Robust EEG time series transient detection with a momentary frequency estimator for the indication of an emotional change

Gernot Heisenberg, Ramesh Kumar Natarajan, Yashar Abbasalizadeh Rezaei, Nicolas Simon, and Wolfgang Heiden

Institute of Visual Computing
Department of Computer Science
Bonn-Rhein-Sieg University of Applied Sciences, Germany
{gernot.heisenberg,ramesh.natarajan,yashar.abbasalizadeh,nicolas.simon, wolfgang.heiden}@h-brs.de
http://www.emotion-computing.org
http://vc.inf.h-brs.de

Abstract. This paper describes adaptive time frequency analysis of EEG signals, both in theory as well as in practice. A momentary frequency estimation algorithm is discussed and applied to EEG time series of test persons performing a concentration experiment. The motivation for deriving and implementing a time frequency estimator is the assumption that an emotional change implies a transient in the measured EEG time series, which again are superimposed by biological white noise as well as artifacts. It will be shown how accurately and robustly the estimator detects the transient even under such complicated conditions.

Keywords: momentary frequency, emotion computing, EEG, time series processing, adaptive filters, affective computing, brain computer interfaces

1 Introduction

In empiric sciences, one often has to deal with measured data sets, trying to interpret the underlying nature of an observed global system by the interactions of its partial systems. However, in most scientific areas it is simply not possible to separate the partial systems either experimentally nor theoretically such that a separate investigation becomes feasible. When there is no chance to divide the overall system into partial ones and instead the only possible interpretation is observing the global appearance and reaction of the system, time series processing often becomes the mean of choice in order to solve this inverse problem. In the optimal case it becomes possible to create a model out of the measured data sets. With this model one may again conclude the underlying process which is responsible for the production of the measured data in the sense of at least sufficient, in the optimal case, necessary conditions for their creation. Unfortunately this is not possible with EEG data sets. Here it is rather possible to classify the processes by extracting features from the data sets. Moreover, EEG data sets are usually very noisy and transient and are created by an underlying non-stationary and stochastic dynamics. Hence, for the analysis of human emotional stress states stochastic analysis methods are one set of tools of choice. However, turning an experimental person from one emotional state into another, e.g. from being relaxed into being stressed, implies to be able to focus with the methods on the transient itself even though the transient is heavily superimposed with noise. The aim of this paper is to present a detection of this transient during an on-the-fly analysis. The momentary frequency estimation algorithm proposed by Grieszbach et al. [1] was considered and integrated into the openVibe [2] software framework.

2 Related Work

In Non-Invasive Brain-Computer Interface (BCI), to effectively interpret the brain signals to meaningful features for further application in various fields, a systematic approach with four different phases is to be used [3]:

- Signal Acquisition
- Signal Pre-processing
- Feature Extraction
- Signal Classification

Many Researchers have contributed to the BCI field especially detecting people's emotional state by adapting different techniques and algorithms for each of the above mentioned phases with a reasonable success rate. The emotion-recognition system developed by Kwang-Eun Ko et al., [4] uses relative power values and a Bayesian network. In this system, the power spectrum of the EEG signals is analyzed by applying a Fast Fourier transform (FFT) and by decomposing the signals into five bands of Alpha, Beta, Gamma and Theta for further classifications. The relative power values of the prominent frequency band is calculated by dividing the current absolute band to the sum of the frequency ranges. The same method is adapted also by Kwang Shin Park et al. [5]. The emotion-recognition system implemented by Hosseini [6] uses the thermodymanic property called entropy, that calculates the amount of disorder in the system by which each emotion state is estimated using approximate entropy and wavelet entropy. Four different emotions (disgust, happiness, surprise and fear) are recognized by two different lifting based wavelet transforms (LBWT) and then classifying them by Fuzzy C-Means (FCM) clustering [7]. The signal features of an emotional response due to various tastes have been extracted by Common Spatial Pattern (CSP) [8]. In the systems [4], [5], [6], [8], [9], the EEG signals are separated into various frequency bands using band-pass filters except for [7] which uses Average Mean Reference (AMR) for filtering. All the systems ignored the delta range $[0 - 4Hz]$ to reduce eye blinks and other physiological artifacts but the major drawback in ignoring the delta band causes the loss of valuable data for monitoring sleep waves in an adult. Usually, EEG signals are prone to more noise since data is recorded non-invasively using electrodes. In addition, the problem using band-pass filters for distinguishing various frequency bands is that the results are not convincing if the signal-to-noise ratio is high and this leads to heavy preprocessing of the EEG signals before meaningful features can be extracted. Moreover, emotional change in a normal human is more gradual and continuous and so band-pass filters cannot be used in real-time scenarios (e.g. monitoring pilots) where there is subtle change of the emotional state. An emotion-recognition system which can track these subtle emotional changes using the same technique for both, signal pre-processing and feature extraction, can improve the processing speed and can also provide an intuitive real-time emotion monitoring. In order to address the above mentioned problem, a frequency estimation algorithm which shows robustness and also allows for real time emotion monitoring is introduced and its applicability is explored using EEG data.

3 Estimation of Momentary Signal Parameters

A classical example for an estimation algorithm is the estimation of the mean value M_n which is based on a sequence of independent random values $\{\xi_n\}_{n=0,1,2,...}$. If x_i will denote the realization of the random value ξ_i, then

$$M_n = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{1}$$

is a consistent estimation for $E(\xi_i)$. M_n can be easily turned into a recursive order. It is

$$\begin{aligned} M_0 &= x_0 \\ M_{n+1} &= M_n - \frac{1}{n+1}(M_n - x_{n+1}) \qquad n = 0, 1, 2, ... \end{aligned} \tag{2}$$

In this form the algorithm is already real-time capable since it needs only the previous estimation value M_n, the current data value x_{n+1} and the current time $n + 1$. With this, the continuously recursive computation of the times series is possible. Put into a more general form, the estimation procedure S looks like

$$\begin{aligned} S_0 &= s_0 \\ S_{n+1} &= S_n - c_n K(S_n, x_{x+1}) \qquad n = 0, 1, 2, ... \end{aligned} \tag{3}$$

where $X = \{x_i\}_{i=0,1,2,...}$ denotes the measured data points, K is a correction term for the estimation which itself depends on S_n, the momentary data point x_{i+1} and the adaptation constant c_n. Comparing this with equation 2, the adaption constant turns into $c_n = \frac{1}{n+1}$ and following the conditions

$$\sum_{n=0}^{\infty} c_n = \infty, \quad \sum_{n=0}^{\infty} c_n^2 < \infty \tag{4}$$

the estimation procedure converges with the probability of 1 against the constant expectation value of a stationary time series.

3.1 Adaptive Time Frequency Analysis

Before introducing the concept of a momentary frequency estimation a more general definition of frequency has to be provided. Normally, frequency is the parameter of sinusoidal periodical functions, with which the number of periods per time unit is characterized [1]. Thus, for this set of functions, frequency is also defined by half the number of zero crossings. Now, with this definition the frequency characterization can be applied to our EEG times series. Since it is evident that the EEG time series do not oscillate around zero but around a finite value the momentary mean of the time series has to be estimated too. The schematic representation of the concept of this estimation is shown in figure 1. $\mathbf{L}(X)$ denotes the time shift operator, $\mathbf{M}^c(X)$ denotes the momentary mean

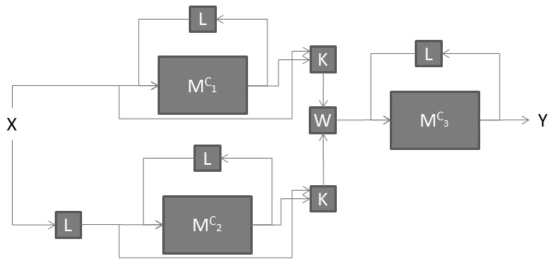

Fig. 1. Schematic for the momentary, adaptive frequency estimation.

operator. In addition, the following comparison operators are used: $\mathbf{K}(X,Y)$ (bigger) and $\mathbf{W}(X,Y)$ (unequal). $\mathbf{M}_1^c(X)$ estimates the momentary mean value of the signal whereas $\mathbf{M}_2^c(X)$ estimates the momentary mean value of the direct past. After that both mean values get interpreted by the comparison operators whether or not a "zero crossing" has occurred which is basically a crossing through the momentary mean value or not.
The adaption constant from equation 3 just needs to fulfill the condition $0 < c < 1$ in order to guarantee a convergence to the expectation value. Higher values of c will result in a faster adaptation to the time series mean value after a transient has occurred. However, this is accompanied by quite high variation. Vice versa, a smaller c means slower but smoother adaptation. In order to understand this have a look at equation 2 which is

$$\begin{aligned} M_0 &= m_0 \\ M_{n+1} &= M_n - c(M_n - x_{n+1}) \qquad n = 0, 1, 2, ... \end{aligned} \tag{5}$$

Putting it into the form

$$M_{n+1} - M_n = -c(M_n - x_{n+1}) \qquad n = 0, 1, 2, ... \tag{6}$$

and dividing both sides by the sampling frequency δt,

$$\frac{M_{n+1} - M_n}{\delta t} = -\frac{c}{\delta t}(M_n - x_{n+1}) \qquad n = 0, 1, 2, ... \tag{7}$$

it becomes obvious that equation 7 is the discretized form of

$$\frac{\partial M}{\partial t} = -\frac{1}{\tau}(M - x) \tag{8}$$

where τ denotes the adaption time. Now it becomes evident, that if the adaption time is chosen to be large in comparison to the sampling frequency δt, the adaption constant $c = \frac{\delta t}{\tau}$ will become small and vice versa.

4 Application

Before applying the momentary frequency algorithm to real measured EEG time series, two examples for precomputed transients are shown. Fig. 2 shows the momentary frequency estimation for a computed signal containing two transients. The first transient appears when the signal changes from pure white noise into

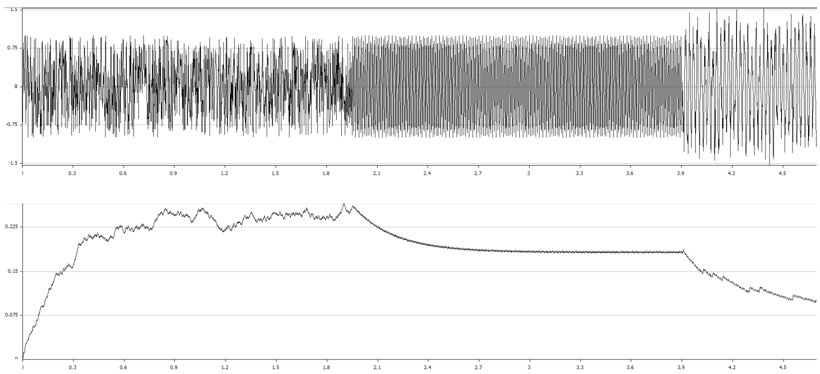

Fig. 2. This figure shows the momentary frequency estimation for a signal containing two transients, from white noise to a pure sinusoidal wave and then to a sine wave with a different frequency superimposed with white noise.

a pure sinusoidal oscillation. The estimator is able to detect the frequency jump and estimates the frequency of the sine wave. The third part of the signal is a superposition of white noise and another sinusoidal wave with a different frequency. The estimator detects this frequency jump as well and adapts very quickly. The adaption time for computations was set to $c = 0.008$.

Fig. 3 shows again a computed signal containing three different parts. Now, the difference to fig. 2 is that the third part is a superposition of the same sinusoidal wave of part two with the white noise from the first part of the signal. The estimation though is robust against the white noise and shows the same frequency. Just the variance of the signal is slightly increased which was to be expected.

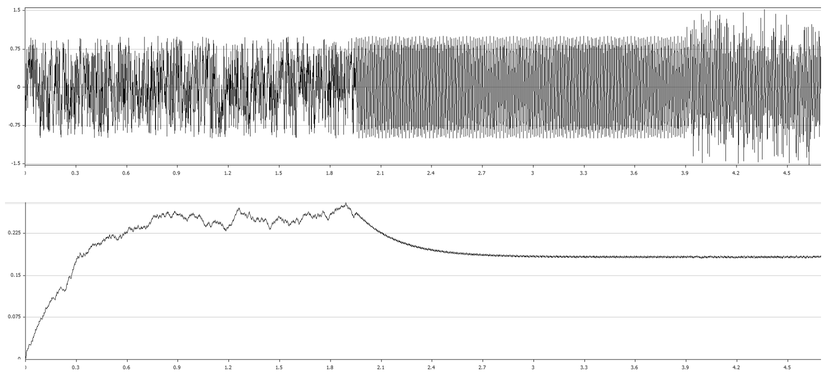

Fig. 3. This figure shows the momentary frequency estimation for a signal containing two transients again. This time the third part is a superposition of the white noise from part 1 and the sine from part two. As a result the white noise is filtered entirely.

The experiment

In order to stimulate five healthy male probands between 25-30 years old, the following experiment was carried out. The task was to play a challenging number table concentration game (`http://www.salticid.com/concentration.htm`) in a web browser. For data acquisition a non-invasive brain computer interface with 14 channels, P3 and P4 referenced, was used. For recording and processing the data stream openVibe was taken and the momentary frequency algorithm had been implemented as a box module. After 300s of high concentration the EEG

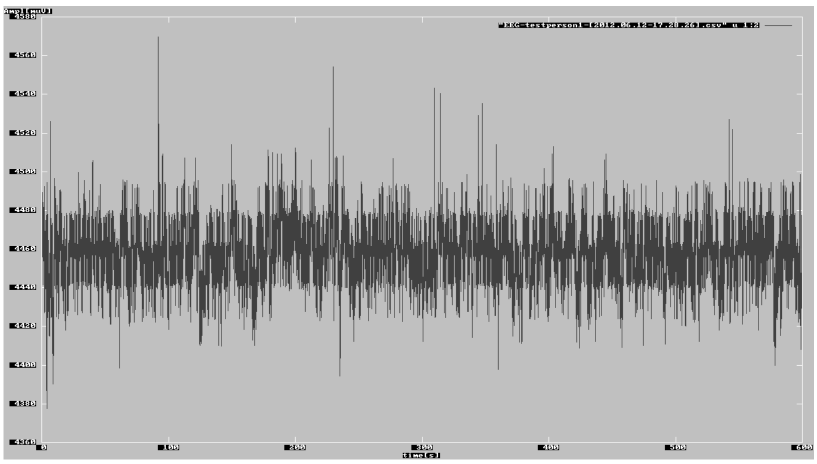

Fig. 4. 600s EEG data from the T7 electrode.

data showed a strong activity in the beta band which was to be expected. The momentary frequency estimator oscillated around $18Hz$ which indicated strong mental activity due to the concentration. Fig 4 shows the recording of the EEG at the T7 electrode. After $300s$ the subjects were exposed to a $80s$ long sequence of images, lasting for about $10s$ each. The images were showing relaxing content such as beaches, holiday situations etc.. During this interval the concentration game was paused and the entire focus was on the visual consumption of the image sequence. However, the *raw* data in fig 4 does not show any significant change after the relaxing image sequence stimulus had been sent to the probands. In comparison, fig. 5 shows the momentary frequency together with the moving

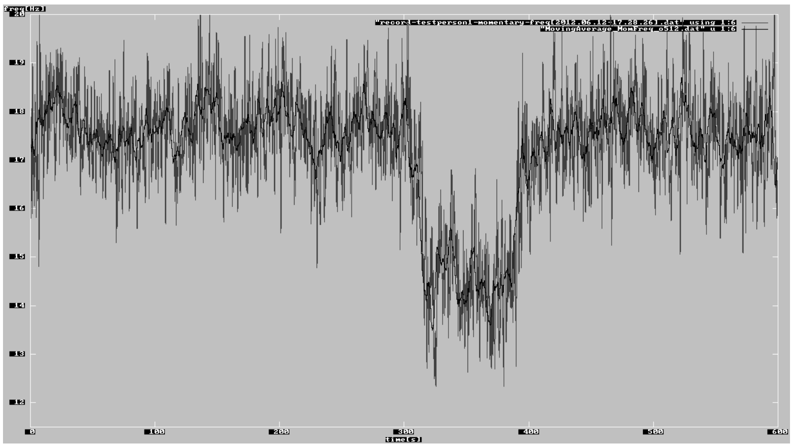

Fig. 5. Momentary frequency plotted together with its moving average of order 512 for $600s$ EEG data recorded by T7.

average of order 512 for the entire $600s$. The momentary frequency estimator was possible to detect a significant decrease down to approx. $15Hz$. After the image sequence was finished the subjects continued playing the concentration game. The momentary frequency increased quickly and reached the previous $18Hz$ again.

5 Conclusions and Future Work

This paper described adaptive time frequency analysis of EEG signals, both in theory as well as in practice. In particular, the momentary frequency estimation algorithm developed by Grieszbach et al. [1] has been derived and integrated into the openVibe software framework from INRIA and was applied to different computed and measured time series. The momentary frequency has proven its ability to detect transients in times series numerically correct (see fig. 3). Even white noise added to the signal has been filtered robustly (see fig. 2). In order to obtain the same result with a band-pass filtering approach the algorithm would looked

like: (1) recording the signal, (2) computing a power spectrum and looking for the main frequency contributions, (3) filtering the signal with a small frequency windowing of about 1-2 Hz width and (4) matching the result with the applied stimulus. Now it becomes evident, that the clear advantage of the momentary frequency estimation compared to band-pass filtering is that the unknown frequency of the transient is robustly computed without any preprocessing, the time is delivered implicitly when the transient appears, and most importantly, the algorithm allows for on-the-fly processing and does not need any storage of the signal. Since our future work will focus on carrying out further transient inducing experiments for detecting ERD (event related desynchronization) and ERP (event related potentials) and since we want to combine this with machine learning algorithms, the momentary frequency algorithm is the mean of choice.
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References

1. Grieszbach, G., Schack, B., Putsche, P., Bareshova, E., Bolten, J.: Dynamic description of stochastic signal by adaptive momentary power and momentary frequency estimation and its application in analysis of biological signals. Medical and Biological Engineering and Computing **32** (1994) 632–637
2. Renard, Y., Lotte, F., Gibert, G., Congedo, M., Maby, E., Delannoy, V., Bertrand, O., Lécuyer, A.: OpenViBE: An Open-Source Software Platform to Design, Test and Use Brain-Computer Interfaces in Real and Virtual Environments. Presence: Teleoperators and Virtual Environments / Presence Teleoperators and Virtual Environments **19**(1) (April 2010) 35–53 Département Images et Signal Département Images et Signal.
3. Sejnowski, T.J., Dornhege, G., Millán, J.d.R., Hinterberger, T., McFarland, D.J., Müller, K.R.: Toward Brain-Computer Interfacing (Neural Information Processing). The MIT Press (2007)
4. Ko, K.E., Yang, H.C., Sim, K.B.: Emotion recognition using EEG signals with relative power values and Bayesian network. International Journal of Control, Automation and Systems **7**(5) (October 2009) 865–870
5. Kwang Shin Park, Hyun Choi, Kuem Ju Lee, Jae Yun Lee, K.O.A., Kim, E.J.: Emotion recognition based on the asymmetric left and right activation. International Journal of Medicine and Medical Sciences **3(6)**(June) (2011) 201 – 209
6. Hosseini, S.A.: Emotion recognition method using entropy analysis of EEG signals. International Journal of Image **3**(5) (2011) 30
7. Murugappan, M., Rizon, M., Nagarajan, R., Yaacob, S., Zunaidi, I., Hazry, D.: Lifting scheme for human emotion recognition using EEG. In: 2008 International Symposium on Information Technology, IEEE (2008) 1–7
8. Park, C., Looney, D., Mandic, D.P.: Estimating human response to taste using EEG. Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference **2011** (January 2011) 6331–4
9. Mikhail, M., El-Ayat, K., El Kaliouby, R., Coan, J., Allen, J.J.B.: Emotion detection using noisy EEG data. In: Proceedings of the 1st Augmented Human International Conference on - AH '10, New York, New York, USA, ACM Press (April 2010) 1–7