Real-time assessment of mental workload with Near Infrared Spectroscopy: Potential for human-computer interaction

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Introduction: Human computer interaction (HCI) is an interdisciplinary field that involves the study and development of user interfaces for computers. One challenge of HCI is the collection of quantitative information on human computer users, which is fundamental for evaluation purposes and real-time input [1]. The collection of neurophysiological data of cognitive workload has been proposed using multivariate electroencephalography (EEG) [2] and also functional near infrared spectroscopy (fNIRS) [3]. In this work we propose to use machine learning algorithms for the analysis of near-infrared data, and apply this approach to process data collected on the forehead of human subjects while they perform tasks of increasing cognitive workload levels. The purpose is to develop a tool for quantitative and real-time assessment of cognitive workload to provide continuous feedback to a dynamic human-computer interface.

Methods and results: The experimental apparatus and the protocol are shown in the section on top. In the central section are shown the relative change of intensity (left side) and some folding average results for Δ[Hb] and Δ[HbO] (right side) obtained with modified Beer-Lambert law. The folding average results were obtained after a moving average band-pass filter in the range (0.01, 0.1) Hz. One period of activation/rest lasts about 85 sec. From the graphs of intensity change we can already see clear activations at all the source-detector distances. The trends of Δ[HbO] and Δ[Hb] shown in the folding average results are opposite of those usually expected for cerebral activation during finger tapping. However in the literature these inverted trends during mental tasks were already reported [4]. In the section on the bottom are shown the results of the classification of three workloads according to two machine learning algorithms, namely the dynamic time warping (DTW) and the symbolic aggregate approximation (SAX). In the tables are shown the details and percentage of successful classifications.

Conclusion and future work: Machine learning algorithms applied to fNIRS data show good potential for distinguishing different levels of mental workload. This is the first step towards the development of interactive human-computer interfaces. Future work will be directed for finding more efficient and systematic ways to choose the right instances (period of activations) from which we can get the best classifications according to machine learning algorithms. Towards this goal the standard analysis carried out in NIRS including folding average procedures will help to select those channels showing activation.

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References:

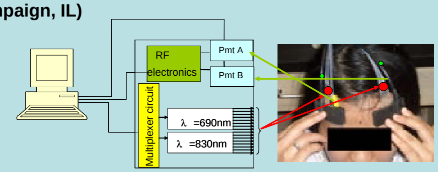
1. Z. Duric et al. "Integrating perceptual and cognitive modeling for adaptive and intelligent human-computer interaction," Proc. IEEE 90, 1272-1289 (2002).
2. M. E. Smith et al., "Monitoring task loading with multivariate EEG measures during complex forms of human-computer interaction," Human Factors 43, 366-380 (2001).
3. K. Izzetoglu et al., "Functional optical brain imaging using near-infrared spectroscopy during cognitve tasks," Human-Computer Inter. 17, 211-227 (2004).
4. Y. Hoshi et al., "Detection of dynamic changes in cerebral oxygenation coupled to neuronal function during mental work in man," Neurosci. Lett. 150, 5-8 (1993).

Experimental apparatus

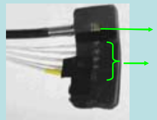
OxiplexTS (ISS, Inc., Champaign, IL)

Modulation Frequency: 110MHz

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



Detail of the probe



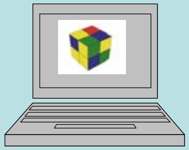
Detector

Sources :

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

Protocol

a) Computer interface



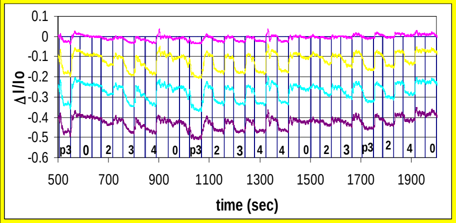
b) Physical cube

The physical cube was placed on a platform and manually rotated

Each side of the cube was presented to the subjects for 8 sec; then the cube rotated (2-3 sec) and stopped when another side was facing the subject; 2-3 extra seconds were given to the subjects at the end of the last rotation in order to count also the colored squares on the top. This cycle defines a WORKLOAD (≈ 45 sec). Each workload was followed by about 40 sec of rest. Five different workloads, defined by the number of colors in the cube, were presented randomly six times to the subject.

NIRS DATA

Change of intensity (detrended data, λ=690 nm, channel B)

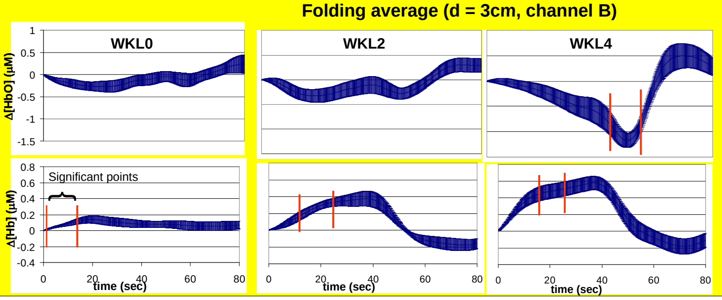


WORKLOADS: 0, 2, 3, 4, PHYS, REST

0	**NO CUBE ON SCREEN**
2	**TWO COLORS**
3	**THREE COLORS**
4	**FOUR COLORS**
P3	**PHYSICAL CUBE (3 colors)**

Results obtained on subject 4 (see section below). In the figure on the left are plotted the changes of intensity with respect to baseline (Io). The source-detector distances are d= 1.5, 2, 2.5, d=3 cm (from top to bottom). On the right are plotted the changes of [HbO] (top row) and the changes of [Hb] (bottom row) occurring at d=3 cm in channel B. Each column represents a different workload.

Folding average (d = 3cm, channel B)



Machine learning algorithms (DTW, SAX)

RESULTS OF CLASSIFICATION OF WORKLOADS 0, 2, 4

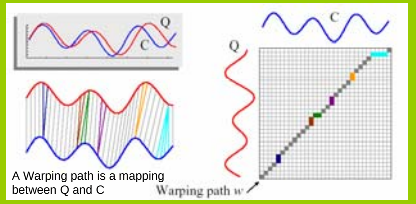
DTW

Subjects	1	2	3	4	5
Percentage	83.3%	77.8%	88.9%	77.8%	94.4%
Neighbors	2	1	1	1	1
HbO Channel	A, d= 2cm	None	A, d= 3cm	B, d=2 cm	B, d= 2cm
Hb Channel	A, d= 2cm	A, d =1.5 B, d=3 cm	B, d= 3cm	A, d= 3cm	None

SAX

Subjects	1	2	3	4	5
Percentage	72.2%	83.3%	88.9%	94.4%	88.9%
Neighbors	3	2	3	1	1
HbO Channel	A, d= 3 cm	B, d=1.5 cm	A, d= 2.5 cm	B, d=2 cm	B, d= 2.5 cm
Hb Channel	A, d= 3 cm	B, d =1.5	A, d= 2.5 cm	B, d= 2 cm	B, d=2.5 cm
Word size	6	6	5	5	6
Alphabet size	13	12	9	13	9

Dynamic Time Warping (DTW)



A Warping path is a mapping between Q and C

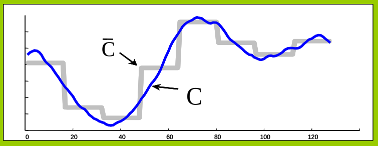
Adapted from: Keogh, Eamonn, *Exact Indexing of Dynamic Time Warping.* 2002

a) The time series must be z-scored
b) Define "instance" a section of time series during 45 sec of activation
c) Define a similarity metric between instances (Euclidian, warping path metrics)
d) Calculate the minimum distance between a query instance (Q) and another (C)
e) Use K-nearest neighbors (KNN) for the classification of Q.
f) Repeat the procedure changing the query instance

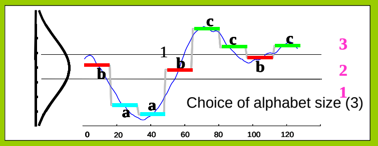
$$D(Q,C) \equiv \sqrt{\sum_{i=1}^{n} (q_i - c_i)^2}$$ **Euclidian metric**

Symbolic Aggregate Approximation (SAX)

a) Use a Piecewise Aggregate Approximation (PAA) of C



b) Choose an alphabet size to map PAA values into words



Repeat the steps c) - f) of the DTW algorithm.