Application of correlation analysis tools for the classification of mental workloads in functional near-infrared spectroscopy

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Introduction

In the field of Human-Computer Interaction researchers are challenged to find new and objective metrics for the measurement of mental workloads. These metrics should eventually substitute the Usability Testing which is a qualitative survey currently carried out at the end of designed experiments where the subjects interact with a computer interface. The long term goal is to build adaptive user interfaces based on objective measures of mental workloads as a passive input to provide real-time information on the user's state. Adaptive computer interfaces can be useful both in daily settings and also as adjuvant for impaired subjects. Electroencephalography (EEG) has shown some potential for the classification of mental workloads [1, 2]. Typical scores for the discrimination of low against high and medium against high mental workloads are around 95%, 80%, respectively [1]. However while EEG looks promising in a controlled laboratory setting, it suffers of some drawbacks when it is translated in daily settings, due to long preparation times required to place the electrodes (on average 45 minutes) and sensitivity to motion and noise artifacts. Recently functional near-infrared spectroscopy (fNIRS) has been used for the discrimination of mental workloads [3-6]. fNIRS offers some advantages in terms of portability and insensitivity to motion artifacts. In this work we describe recent advances in the implementation of a real-time system which uses machine learning algorithms and some tools of correlation analysis in order to distinguish levels of mental workloads.

Methods and results

In order to find new valuable metrics for discriminating brain states, especially the difference between an "activation" state and a "rest" state, we have used Pearson coefficient and the concept of phase synchronization of chaotic oscillators [7] applied to low frequency spontaneous oscillations (LFO), that is around 0.1 HZ. These two parameters are used in the attempt to distinguish between rest and mental workloads during a cognitive task involving the working memory. The protocol consists in 12 blocks of 60 sec each, divided in 6 blocks at "workload 4" (WKL4) and six block at "workload 0" (WKL0). During the first 30 sec of WKL4 the subject is looking at a rotating cube and trying to memorize how many sides of each colors (4 colors) are present. During the remaining 30 sec the subject is recovering. During WKL0 a uniformly grey cube is rotating and the subject is resting. We have found some discriminatory power (between WKL0 and WKL4) by using the Pearson coefficient; however even if the phase synchronization index (PSI) yielded another type of usable metrics, we are still in the process to extract information from this method. However this investigation confirmed that correlation analysis and phase synchronization analysis provide different information. We have also made progress for the realization of a software system that allows for real time fNIRS brain signal analysis and machine learning classification of affective and workload states called the Online fNIRS Analysis and Classification system (OFAC). This system receives and processes brain signals and event markers, automatically recognizes the current cognitive or affective state using a database of previously recoded signals and machine learning techniques, and outputs this state to the interface, allowing for the creation of interfaces that adapt and change in real time according to traditional inputs as well as cognitive activity. OFAC offers the user an additional communication channel based on brain activity, providing multimodal interaction.

Our work with the OFAC system aimed at reproducing the procedures used offline in previous work [6], adapting them to be suitable for real time input to a user interface. A first study compares a previous offline analysis with our real time analysis to test and prove the system's reliability and potential .The high accuracy found during real time analysis (82.0%), compares well with the value found during offline analysis 94.4%.

Conclusions

We have used correlation analysis tools in order to distinguish brain activation from rest state. The motivation of this choice is that correlation analysis are based on the change of spatio-temporal patterns of low and very low frequency spontaneous oscillations associated with activation. Therefore they can provide a non localized signature of the activation state. Pearson coefficient has shown some potential in distinguishing between two mental workloads that involve working memory; phase synchronization defines a different kind of usable metrics which we are still investigating. We are currently exploring the change in phase synchronization in block in sections of the signals which might provide some missing information. We have also implemented an online classification of mental states procedure based on machine learning algorithms, which they show their superior discriminating power.

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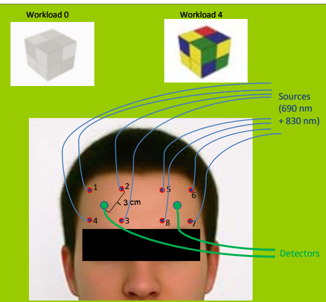
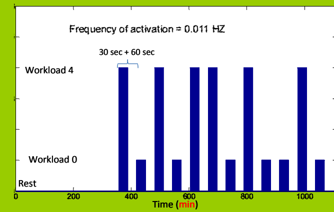
Correlation Analysis



Fibers arrangement



Schematic of protocol

Correlation calculated at the frequency band of 0.1 HZ

Pearson Coefficient between Δ[HbO] and Δ[Hb]

Phase Synchronization Analysis

Definition of phase for arbitrary signal

Analytic Signal of a signal s(t)

$$\psi(t) = s(t) + j\tilde{s}(t) = A(t)e^{j\phi(t)}$$

Where s(t) is either the filtered Δ[HbO] or Δ[Hb]

$\hat{S}(t)$ Hilbert transform of filtered Δ[HbO] and Δ[Hb]

$$\Delta\phi = \phi(\Delta[HbO]) - \phi(\Delta[Hb])$$

We calculate an histogram Of the different values of Δϕ

Shannon Entropy

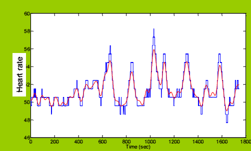
$$S = -\sum_{i=1}^{N} P_i \ln(P_i)$$

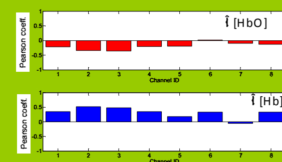
Entropy of the distribution of Δϕ: $P_i \doteq \Delta\phi_i$

Phase Synchronization Index

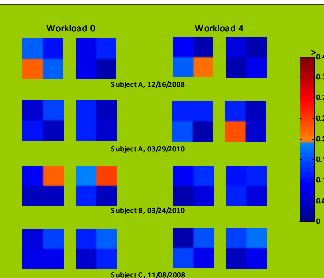
$$PSI = 1 - S/\ln(N)$$

Ln(N) is the largest value of Entropy, obtained for a uniform distribution





Heart rate contribution to optical signals around 0.01 HZ;
No correlation is found around 0.1 HZ



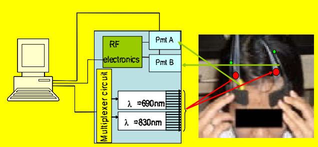
Phase synchronization index (PSI) between Δ[HbO] and Δ[Hb]

Online fNIRS Analysis and Classification system (OFAC).

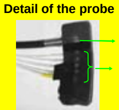
OxiplexTS (ISS, Inc., Champaign, IL)

Modulation Frequency: 110MHz

Acquisition time: 20ms per source, 160ms per cycle through all sources.



Detail of the probe

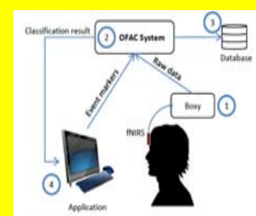


Detector

Sources :

Source-detector distance: 1.5, 2.0, 2.5, 3.0 cm

The use of fNIRS in typical computer settings



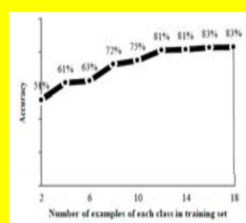
OFAC system's architecture.
OFAC provides both online and offline data analysis

Results of OFAC

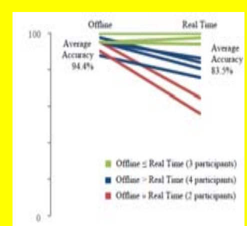
PACMAN GAME

Schematic of Pacman game

Participants completed ten sets of two trials (one in each difficulty level) over a twenty minute period. In each trial, participants played the game for a period of thirty seconds and rested for thirty seconds to allow their brain to return to baseline



The first 12 examples (or more) in the training set produces a stable average accuracy of approximately 82%



Comparing the real time and offline classification accuracy for each participant