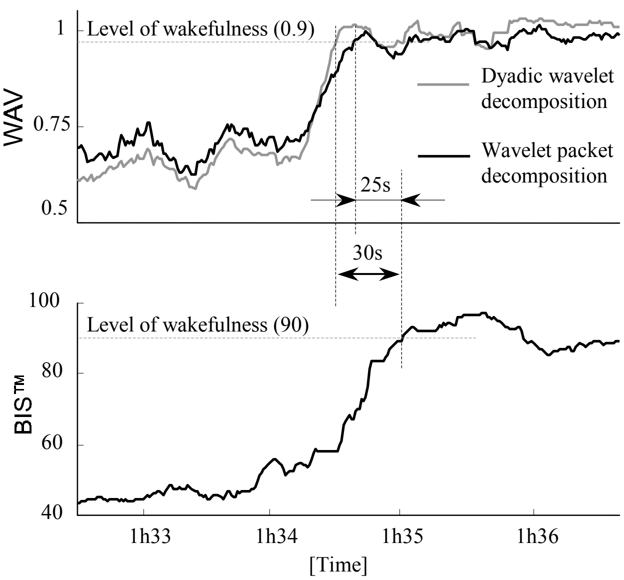

Fig. 6. Details from the emergence. Comparison with the bispectral index yields a lead of approximately 25 to 30 s.

Obviously, these results need to be verified by extensive clinical studies (currently underway). We are currently developing a wavelet-based index that exhibits graded changes with different concentrations of general anesthetics.

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