Moving Average Convergence Divergence Filter Preprocessing for Real-Time Event-Related Peak Activity Onset Detection : Application to fNIRS Signals

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Abstract— **Real-time solutions for noise reduction and signal processing represent a central challenge for the development of Brain Computer Interfaces (BCI). In this paper, we introduce the Moving Average Convergence Divergence (MACD) filter, a tunable digital passband filter for online noise reduction and onset detection without preliminary learning phase, used in economic markets analysis. MACD performance was tested and benchmarked with other filters using data collected with functional Near Infrared Spectoscopy (fNIRS) during a digit sequence memorization task. This filter has a good performance on filtering and real-time peak activity onset detection, compared to other techniques. Therefore, MACD could be implemented for efficient BCI design using fNIRS.**

I. INTRODUCTION

Functional Near Infrared Spectroscopy (fNIRS) is a non-invasive neuroimaging technique that has gained interest over the last decade. Due to its portability, low-cost and high spatial resolution, fNIRS is considered a prominsing technique for use in Brain Computer Interfaces (BCI)[1], alone or as a complement of other imaging devices such as Electroencephalography (EEG).

However, signal processing (i.e., feature extraction and translation) represents a main challenge and a fundamental requirement for BCI design [2], as the features extracted have to be available in real-time. It is especially true concerning fNIRS, whose signal processing techniques still have to be developed to reduce noise and to improve usability of the signal [3], [4].

In fNIRS, both low and high frequency components undermine the signal [5], [6], requiring bandpass filtering. However, low order digital filters are prefered for use in real-time, to reduce processing complexity and latencies.

In this paper, we propose a Moving Average Convergence Divergence (MACD) low order digital filter, as a tunable tool for real-time bandpass filtering of fNIRS signal. This filter, already employed in economic market analyses, performs a first derivative estimation of the signal and can be used to perform online detection of stimuli onsets [7] without use of a preliminary learning phase. Notably, this type of filter was already used by Utsugi and colleagues for noise reduction in previous fNIRS BCI design [8]. However, the filter still not has been compared to classical types of filter, and still has not been used to perform peak activity onset detection on fNIRS data. We performed MACD filtering and onset detection on real fNIRS data collected during a digit sequence memorization task, and analyzed the influence of filter parameters on magnitude response and detection accuracy.

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II. METHODS

Nine participants (Mean age = 24; SD = 3.6 ; eight males, eight right handed) participated in the study. The volunteers performed a digit sequence memorization task, while NIRS measurements of the prefrontal cortex were recorded.

Each trial of the experiment consisted in the presentation, on a computer screen, of a series of 5 to 10 randomly chosen digits that the subjects had to memorize. The size of the series defined a level of difficulty. The digits appeared in white at the center of a black screen for $600ms$, then the screen turned black for $300ms$ until the next digit presentation. After the last digit presentation, a fixation cross appeared. The subjects then had $8s$ to type the memorized sequence on the keyboard. Between two consecutive trials, the subjects looked passively at the fixation cross for 6 to $9s$ (the inter-trial interval was chosen randomly to avoid task periodicity). Fig.1 summarizes the time sequence of a trial. The experiment consisted of 24 trials (four trials for each of the six levels of difficulty), presented in a random order.

A. Data Acquisition

During the experiment, hemodynamics data of the prefrontal cortex were recorded using a fNIR100 (Biopac®) device with 16 optodes regularly placed on the forehead, and a sampling frequency of 2Hz. We calibrated the device using a baseline of ten seconds at the beginning of the experiment, during a rest period. The relative concentration in oxygenated hemoglobin $[HbO_2]$ measured across optodes was averaged and used as a prediction signal.

B. MACD filtering module

We chose a filtering module used in economic market analyses [7] based on the principle of Exponential Moving Averages (EMA), described in equation 1.

$$y = EMA_N(x) \Leftrightarrow y_n = \frac{2}{N+1}x_n + \frac{N-1}{N+1}y_{n-1} \quad (1)$$

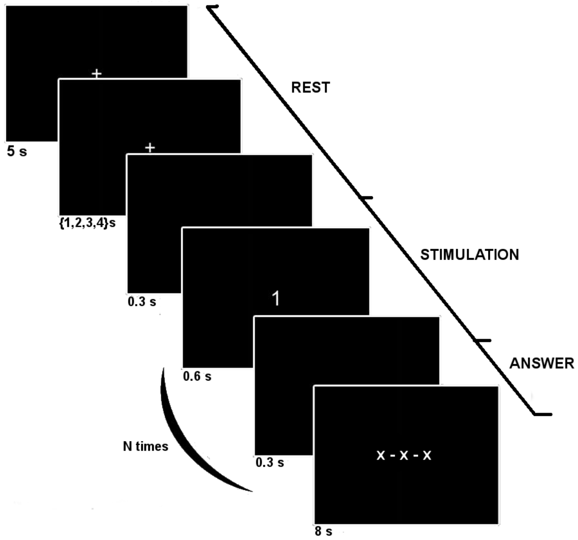

Fig. 1. Time course of one trial of the experiment. The experiment consisted of a total of 24 trials (four for each level of difficulty N = digit sequence size from 5 to 10), presented in a random order.

EMA filtering computes the output as a weighted average of past values of the input, using a first order Infinite Impulse Response (IIR) filter. The average weights defined by the parameter N decrease exponentially over time, so that the output value is computed giving more weight to more recent values. As a consequence, a large value of N produces an output sensitive to slow variations of the input, whereas a small value of N results in an output sensitive to fast variations.

We obtained a bandpass MACD filter by subtracting a long-term EMA filter from a short-term one (cf. equation 2), thus obtaining an output corresponding to instantaneous variations of the input signal.

$$MACD_{N_{short},N_{long}}(x) = EMA_{N_{short}}(x) - EMA_{N_{long}}(x) \quad (2)$$

In this experiment, data from each participant were filtered using MACD filters with parameters (N_{short}, N_{long}) in the interval $([1; 20], [N_{short}+1; N_{short}+20])$, in order to remove low frequency and high frequency components. An example of filtered signal is shown on Fig.2a.

In order to estimate MACD filtering power, we analysed its magnitude and phase responses, compared with three other types of filters : Finite Impulse Response (FIR), Infinite Impulse Response (IIR) Butterworth, and Elliptic, all of order 2. The bandwidth of these filters was equivalent to the MACD one ([0.02 ; 0.3]). We also computed the correlation between the filtered signal and the first derivative of the raw signal.

C. Onset prediction

A prediction technique used by economists is to associate stable increases of the raw signal with zero-crossovers of a histogram line computed from MACD. The histogram line is usually obtained by subtracting an EMA filtering with $N = 10$ of MACD data (called "*signal line*") [7] from the unfiltered MACD data, as descripted in equation 3. Thus, a zero-crossover of the histogram line correponds to the moments when MACD is increasing and crosses the signal line. An example of histogram is presented in Fig.2b. We used this technique to predict trial onsets as $\{t|h(t) = 0, h(t-1) < 0, h(t+1) > 0\}$.

$$h(x) = MACD(x) - EMA_{10}(MACD(x)) \quad (3)$$

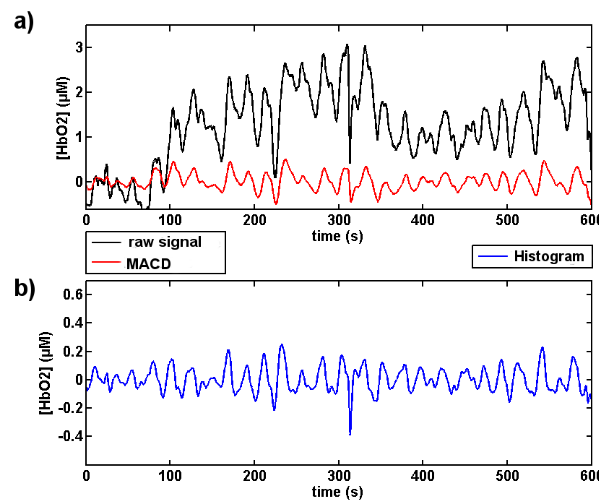

Fig. 2. Filtering module output for participant 1. a) Raw (in black) and MACD-filtered (in red) signals, obtained with MACD parameters $N_{short} = 12$ and $N_{long} = 30$. b) Histogram obtained with $N_{signal} = 10$.

An onset detection was considered a *True Positive* when the real onset (at the beginning of the stimulation period) occured in the range $[t_{detection} - 7sec; t_{detection} + 3sec]$, to account for hemodynamics response delays and stimulation duration[9], [10]. Otherwise, the onset detection was considered as a *False Positive*. An example of onset detection is shown on Fig.3.

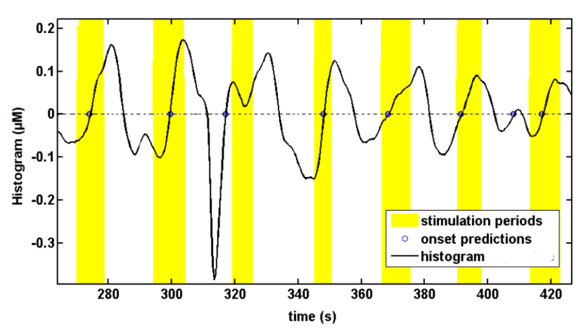

Fig. 3. Onset detections obtained from seven trials of participant 1, using MACD filtering with $N_{short} = 12$ and $N_{long} = 30$. The stimulation period length, in yellow, depends on the length of the digit sequence size.

We computed the Correct Detection Rate (CD Rate) as the percentage of real onsets effectively leading to an onset detection. As our objective was to jointly maximize the CD Rate and to minimize the False Positive Rate (FP Rate), we computed the corresponding ratio (i.e. Performance Ratio) to be maximized.

We performed the same analysis on onset predictions obtained by applying a threshold ($[HbO_2] = 0.2\mu M$) on data filtered by IIR Butterworth filter (which is a widely used filter in signal processing) of order 2, to compare the performance of MACD onset detection method. In this method, onset prediction was associated with crossover between filtered fNIRS signal and threshold.

III. RESULTS

A. Filtering power

The magnitude response of MACD, in comparison with FIR, Butterworth, and Elliptic filters, is presented in Fig.4. MACD has same bandpass behaviour as other filter types, although all frequential components are attenuated to at least 8dB, leading to a smaller signal amplitude than the one which would be obtained with "classical" filtering. However, this attenuation does not impede noise rejection, especially concerning low frequencies ($< 0.02Hz$). The phase response of MACD filter is comparable to IIR structure, with quasi-linear phase in its bandwidth.

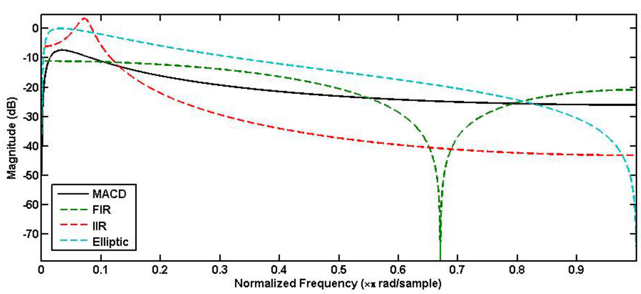

Fig. 4. Magnitude response of MACD filter (in black) with $N_{short} = 12$ and $N_{long} = 30$, compared with FIR filter (in green), IIR Butterworth filter (in red), or Elliptic filter (in blue).

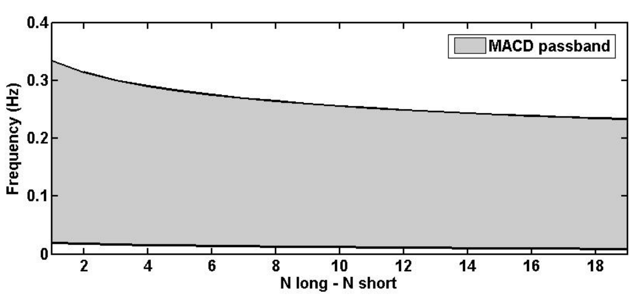

Fig. 5. MACD bandpass in function of the difference $N_{long} - N_{short}$.

MACD implements bandpass filtering, whose bandwidth and cutoff frequencies depend on the difference between parameters N_{long} and N_{short}, as a higher gap between those parameters brings a narrower bandpass. Their evolution is given on Fig.5.

Furthermore, the MACD filtered signal is highly correlated with the first derivative of raw signal ($r_{Pearson} = 0.63$; $SD = 0.06$), thus MACD can be considered as a first derivative estimate.

B. Onset prediction and MACD parameters

We observed the variations of the mean CD Rate across subjects, with different values of MACD filtering module parameters. We also computed the ratio between the CD Rate and the FP Rate across subjects. The results are shown on Fig.6.

A decrease in the value of $N_{long} - N_{short}$ triggers an increase in the CD Rate and also leads to a reduction in the Performance Ratio, as shown in Fig.6. However, the Performance Ratio reaches local maximum values for MACD tuning parameters on a curve $\mathcal{M}_k = \{(N_{short}, N_{long}) | N_{long} = \frac{2}{3}N_{short} + 10k + 2\}$ (graphically obtained from Fig.6). Table I sums up the average onset prediction performances measured on these curves, showing the trade off between the Detection Rate and the Perfomance Ratio.

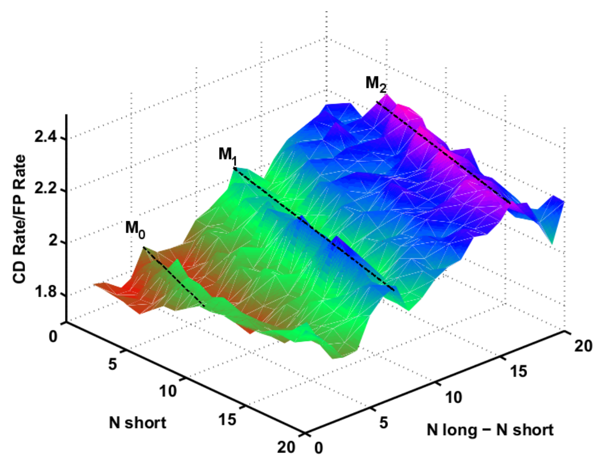

Fig. 6. Performance Ratio (Mean Correct Detection Rate divided by False Positive Rate) across subjects, in function of MACD parameters N_{short} and N_{long}. Local maxima curves $\mathcal{M}_i$ are indicated in dashed lines.

TABLE I

MEAN ONSET PREDICTION PERFORMANCE OVER LOCAL MAXIMA CURVES $\mathcal{M}_1$,$\mathcal{M}_2$ AND $\mathcal{M}_3$ (AND 95% CONFIDENCE INTERVALS), COMPARED WITH A THRESHOLDING METHOD USING IIR FILTER

	CD Rate (%)	FP Rate (%)	Performance Ratio (arb. units)
$\mathcal{M}_0$	0.99 [0.98 ; 1]	0.54 [0.52 ; 0.57]	1.83 [1.75 ; 1.92]
$\mathcal{M}_1$	0.88 [0.83 ; 0.91]	0.42 [0.35 ; 0.47]	2.30 [1.93 ; 3.34]
$\mathcal{M}_2$	0.84 [0.79 ; 0.89]	0.39 [0.32 ; 0.44]	2.39 [1.99 ; 3.25]
IIR	0.51 [0.28 ; 0.65]	0.42 [0.30 ; 0.64]	1.76 [1.01 ; 2.38]

The 95% confidence intervals were computed using a bias corrected and accelerated percentile method with *bootci* function of Matlab©. Results show that the CD Rate is significantly better when using MACD rather than IIR. In particular, MACD parameters on curves $\mathcal{M}_1$ and $\mathcal{M}_2$ give significantly better CD Rate, FP Rate and Performance Ratio than curve $\mathcal{M}_0$. Notably, the confidence intervals of the performance obtained using MACD technique are lower than the ones obtained with IIR.

IV. DISCUSSION AND CONCLUSION

The objective of this paper was to test the usability of the MACD filter as an online noise reduction and analysis technique for fNIRS signal. On this purpose, we conducted an experiment on nine subjects involving memory task. Overall results revealed the efficiency of this filter, and in particular, MACD has the same filtering behaviour as IIR, FIR, and Elliptic filters of the same order (Fig.4), and especially better reject low frequency components ($< 0.02Hz$). These results confirm the relevance of this method for noise reduction, as it has already been done in previous BCI design [8]. In particular, the low order of MACD filter enables utilisation with few latency even when sampling frequency is low.

Moreover, the real-time detection of stimuli onsets using MACD shows good and homogeneous results (Table I), compared to classical method based on IIR filtering. This good performance is similar to previous studies investigating the suitability of first derivative estimate of hemodynamics data for detection of event-related hemodynamic activity [11], [3]. In particular, the optimal parameters for real-time detection using MACD (Fig.6) are coherent with physiological time characteristics of hemodynamic response [9], [10] .

Nevertheless, a challenge remains in decreasing the false positive rate of onset detection. One possibility is to test the influence of the window length used for histogram line calculation (set as 10 in this study, which is mainly used [7]). This possible investigation is a direction for future work. Additionally, a reduction in the false positive rate could be obtained by using a multimodal approach [4], i.e. by combining fNIRS with other devices such as EEG [12].

Notably, the MACD technique could be applied to every physiological signal that has an event-related peak activity, such as fMRI BOLD response [11] or Electrocardiography (ECG) QRS wave detection [13]. Eventually, the use of MACD as a real-time onset detection technique could open up new perspectives of real-time improvement of event-related response without a priori information on the onset, based on the use of impulse response models [14] and Kalman filtering [15].

Although further investigation is still needed to test the detection technique in more ecological situations (especially involving multitasking), MACD appears to be an easy to implement technique, suitable for real-time noise reduction and onset detection without learning, supporting the potential usage of fNIRS for BCI design. In particular, this technique would be useful for idle modes detection [16], [3], when the user does not request any command.

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