

Chapter 6

Cognitive Load Measurement Based on EEG Signals

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ABSTRACT

Measurement of the cognitive load should be advantageous in designing an intelligent navigation system for visually impaired people (VIPs) when navigating unfamiliar indoor environments. Electroencephalogram (EEG) can offer neurophysiological indicators of the perceptive process indicated by changes in brain rhythmic activity. To support the cognitive load measurement by means of EEG signals, the complexity of the tasks of the VIPs during navigating unfamiliar indoor environments is quantified considering diverse factors of well-established signal processing and machine learning methods. This chapter describes the measurement of cognitive load based on EEG signals analysis with its existing literatures, background, scopes, features, and machine learning techniques.

INTRODUCTION

To understand cognitive load, we must first understand the working memory and to understand working memory we have to know what memory is. The memory is the aptitude of brain that deals with encoding, storing and retrieving information as needed. This information is received and transmitted from external environment by sensory nervous system in the form of chemical or physical stimuli and processed by memory in central nervous system. Now memory is classified into two categories: (1) short term or working memory that holds information temporarily (Miyake & Shah, 1999) and allows manipulation

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of stored information for reasoning, decision making, guiding behavior etc., (2) long term memory that can stock data for a long period.

Cognitive load is the quantity of working memory in use. There is another notion called “long-term working memory” that is a set of rescues of parts of long-term memory enabling continuous access to data required for daily activities (Ericsson & Kintsch, 1995). Cognitive load is the basis of problem solving and learning (Sweller, 1998).

Now comes the question, why do we need to measure cognitive load? Cognitive load is associated with learning new things whether be it a study matter or a new skill. So, to design a lesson plan it is important to understand how can a learner learn or memorize it easily and quickly where the measurement of cognitive load comes handy. The constructions and roles of human cognitive built have been used to develop a range of instructional means aiming for the reduction of load of working memory in learners and encouragement of diagram construction (Sweller et al., 1998). Furthermore, there are many other purposes of measuring cognitive load, such as, to know how a disease (neurodegenerative diseases, carcinomas etc.) or it's treatment (chemotherapy, radiotherapy, immunotherapy etc.) affects human cognition. This measurement is also very important for different researches including age related cognitive declines, learning task performances and multiple document handling (Cerdan et al., 2018), Designing navigation aid for blind people (Kalimeri & Saitis, 2016) etc.

Researchers formulated many ways of measuring cognitive load such as subjective scales, task-invoked pupillary response (Paas et al., 2003; Skulmowski & Rey, 2017), EEG signals (Antonenko et al., 2010), fMRI etc. Distraction causes increase in cognitive load (Paas & Sweller, 2012).

Subjective scales vary with varying perception in different individuals; thus, such scales are less reliable. Again, pupillary responses is equivalent to a range of events requiring psychological efforts which may be perceptual, cognitive and/ or response related, thus it is not indicative of cognitive load being linked to task performance (Kramer, 1991). EEG and fMRI give more precise results regarding cognitive load related to task performance although they are expensive and complicated to operate. Compared to fMRI, EEG is easier to perform and read as various software are available now for EEG interpretation.

In this chapter Measurement of cognitive load based on EEG signals is discussed taking references from a study of learning processes of visually impaired people (VIP) while navigating through unfamiliar indoor environment using EEG signal (Afroz et al., 2019).

LITERATURE REVIEW

First, we review the prior research in the area of cognitive load measurement using EEG signals. Much work has been devoted in this area by extracting various features from EEG signals and then machine learning approaches have been applied to quantify cognitive load over years.

Fraser et al. (Fraser et al., 2015) argued that intrinsic cognitive load needs to be adjusted to level of the apprentice, extraneous cognitive load needs to be abridged, and germane load needs to be augmented until the boundaries of working memory are not exceeded.

Gevins et al. (Gevins et al., 1997) studied cortical activity throughout working memory tasks and found that a sluggish (low-frequency), parieto-central, alpha signal lessened as working memory load amplified.

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