# ON-LINE EEG CLASSIFICATION AND SLEEP SPINDLES DETECTION USING AN ADAPTIVE RECURSIVE BANDPASS FILTER

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## ABSTRACT

This paper presents a novel adaptive filtering approach for the classification and tracking of the electroencephalogram (EEG) waves. In this approach, an adaptive recursive bandpass filter is employed for estimating and tracking the center frequency associated with each EEG wave. The main advantage inherent in the approach is that the employed adaptive filter only requires one coefficient to be updated. This coefficient represents an efficient distinct feature for each EEG specific wave and its time function reflects the nonstationarity of the EEG signal. Extensive simulations for synthetic and real world EEG data for the detection of sleep spindles show the effectiveness and usefulness of the presented approach.

## 1. INTRODUCTION

Computer-aided analysis of the electroencephalogram (EEG) signal, especially during sleep, is of essential interest to facilitate the analysis of over a great amount of recorded data [1]-[3]. Various computer procedures employ a first preliminarily stage of feature extraction, followed by decision-making for classification and segmentation tasks. A classical procedure is to apply the Fourier transform to a successive classification of the EEG signal, the frequency spectrum is observed to vary over time. The main assumption associated with these procedures is that the EEG signal recorded during sleep or awaking stage (e.g., performing different mental tasks) is a piecewise stationary. However, due to strong nonstationarity property of the EEG signal, using either stationarity-based methods or block-wise adaptive methods are often not satisfactory for the analysis of EEG signal.

A time-varying autoregressive (TV-AR) modeling has been used for the analysis and segmentation of the EEG signal during sleep and during mental tasks [1], [2], [4], [8], [9]. In these approaches, coefficients of the AR model are computed by processing successive windows of the EEG signal which necessitates a piecewise stationary assumption. Besides, these approaches suffer from tedious heavy computation since they try to update all coefficients of the AR model and to use these coefficients for the on-line computation of the signal spectrum.

In this paper, an alternative efficient approach is proposed for the classification and on-line tracking of the EEG waves. In this approach an adaptive recursive bandpass filter is used to track the center frequency of the EEG signal. The employed adaptive filter only has one unknown coefficient. This coefficient is updated in order to adjust the center frequency of the filter bandpass to be matched with that of the input signal. Thus the proposed wave classification is based on the on-line estimation of the center frequency of the EEG signal and the classification parameter is described by the adaptive filter coefficient. Therefore, the advantage inherent in the presented approach is to make the classification and the tracking process a function of only one parameter, providing accurate and relative simple on-line discrimination of the EEG waves.

## 2. BANDPASS ADAPTIVE FILTER

### 2.1. Filter Structure

The bandpass filter applied to tracking the center frequency of a bandpass signal could be the fourth-order Butterworth filter whose transfer function is expressed as [5], [6]

$$H(z) = \frac{a_0 + a_2 z^{-2} + a_4 z^{-4}}{1 + b_1 w(n) z^{-1} + (b_2 w^2(n) + b_2')z^{-2} + b_3 w(n) z^{-3} + b_4 z^{-4}} \quad (1)$$

where

$a_0 = a_4 = 1/(k^2 + \sqrt{2}\,k + 1)$, $a_2 = -2a_0$, $a_1 = a_3 = -4a_0$,
$b_1 = -2k(2k + \sqrt{2})a_0$, $b_2 = 4k^2 a_0$, $b_2' = 2(k^2 - 1)a_0$,
$b_3 = 2k(-2k + \sqrt{2})a_0$, $b_4 = (k^2 - \sqrt{2}\,k + 1)a_0$, $k = \mathrm{cotan}(\pi B)$,

and

$$w(n) = \frac{\cos(\pi(f_2(n) + f_1(n))}{\cos(\pi B)} \quad (2)$$

with $f_1(n) =$ normalized lower cutoff frequency as a function of discrete time *n*, $f_2(n)$ = normalized higher cutoff frequency as a function of discrete time *n*, and $B =$ normalized bandwidth of the filter.

From (1) and (2), it is obvious that with the assumption that the bandwidth *B* is a constant, *w*(*n*) is the only-center frequency dependent parameter. Therefore, the bandpass adaptive filter *H*(*z*) has only a center frequency dependent coefficient to be updated. It is worthwhile to mention that the stability constraints on *H*(*z*) are

$$k > 0 \quad \text{and} \quad |w(n)| < 1 \quad (3)$$

### 2.2. Adaptive Algorithm

Maximizing the output power of the filter *H*(*z*) makes the filter be self-adjusted to the center frequency of the input signal [5], [6]. The adaptive filter coefficient *w*(*n*) is then updated for the maximization of the expected output power $E\{y^2(n)\}$. A standard gradient ascending approach could be used for achieving such maximization. The resulting algorithm, called the recursive maximum mean-square (RMXMS) algorithm for updating $w(n)$, can be described as follows. The update equation in order for $w(n)$ to maximize $E\{y^2(n)\}$ is given by:

$$w(n+1) = w(n) + 0.5\mu_n \nabla(E\{y^2(n)\}) \qquad (4)$$

where $\mu_n > 0$ is a normalized step-size and $\nabla(E\{y^2(n)\})$ is the gradient with respect to the adaptive coefficient $w(n)$. Using the instantaneous gradient $\nabla\{y^2(n)\}$ as a stochastic approximate for the true gradient in (4), we obtain

$$w(n+1) = w(n) + \mu_n y(n)\alpha(n) \qquad (5)$$

where $\alpha(n) = \nabla(y(n))$. The filter output $y(n)$ is given by

$$\begin{aligned} y(n) &= a_0 x(n) + a_2 x(n-2) + a_4 x(n-4) - b_1 w(n) y(n-1) \\ &- (b_2 w^2(n) + b_2')y(n-2) - b_3 w(n) y(n-3) \\ &- b_4 y(n-4) \end{aligned} \qquad (6)$$

and therefore computing $\alpha(n) = \dfrac{\partial y(n)}{\partial w(n)}$ from (6) yields

$$\begin{aligned} \alpha(n) &= -b_1 y(n-1) - 2b_2 w(n) y(n-2) - b_3 y(n-3) \\ &- b_1 w(n)\alpha(n-1) - (b_2' + b_2 w^2(n)\alpha(n-2) \\ &- b_3 w(n)\alpha(n-3) - b_4 \alpha(n-4) \end{aligned} \qquad (7)$$

The normalized step-size $\mu_n$ is given by

$$\mu_n = \mu / r(n) \qquad (8)$$

where $\mu$ is a fixed positive step-size and $r(n)$ is a recursive estimate of the power of the gradient given by

$$r(n) = \lambda\, r(n-1) + \alpha^2(n) \qquad (9)$$

with $0 << \lambda < 1$ is so-called forgetting factor. Finally, it should be mentioned that for stability guarantee if the update $|w(n+1)| \geq 1$, then $w(n+1) = w(n)$.

## 3. PRACTICAL IMPLEMENTATION OF THE PROPOSED APPROACH

To track the center frequency of the EEG waves, the EEG signal could be filtered by the adaptive bandpass filter described in the previous section. The adaptive filter coefficient $w(n)$ is then function of the center frequency $(f_1(n) + f_2(n))/2$ of each EEG wave since the filter bandwidth is chosen constant. Then the time function of $w(n)$ reflects the nonstationarity behavior of the EEG signal and could be used as a classification parameter. It should be noted that the employed adaptive filter is a bandpass filter while the EEG signal is lowpass signal. This causes that for some low frequency waves $w(n) \geq 1$, making the filter unstable. To overcome this problem, a high frequency shifting process is proposed to shift the actual EEG frequencies to highest ones before adaptive bandpass filtering. A simple high-frequency shifter is by modulating the amplitude of a single tone using the actual EEG signal and to pass only the lower sideband modulated signal. We assume that the EEG signal is observed in additive white noise. In practice, for some specific time windows, the observed signal could be rather white noise and they don't represent any specific EEG waves. In such case we need another procedure to classify this signal-free noise hypothesis. This classifier can be realized by passing the raw EEG signal through an *M*th-order adaptive linear predictor. The output of the linear prediction error (LPE) filter is given by

$$e(n) = x(n) + \sum_{i=1}^{M} g_i(n) x(n-i) \qquad (10)$$

The coefficients $\{g_i(n)\}$ are updated using the normalized least-mean square (NLMS) algorithm written as

$$g_i(n+1) = g_i(n) - \gamma\, e(n) x(n-i) / \sum_{i=1}^{M} x^2(n-i) \qquad (11)$$

where $\gamma$ is a positive step-size. If the measured EEG signal contains only random white noise then the LPE filter coefficients $\{g_i(n)\}$ are close to zero and a parameter $G(n)$ expressed as

$$G(n) = \sqrt{\frac{1}{M}\sum_{i=1}^{M} g_i^2(n)} < \varepsilon \qquad (12)$$

is taken as a whiteness detector. If $G(n)$ is less than a small positive threshold value $\varepsilon$, $x(n)$ can be considered as white noise. Figure 1 shows a conceptual scheme for the proposed adaptive filtering approach for classification and tracking of the EEG waves.

## 4. SIMULATION AND EXPERIMENTAL RESULTS

### 4.1. Simulation Results

To evaluate the adaptive approach presented for the classification and tracking of the EEG waves, we track 20 simulated realizations of the EEG signal. Each EEG signal is composed of different waves such as Alpha, Beta, etc. (see Table 1 and 2). Each wave is generated by passing a zero-mean white Gaussian noise through a Hamming weighted FIR filter of length 64 whose bandwidth is equal to the corresponding wave bandwidth.

***Example 1*- (*Tracking Different Waves*):** In this Example each EEG realization is composed of the waves given in Table 1. The sampling and normalized carrier frequencies are 160 *Hz* and 0.34, respectively. The normalized bandwidth *B* is 0.1. The forgetting factor and the step size of the adaptive algorithm are 0.95 and 0.9, respectively. The initial values for $r(0)$ and $w(0)$ are 100.0 and 0.0 respectively. The step-size $\gamma$ and the order *M* of the whiteness detector are 0.01 and 2, respectively. The initial coefficients of the LPE filter are zero. Figures 2 and 3 show results for noise-free (i.e., $\infty$ dB SNR) and 10.0 dB SNR cases, respectively. In these Figures one realization of the EEG signals, the trajectory of $w(t)$ and the trajectory of $G(t)$ are depicted respectively from up-to-down. It is obvious that trajectory of the coefficient $w(t)$ can efficiently classify the different waves of the EEG signal. Comparing the values of $w(n)$ with the true values computed using (2) and given in Table 1 shows that the presented approach provides efficient tracking properties. It is also obvious that $G(t)$ is greater than a very small threshold value even in the 10.0 dB SNR case.

***Example 2*- (*Sleep Spindles detection*)*:*** In this example, each realization of simulated EEG signal is generated as given in Table 2. The wave whose bandwidth is 6-15 *Hz* is corresponding to the sleep spindle. All the parameters and initial values of the scheme are adjusted as in the previous examples. The sampling and the normalized carrier frequency are 100.0 *Hz* and 0.29, respectively. Figure 4 shows the results of this example for the 10.0 dB SNR case. It is obvious that the adaptive scheme is capable of detecting the sleep spindles even in the case of 10.0 dB SNR. It is worth to mention that the presented approach also provides reliable classification capability for the 0.0 dB SNR case.

## 4.2. Experimental results

***Sleep spindles detection:*** To examine the capability of the proposed adaptive approach for the detection of sleep spindles from real world EEG signal, we carry out the following experiment. About 12 seconds recording of 18 channels of EEG (Fp1, F8, F4, Fz, F3, F7, T4, C4, Cz, C3, T3, T6, P4, Pz, P3, T5, 02, 01) was used for demonstrating the performance of the presented approach for the detection of sleep spindles. Electrodes were placed according to the international 10-20 system. The data were sampled with a sampling frequency 102.4 *Hz*. The measured signals are filtered by a Butterworth bandpass filter between 10 and 20 *Hz*. The signals are passed forward and backward through the filter to avoid phase distortion [7]. The normalized carrier frequency, the forgetting factor, the step-size are 0.29, 0.9, 0.95, respectively. The initial values for $r(0)$ and $w(0)$ are 100.0 and 0.0 respectively. The normalized frequency bandwidth $\boldsymbol{B}$ is 0.15. Figure 5 shows the first 10 channels of the measured EEG signals and the trajectory of the adaptive coefficient $w(n)$ for each channel. Investigating the results confirms that the presented adaptive approach can be applied for a reliable detection and tracking sleep spindles of real world EEG signal.

## 5. CONCLUSION

In this paper an adaptive approach for the classification and tracking of the EEG waves has been presented. In this approach an adaptive recursive bandpass filter implemented as a fourth-order Butterworth filter is employed for tracking the center frequency of each EEG wave. The time function of only one adaptive filter coefficient is taken as a distinct feature to represent the spontaneous behavior of each specific wave. The main advantage of the approaches is then due to using only one classification parameter, which facilitates the analysis of the EEG signal. A white noise classifier is also introduced to distinct the only noise hypothesis. The proposed approach has been successfully applied to real world EEG data for the detection of sleep spindles. Classification of different kinds of sleep spindles is also possible.

## 6. REFERENCES


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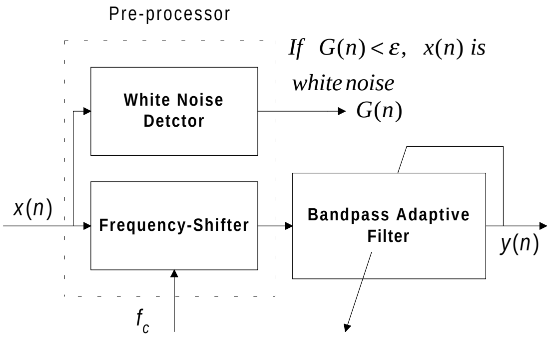


**Figure 1**. A conceptual adaptive filtering scheme for classification and tracking of EEG waves.

**Table 1.** The EEG waves used in Example 1 and the corresponding true value of the adaptive coefficient $w(n)$.

| **Wave** | **Bandwidth (*Hz*)** | **Time range (*sec*)** | **True value of $w(n)$** |
|---|---|---|---|
| Delta | 0.5-3.5 | 0-5 | –0.4920 |
| Sigma | 12.5-15 | 5-9 | –0.0268 |
| Gamma | 20-40 | 9-13 | 0.6046 |
| Alpha | 7.5-12 | 13-16 | –0.1909 |
| Sigma | 12.5-15 | 16-20 | –0.0268 |

**Table 2.** The EEG waves used in Example 2 and the corresponding true value of the adaptive coefficient $w(n)$.

| **Wave** | **Bandwidth (*Hz*)** | **Time range (*sec*)** | **True value of $w(n)$** |
|---|---|---|---|
| Theta | 4-7 | 0-4,7-11,14-18, 21-25 | 0.0990 |
| Sleep Spindles | 6-15 | 4-7,11-14,18-21 | 0.4298 |

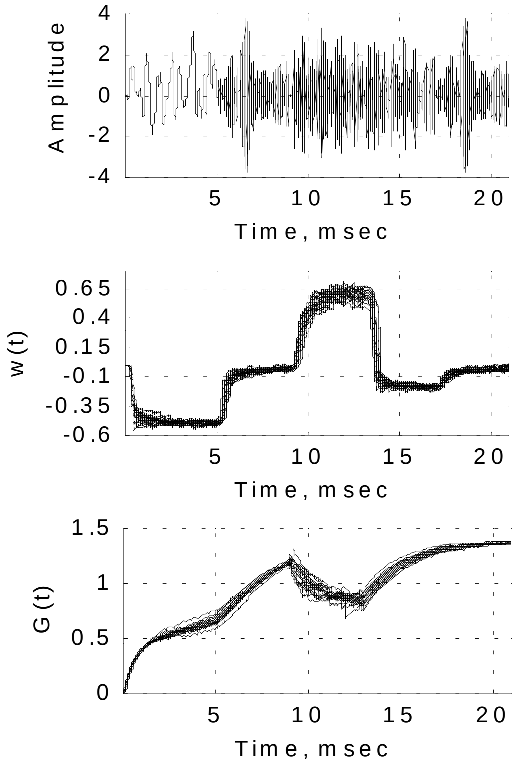


**Figure 2.** Results of Example 1 for the noise-free case: one exemplary realization of the 20 EEG signals; the adaptive coefficient of the 20 realizations; and the whiteness detector *G*(*t*), from top-to-bottom respectively.

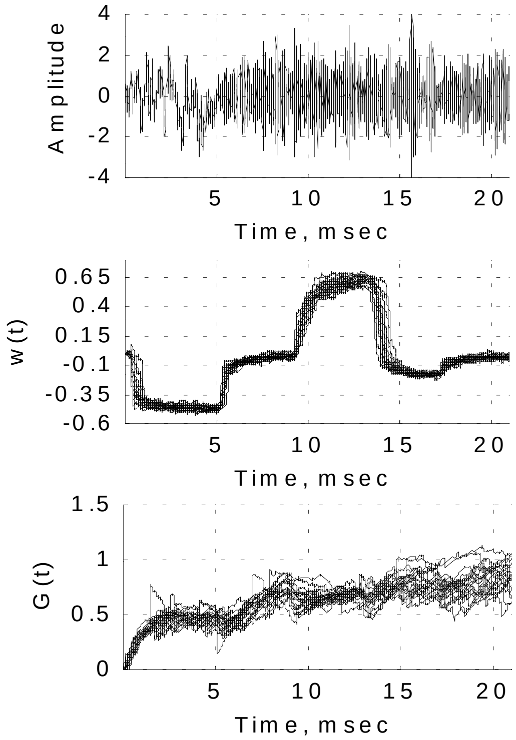


**Figure 3.** Results of Example 1 for the 10.0 dB SNR case.

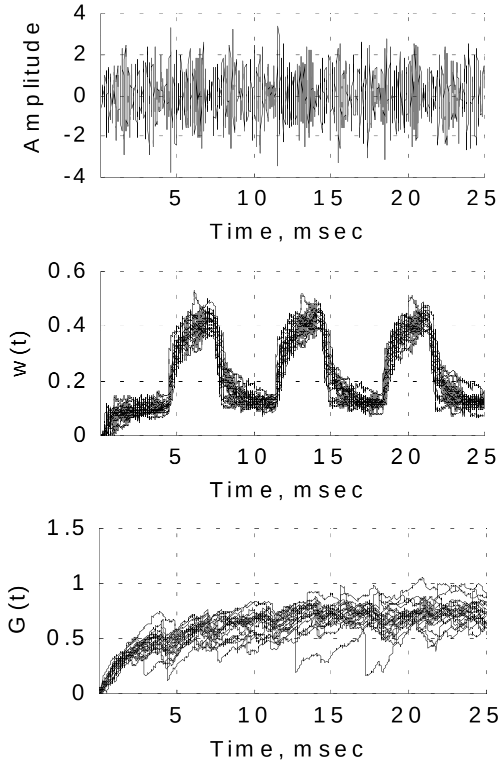


**Figure 4.** Results of Example 2 for the 10.0 dB SNR case, the noise-free case is omitted for space limitation.

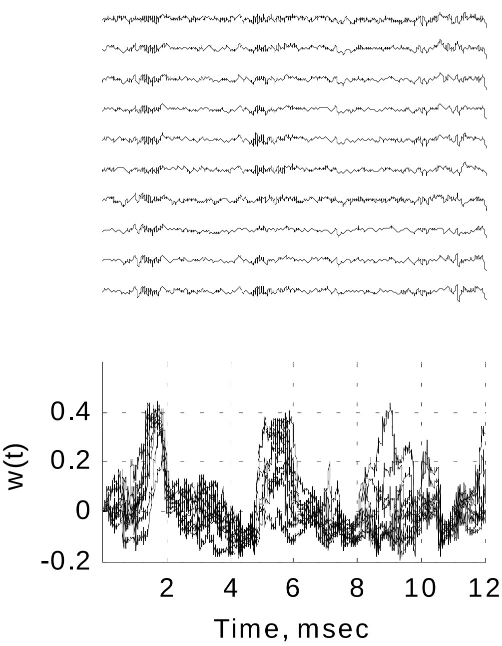


**Figure 5.** Results of the experimental example: above, the signals of the 10 EEG channels; and bottom, the adaptive coefficient *w*(*t*) for all channels.