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Window Functions Analysis in Filters for EEG Movement Intention Signals

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Abstract. The aim of this work is to compare the different windows performance in EEG signals related to movement intention, to find the adequate window in specific frequency bands filters. For this purpose, FIR filters using different window functions were implemented in two kinds of signals: a set of simulated signals and a dataset containing EEG movement intention records taken of PhysioNet. The movement intention could be understood as the product of the neuronal synchronization before the movement onset. The similarity of the results was measured using the Euclidean distance. The results obtained suggest the existence of a window function as the most suitable and robust for the EEG movement intention analysis.

Keywords: Digital filter · EEG · Movement intention · PhysioNet · Euclidian distance

1 Introduction

The window functions are commonly used in different digital signal processing (DSP) applications as signal preprocessing (denoising), analysis and estimation signal, digital filter design and speech processing. There are a large number of windows with completely different properties in time and frequency domains and that derive into a different enhancement of the studied signal. Some examples of these windows are Bartlett, Blackman, Hanning, Hamming, Kaiser, Rectangular, Triangular etc., [1–3], being the most popular and widely used in different DSP applications the Hanning, Hamming and Kaiser windows.

However, there is not a standard approach to select a window function. Every window offers advantages and disadvantage relative to the others; some are effective for specific types of signal and others improve the frequency resolution. Since the correct window choice depends on the signals nature and the applications, it is necessary to compare the performance of the different window functions to find the best one for the specific application. The objective of this work is to find the adequate window function that enhance the movement intention signals in electroencephalography (EEG).

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The movement intention could be understood as the product of the neuronal synchronization before the movement onset. In movement intention, some features can be extracted as motor imagery (MI) and motor execution (ME) from upper and lower limbs [4–6]. Motor imagery (MI) is the ability to imagine performing a movement without executing it [7]. It has been shown that the imagination of a limb activation can modify brain electrical activity [8]. Depending on the MI task used, multiple neuro imaging studies have revealed the functional participation of motor, pre-motor, and supplementary motor cortices. In addition, other structures play an important functional role in motor imagery as it occurs with the cerebellum, the basal-ganglia, the superior and inferior parietal lobules, and the pre-cuneus [9].

The electroencephalogram (EEG) records the brain electric activity, usually described in five frequency oscillations known as brainwaves: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and Gamma (30–128 Hz) [10]. There is also the Mu (μ) rhythm that it is a sub-band of alpha (9–11 Hz) [10], this rhythm is directly related with the movement [11]. The EEG presents some characteristics such as the non-periodicity, non-standardized patterns, and small voltage amplitudes. These attributes lead to the EEG signal to be easily mixed up with noise, making it harder to recognize and extract meaningful information from the EEG signals, particularly electrophysiological information. Several factors can generate noise and distortions, *e.g.* room exposure, energetic radiation, electromagnetic couplings, heart rate, muscle movements, and eyes movements. Other parameters, such as a sudden change in phase and loss of signal amplitude, can also contribute to the signal contamination [12]. In this context, Finite Impulse Response (FIR filters) using different window functions have been widely used to reduce noise and distortions.

In this work, we compare the performance of six window functions (Barlett, Blackman, Kaiser, Hamming, Hann and Rectwin) in simulated signals to fix the function that retains the frequential band related to the movement intention activity (alpha). Then the choose window is applied in real EEG signals.

2 Method

The methodology implemented in this work has been divided into three steps: (i) Database (simulated and real signals), (ii) Window Analysis and, (iii) Similarity measure.

2.1 Real Signal Database

The dataset used was from PhysioNet [13]. PhysioNet contains a lot of different types of dataset. The database of interest was the EEG motor movement intention dataset (EEG Motor Movement/Imagery Dataset). This dataset was created and contributed to PhysioNet by the developers of the BCI2000 instrumentation system [14,15]. The database contains different 109 recording from different subjects who perform motor/imaginary task for two minutes, using 64 channels as the international 10-10 system.

For this work, we considered four EEG records, with a low presence of artefacts. In these records, subjects performed motor/imaginary tasks over two minutes with a sampling frequency at 160 Hz. Each participant executed 3 tasks per recording with the annotation task (T0, T1 and T2). The task T0 corresponds to resting state, the T1 corresponds to open and close the left fist and T2 corresponds to open and close the right fist. We considered the electrode C3 for the task T2 and the electrode C4 for T1. Each EEG signal is 120 s long (seven T1 fragments and seven T2 fragments and each one is preceded by a T0 fragment). Figure 1 shows an example of the first 32 s in an EEG signal. The blue segment corresponds to the resting state (T0), the red color is related to the opening and closing of the left fist, while the orange fragment corresponds to the same movement but to the right fist.

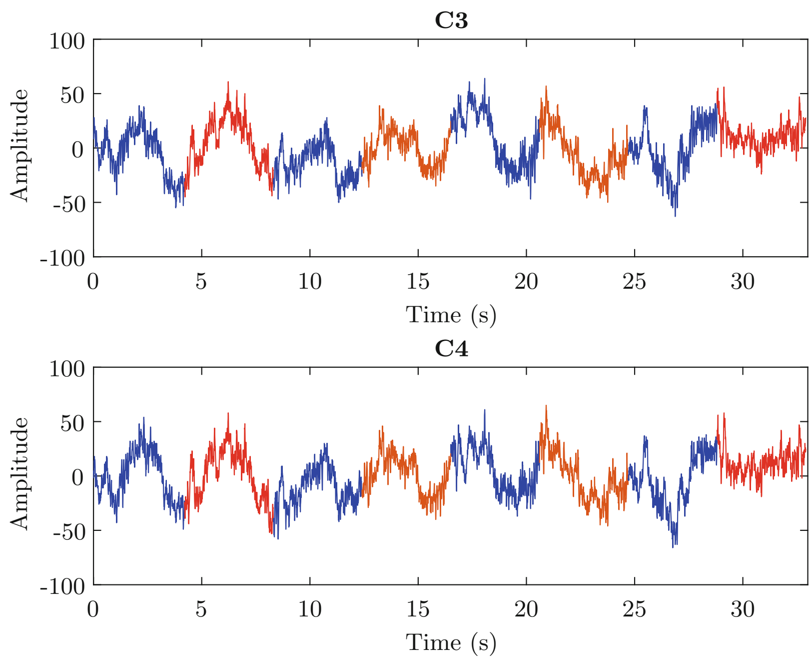

Fig. 1. Example of first 32 s of C3 and C4 EEG signals including the T0, T1, and T2 tasks.

The movement intention potential is found 2 s before T1 or T2 state starts that is, in the last 2 s of T0. The intention signal of the resting state in T0 (the signal before the last 2 s) is subtracted from the intention movement potential. This intention signal is present in the electrophysiological α band [11]. Each intention EEG signal recorded was normalized with respect to the mean and the standard deviation before Fourier Transform estimation to know the frequencies in the signal. Figure 2 shows an EEG movement intention signal (A) with its spectra (B) and this EEG signal filter in alpha band (C) with its spectra (D).

2.2 Simulated Signal Database

In order to obtain the α band (where the intention movement signal is present) of the EEG electrophysiological band, it is necessary to implement a filter. It is imperative not to lose information. In this context, it is important to have the appropriate window for the filter restrict the attenuation of the frequency content in the α band and, consequently, improves the identification of the movement intention signal.

Thus, 20 random alpha frequency signals were computed to evaluate the windows Barlett, Blackman, Kaiser, Hamming, Hann and Rectwin with respect to the data sets *S00603.edf, S030R03.edf, S029R03.edf, S102R03.edf* from the PhysioNet database.

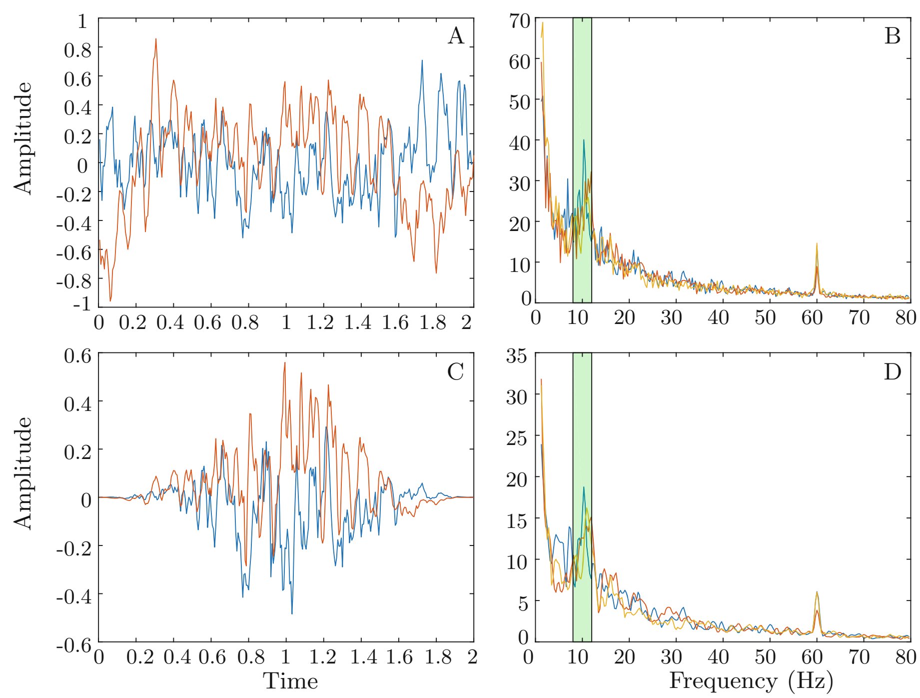

Fig. 2. (A) EEG movement intention signals (in blue the left movement and in orange is the right movement), (B) The corresponding spectra of each movement (the frequency band related to the movement intention is marked in green), (C) the signals convoluted with the Bartlett window to enhance the activity in the alpha band, (D) the spectra of both movement after the convolution with the Bartlett window.

2.3 Window Analysis

To evaluate the suitability of the window function, all signals (real and simulated) were convoluted with the six selected window functions (Barlett, Kaiser, Blackman, Hanning, Hamming and, Rectwin) and then transformed into the frequency domain using the Fourier Transform. All simulated signal was divided into the same segments as the real signals before the convolution process.

2.4 Euclidean Distance

Thereafter, to evaluate the performance of each window functions the Euclidean distance between the spectrum of non-convoluted simulated signal and the six convoluted simulated signals was estimated. In this work, the lower the Euclidean distance is, the lower the impact of the windows function to the signal; meaning that the information related to the frequency of interest (α band) is adequately retrieved. To probe the robustness of each window function, several evaluations of different non-convoluted and convoluted signals were performed. We look for the group of Euclidean with the lower scattering.

Firstly, the algorithm starts generating a random signal with components in alpha frequency band and noise was added. Then every simulated signal it is divided in differents parts and convoluted with the six window function to generate the set of convoluted simulated signal. The spectrum of each signal was computed (Eq. 1). Each simulated spectral signal were compared against the complete simulated signal reduced with the same length using the Euclidean distant (Eq. 2). The Euclidean distant represents how a signal stays in the same frequency. The algorithm was developed in Matlab® for its easy programming and operations between matrices, besides it provides the different windows already developed for its use. The procedure (pseudocode) to estimate the Euclidean distance is described in Algorithm 1.

$$X(K) = \frac{1}{N} \sum_{n=0}^{N-1} x_n e^{i2\pi k \frac{n}{N}} \tag{1}$$

$$D_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ki} - x_{kj})^2} \tag{2}$$

Algorithm 1: Algorithm to calculate Euclidean distance

Input :
N; **Total simulated signal to be created**
$name\_file$; **PhysioNet file**
$type\_event$; **Type of the event tast (T1 or T2)**

Output:
$total\_result[N][total\_windows]$; **Result of N signal with respect on total_windows**

for $i = 1$ **to** N **do**
  $X_i \leftarrow$ **simulated_signal**$(alpha)$
end
for $i = 1$ **to** $total\_simulated\_signal$ **do**
  $k \leftarrow$ **number_segment**(X_i);
  for $j = 1$ **to** k **do**
    $part\_signal_j \leftarrow$ **simulated_signal**$(startS, endS)$;
    for $z = 1$ **to** $z = window$ **do**
      $result\_window_{zi} \leftarrow part\_singal_j * window_z$;
    end
  end
  for $j = 1$ **to** $j = window$ **do**
    $len \leftarrow$ **length**$(result\_window_z)$;
    $simulated\_singal_i \leftarrow$ **downsample**(len);
    $result1 \leftarrow$ **fft**$(simulated\_signal_i)$;
    $vec\_window \leftarrow$ **mean**$(result\_window_j)$;
    $result2 \leftarrow$ **fft**(vec_window);
    $total\_result_{ij} \leftarrow$ **Euclidian**$(result1, result2)$;
  end
end

3 Results and Discussion

The Euclidean distances between the non-convoluted and convoluted simulated signals are in the Fig. 3. Visual inspection allows verifying that the Bartlett is the window function that has the lowest scattering, even lower than the widely used Ham-ming window. The standard deviation is of 80.62, (see Table 1). Other interesting window is the Blackman that is the second lowest robust with a standard deviation of 81.01. The dispersion values represent the precision of the windows to estimate the spectrum of a signal, suggesting the Bartlett is the suitable window to study the spectral information of the movement intention in EEG records. The scattering of the windows may be the result of the amount of spectral leakage, a trend that is also showed in Fig. 3. In the case of the Rectangular is the window function that less handle the leakage in the spectrum.

Moreover, is also remarkable that the minimum value in the cloud of Euclidean distance, *i.e.* the accuracy, is not the Hamming window that is the most used in window analysis and filtering, but in the Bartlett and Blackman

Table 1. Mean and standard deviation of Euclidean distance between simulated signals and the simulated signals convoluted with the window functions.

	Hamming	Bartlett	Blackman	Hanning	Rectwin	Kaiser
Mean	1855	1850	1847	1854	1905	1902
STD	81.91	80.62	81.01	81.74	95.72	94.41

windows with mean distance of 1850 and 1847, respectively. This could suggest, besides the lower deviation of both them, that the latter are suitable windows to enhance the α band. It is necessary to emphasize that the worst window performance is the Rectangular with mean distance of 1905 and, standard deviation of 95.72. This is interesting because applying the rectangular window is equivalent to segment or slice the studied signal, a common praxis in signal processing, and our results show that is not the better one.

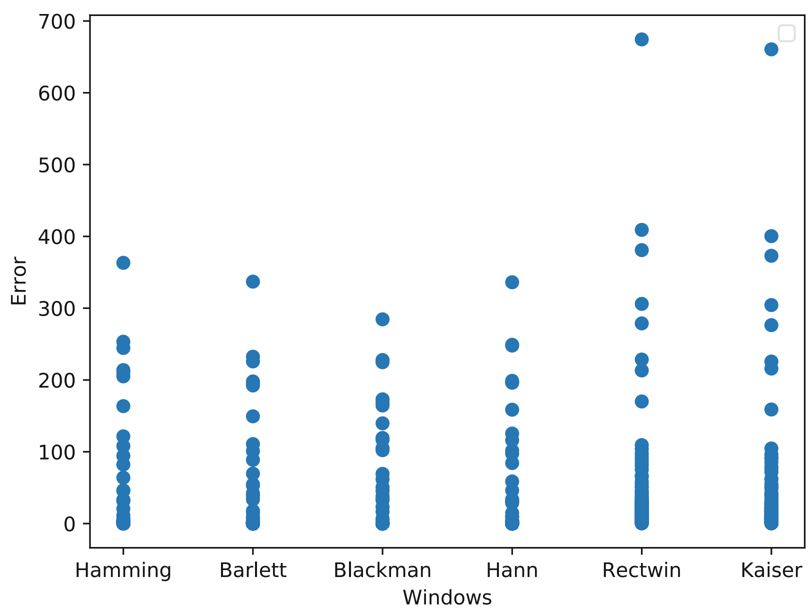

Fig. 3. Euclidean distance between simulated signals for six different windows.

In Fig. 3, the spectra of the two tasks of imaginary movement are displayed. It can be noticed that indeed the activity is distinguishable between the non convoluted signals and the filtered ones. In this work, only the implementation of fix window length was analyzed, in further work the effect of the window length should be studied.

4 Conclusion

The frequency analysis is a powerful tool to characterize brain activities through EEG data [16]. However, there are two principal constraints to use spectral analysis: the non-stationary nature of the EEG and the method itself (*i.e.* Discrete Fourier Transform - DFT, Fast Fourier Transform - FFT) [16]. To avoid these restrictions, the non-stationary EEG signals are convoluted with other functions called windows. The windows are functions that weight the analyzed EEG signals to minimize the spectral leakage and the variance in the obtained spectrum [17].

Despite that the window improves the spectrum, these functions do not cancel completely the spectral leakage. For this reason, there are several window functions that face to these constraints and which are characterized by many parameters (*i.e.* main lobe width; fall of sides lobe, equivalent noise bandwidth) [18]. Hence, choose a window function to calculate the spectrum of a signal, EEG signals in this work, is a crucial step in the signal processing.

For movement intention, the Bartlett window demonstrated to be the most suitable and robust window to study the spectral information of the movement intention. From the results, we could identify that there is a hint of the laterality of this study, but there is no certainty for the lack of information related to laterality of the subjects in the database. As future work, a new database could be recorded taking into account the laterality of the subjects to identify if the differences or similarities are significant in windows with movement intention and lateralization.

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