Cognitive Load Detection on Commercial EEG Devices: An Optimized Signal Processing Chain

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Abstract. Use of Electroencephalography (EEG) to detect cognitive load is a well-practiced technique. Cognitive load reflects the mental load imparted on a person providing a crucial parameter for applications like personalized education and usability testing. There are several approaches to process the EEG signals and thus choosing an optimal signal processing chain is not a straight forward job. The scenario becomes even more interesting while using commercial low-cost, low resolution EEG devices connected to cloud through Internet of Things (IoT) platform. This paper proposes an optimized signal processing chain offering maximum classification accuracy and minimum computational complexity for measuring the cognitive load using low resolution EEG devices.

Keywords: Cognitive load · Mental workload · EEG signal processing · Emotiv

1 Introduction

Mental workload imposed on a person is an important component for human behavior modeling as it gives a direct representation of mental state of the person [1]. Cognitive load (CL) is the total amount of mental activity imposed on our working memory while doing any cognitive process. High CL can significantly influence the performance, leading to poor outcome, stress, or anxiety [1]. This CL information if made available on IoT platform in real-time [2, 3], can be utilized for different applications like personalized education [4], usability testing [5] etc. as depicted in Fig. 1.

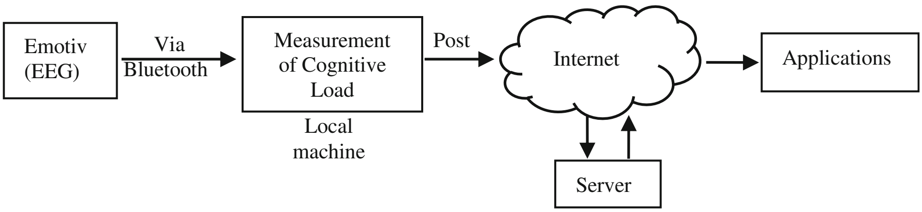


Fig. 1. Mental workload estimation and modeling through IoT

R. Giaffreda et al. (Eds.): IoT360 2014, Part I, LNICST 150, pp. 87–92, 2015.
DOI: 10.1007/978-3-319-19656-5_14

Thus measuring CL while doing any task has been of increasing interest. Subjective measures of CL, including self-reporting like NASA-TLX [6], measurement of error rates etc., are mostly self-biased compared to *object-indirect* (e.g. physiological, behavioral measurements) and *objective-direct* (e.g. brain activity measurement, dual task performance analysis) measurement methods. Physiological measures like brain signals, Galvanic Skin Response, functional Magnetic Resonance Imaging etc. can be used to access CL [7]. We have used electroencephalogram (EEG) technique as it is relatively in-expensive, non-invasive and have excellent temporal resolution. The frontal and central brain are mostly indicative of CL for tasks like problem solving, decision making, and language skills etc. [8, 9]. Different preprocessing steps, features and classifiers can be used for EEG signal analysis. Time-domain [10], frequency-domain [11], and statistical parameters have been used to access the CL. Here we tried detecting CL with commercially available low cost and low resolution Emotiv[1] EEG device. Hence, appropriate signal processing, machine learning steps are needed to get desired information.

The main contribution of this paper lies in proposing an optimal signal processing chain via comparative study among various existing algorithmic approaches using low-resolution devices like Emotiv. EEG signals are very susceptible to artifacts like eye-blinks, facial muscle movements etc., hence we used Hilbert-Huang Transform (HHT) [13] for required correction. The accuracy of classification can be increased by using a spatial filter [14]. We have used advanced Tikhonov-Regularized Common Spatial Pattern (TRCSP) [15]. Results show that it is possible to get good classification accuracy with Emotiv if processing steps are chosen properly.

The paper is organized as follows: Sect. 2 details the experiments and the data collection methods, followed by signal processing steps in Sect. 3. Section 4 presents the results with discussions. Finally, the paper is concluded in Sect. 5.

2 Experiments and Data Collection

For the present study we designed two types of reading tasks similar to [12] with slight modifications, pertaining low and high CL. For *low load* condition, subjects were asked to mentally count the number of two letter words (except 'of') while reading an English passage and report the number at the end. For *high load* condition, subjects were instructed to count two-letter words as well as three-letter words separately (except 'of' and 'the').

A group of 10 participants (aged between 25–30 years) were selected. All of them were right-handed male and had English as second language. These ensures minimum variance in the level of expertise and brain lateralization across all the subjects.

The stimulus were presented on a 9.7-in. iPad. Participant were given two sets of stimulus to work with (i.e. 2 high-load tasks and 2 low-load tasks). The EEG data corresponding to first set of stimulus were used as the training data and the second set were used as the test data and vice versa. An average of these two observations were used as the final result.

[1] www.emotiv.com.

3 EEG Signal Processing

Different algorithmic approaches tried are shown in Fig. 2 and the details are given in Table 1. The numbers provided in the construction of various *paths* in Table 1 are referred to signal processing blocks shown in Fig. 2. We used a feature vector comprising of variance, Hjorth parameters [10], alpha (δ), beta (β), theta (θ), delta (δ), gamma (γ) band powers and ratios of band powers ${}^{\beta}/_{\theta}$ and ${}^{\alpha}/_{\delta}$.

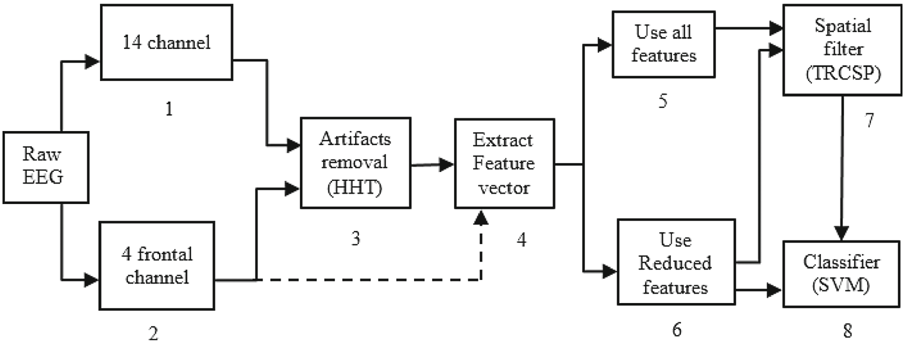


Fig. 2. Different approaches adopted for analyzing EEG signals

Table 1. Details of different Algorithm chains adopted

Motivation	Algorithm chain	Approach used
Choice of brain lobe to be probed :- to examine if a subset of all channels can be used with compromising on accuracy	*Path1:* 1→3→4→5→7→8	i) Probing all the brain lobes(using all 14 channels) ii) Using full feature vector set iii) Using TRCSP on feature vector set iv) SVM for final classification
	Path2: 2→3→4→5→7→8	i) Probing only left-frontal brain(AF3, F7, F3, FC5) [16] ii) Using full feature set on above channels iii) Using TRCSP on feature vector set iv) SVM for final classification
Choice of features to be used :- to examine if a reduced feature set can lead to same accuracy	*Path3:* 1→3→4→6→7→8	i) Probing all the brain lobes ii) Using only alpha and theta band power [16] iii) This reduced feature set fed to TRCSP iv) SVM for final classification
	Path4: 2→3→4→6→7→8	i) Probing only left-frontal brain ii) Using only alpha and theta band power [16] iii)This reduced feature set fed to TRCSP iv) SVM for final classification
Use of spatial filters:- to examine the need of CSP as Emotiv does not have neighboring electrode in true sense	*Path 5*: 1→3→4→6→8	i) Probing all the brain lobes ii) Using only alpha and theta band power iii) Reduced feature set to SVM [12]
	Path 6: 2→3→4→6→8	i) Probing only left-frontal brain ii) Using only alpha and theta band power iii) Reduced feature set to SVM
Effect of HHT:-Eye-blink lies in (0.4-4 Hz) & features in (4-12 Hz). So, tried to examine usefulness of artifacts removal	Preferred path with HHT	i) Selected preferred path from *Path1* through *Path6*
	Preferred path without HHT	ii) Selected same path but without using HHT

3.1 Comparison of Algorithms

Algorithms were compared based on: (i) the cognitive score (CS) obtained while classifying the EEG signals following a particular signal processing path, and (ii) the computational complexity (CC) of that particular algorithm.

CS is defined in (1). Features (reduced feature/output of TRCSP) extracted from training data were used to train SVM. Same features were calculated from test data also and fed to SVM. The analysis was done in a non-overlapping window (5 s) basis. Finally, the over-all cognitive score for a particular trial is given by

$$CS = \frac{\sum m_i \times w_i}{n} \tag{1}$$

where, m_i is the number of windows reported as class i, n is the total number of windows in a test trial and w_i is a weight-factor. For high load class $w_i = 100$ and for low load class $w_i = 0$. Hence for low load trial $CS \approx 0$ and for high trial $CS \approx 100$.

The computational complexity (CC) of an algorithm is the number of processing steps required for a particular input. In our work we have defined CC as

$$CC = n_c \times (L + C_{HHT}) + n_c \times (m_f \times F) + (n_c \times m_f) \times C_{CSP} \tag{2}$$

where, n_c is the number of channels selected, L is the computational complexity for a single channels, C_{HHT} is the computational complexity of HHT filter, m_f is the number of features selected, F is the complexity for extracting a particular feature, C_{CSP} is the computational complexity of using TRCSP filter. Thus (1) and (2) gives a measure of cognitive score and computational complexity for a particular algorithm.

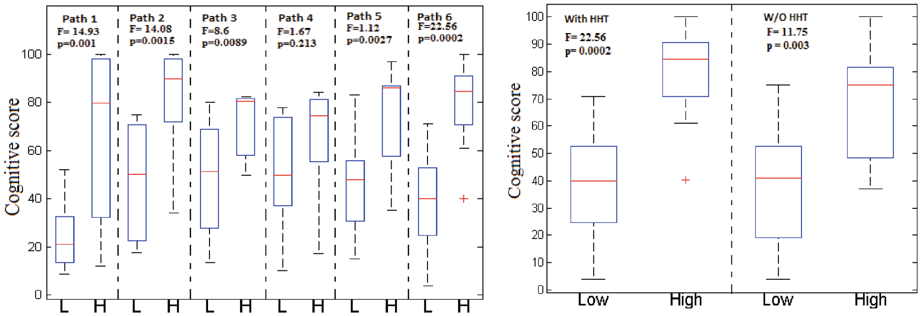
4 Results and Discussions

Table 2 shows the cognitive score of low (L) and high (H) cognitive tasks following *Path1* through *Path6*. Maximum separation between H and L have been marked in 'blue'. The entries for $CS_{High} < CS_{Low}$, have been marked in red. We observed this reverse trend for 3 subjects while following *Path4* and for 1 subject while following *Path1*. Both *Path1* and *Path4* used TRCSP algorithm. Further investigation is needed to conclude whether TRCSP leads to this effect for low resolution EEG device. Figure 3a gives one-way ANOVA analysis of the results given in Table 2. Plot shows *Path6* gives highest difference between mean CS_{High} and CS_{Low} while having minimal intra-class variance. *Path1* gives maximum separation between CS_{High} and CS_{Low} for 6 subjects compared to *Path6* which gives maximum separation between for 1 subject. However, the ANOVA results indicate that the *Path6* is the preferred path as opposed to *Path1*, as the variance for CS_{High} is maximum for the same, which is undesirable.

Thus, we see *Path6* as the best possible approach in terms of classification accuracy while using Emotiv. *Path6* is also the path of least complexity as it: (i) uses only 4 channels instead of 14 channels, (ii) uses reduced feature set – using only these two features saves computational time for feature extraction and (iii) bypasses TRCSP.

Table 2. Comparison of different algorithms in terms of cognitive score

Sub	Path 1		Path 2		Path 3		Path 4		Path 5		Path 6	
	CS (H)	CS (L)	CS (H)	CS (L)	CS (H)	CS (L)	CS (H)	CS (L)	CS (H)	CS (L)	CS (H)	CS (L)
1	79.8	8.7	100	75	58.3	54.2	29	43	56	50	100	4
2	97.4	15.2	89.7	20.4	82.1	23.5	74.3	10.2	85.2	15.2	84.6	18.9
3	12	8.8	34.2	17.6	82.2	76.1	79	73	58	44	61	50
4	84	21	96.3	71.4	81.1	80.2	64.2	50	89	83	89	71
5	100	44	98	51.7	74.5	51.4	65	78	86	55	74	51
6	71.4	29	89.8	70.3	81.6	66.6	83	62	97	48	89	40
7	33.3	52	77.7	23.5	50	29.4	80.5	76.4	86	58	75	58
8	100	23.3	98.4	25.3	80.4	13.6	84	25.2	86	26.5	96	30.2
9	28.5	20.1	54.2	50.1	57.5	42.3	17.5	41.1	35.2	32.1	40.2	26.8
10	67.3	24.6	82.3	45s	71.9	48.5	64.1	50.9	75.4	45.7	78.5	38.8



(a) (b)

Fig. 3. **(a)** Boxplot of different algorithms: *Path6* is the chosen path as it offers maximum F-value and minimum p-value, **(b)** Effect of artifacts removal: maximum F-value is obtained while using HHT filters

Next we investigated usefulness of HHT filters. Figure 3b shows the CS for both tasks with or without HHT. The separation between average CS for H and L is greater and variance for H and L is lowest for artifact removed signals using HHT.

5 Conclusion

In this paper, we proposed the optimal signal processing chain specifically suitable for low-resolution EEG devices like Emotiv. We have introduced a performance score for evaluating different algorithms to choose the optimal signal processing chain for similar low cost devices. The results show that, using Emotiv or similar low-cost low resolution devices, it is possible to measure the CL by probing left frontal brain lobe for a combined text reading and counting memory task. It also shows that the alpha and theta band powers, directly fed to SVM, are sufficient to capture the imparted CL. The proposed optimum signal processing chain also requires least computational resources thereby making it suitable for cognitive load related IoT applications.

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