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An efficient automatic workload estimation method based on electrodermal activity using pattern classifier combinations

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A B S T R A C T

Automatic workload estimation has received much attention because of its application in error prevention, diagnosis, and treatment of neural system impairment. The development of a simple but reliable method using minimum number of psychophysiological signals is a challenge in automatic workload estimation. To address this challenge, this paper presented three different decomposition techniques (Fourier, cepstrum, and wavelet transforms) to analyze electrodermal activity (EDA). The efficiency of various statistical and entropic features was investigated and compared. To recognize different levels of an arithmetic task, the features were processed by principal component analysis and machine-learning techniques. These methods have been incorporated into a workload estimation system based on two types: feature-level and decision-level combinations.

The results indicated the reliability of the method for automatic and real-time inference of psychological states. This method provided a quantitative estimation of the workload levels and a bias-free evaluation approach. The high-average accuracy of 90% and cost effective requirement were the two important attributes of the proposed workload estimation system. New entropic features were proved to be more sensitive measures for quantifying time and frequency changes in EDA. The effectiveness of these measures was also compared with conventional tonic EDA measures, demonstrating the superiority of the proposed method in achieving accurate estimation of workload levels.

1. Introduction

Recently, there has been a growing interest in the use of electronic devices in the workplace. Performing a secondary task during user–system interaction results in an increase in the mental load (Putze and Schultz, 2014). High level of mental load increases the risk of cognitive overload, performance degradation, and compensatory behavior (Putze and Schultz, 2014; Schnotz and Kürschner, 2007). For example, interruptions and multitasking are the most common causes of medical errors in the emergency department (Laxmisan et al., 2007). The major reason for mental overloading is limited capacity of the cognitive system (Paas et al., 2003). Automatic cognitive load estimation system provides an innovative solution to prevent cognitive overloading (Muth et al., 2012). There are other applications of the load estimation system, such as evaluating a broad range of central nervous system impairments and developing the personalized treatment strategies (Chen and Epps, 2013; Spaulding et al., 1999). Therefore, the scientific community has focused on the development of an efficient strategy for automatic cognitive load estimation.

Common methods for measuring cognitive workload can be classified into self-report and psychophysiological measures (Galy et al., 2012). The self-rating questionnaires or performance measures were used in the first method. This method has some limitations such as response bias (Zarjam et al., 2013). In addition, this method cannot provide online monitoring of mental workload. In contrast, psychophysiological method can measure continuous and real-time data. The general validity of this method for mental workload estimation has been shown in the literature (Causse et al., 2010). To date, several psychophysiological data such as electrodermal activity (EDA), heart rate, heart rate variability, electroencephalogram, and pupil dilatation were used (Shi et al., 2007; Van Gerven et al., 2004; Zarjam et al., 2013). EDA refers to the electrical fluctuations in the skin. It measures the activity of sympathetic cholinergic neurons at the sweat gland level (Boucsein, 2012; Zhang et al., 2012). EDA can provide a noninvasive, easily captured, robust, and cheap method of recording psychophysiological data (Nourbakhsh et al., 2012). It contains considerable information of the brain state and information processing (VaezMousavi et al., 2009). EDA is influenced by many cognitive, emotional, and motor processes (Boucsein, 2012; Zhang et al., 2012). The methods of EDA analysis have focused on two main characteristic components of the signal: phasic and tonic. Fast varying activity is related to the phasic component of the signal (i.e., electrodermal response (EDR)). Amplitude, latency time, rise time, area, and recovery parameters are frequently used features of

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EDR (Boucsein, 2012). The tonic component refers to the slow changes over time (i.e., electrodermal level (EDL)). Several tonic measures have been proposed in the literature for EDA analysis, including frequency of nonspecific EDR (NS.EDR), mean, standard deviation (SD) of NS.EDR amplitude, and EDA amplitude (Boucsein, 2012). A systematic review of the literature has shown several problems associated with the evaluation of some phasic measures (Boucsein, 2012). Ambiguous results have also been observed for the tonic parameters derived from phasic changes (Boucsein, 2012). Therefore, a new method to characterize essential features of EDA should be proposed.

Workload estimation using the EDA data is affected by two different sources of complexity. The first is that workload-related patterns vary significantly across subjects. They refer to the interaction between task demands and individual characteristics (Galy et al., 2012). Moreover, psychophysiological data are linked to other mental resource demands (Byrne and Parasuraman, 1996). Hence, there may be no certain general algorithm that can be applied to all subjects with the aim of providing good results. The second reason is that EDA has a complex pattern (Boucsein, 2012) and no single feature can be optimal in all conditions. The focus of the existing method has been limited to the simple linear measures. The EDA signals are nonstationary and nonlinear signals, and the classical linear features fail as they do not capture dynamical changes in the signals. Accordingly, studies that used EDA for cognitive load estimation revealed somewhat variable findings. For example, Shimomura et al. did not find any significant change in skin conductance response (SCR; Shimomura et al., 2008). In contrast, other researchers pointed out that an increase in human workload was associated with increased SCR (Ikehara and Crosby, 2005; Shi et al., 2007). Engstrom et al. concluded that cognitive load during auditory task was unrelated to the skin conductance level (Engström et al., 2005). However, significant effects were found for this measure in the visual task (Engström et al., 2005). The high levels of EDA variation, both within single subject over load levels and between different subjects, implies the need to explore new algorithms. These methods should be able to potentially reduce individual differences.

To date, several causal psychophysiological models have been developed to inference psychological states from measured EDR (Bach and Friston, 2013; Staib et al., 2015). These models can be divided into peripheral and neural models (Bach and Friston, 2013). The peripheral models are based on the positive monotonic association between amplitude of SCR and firing of sudomotor nerve (SMN). The latter models provide the mapping between sympathetic arousal and parameters of SMN activity (SMNA; number of responses or amplitude of responses; Bach et al., 2011; Bach et al., 2009). The deterministic nature of the basic peripheral model is an unsupported claim about reality (Bach, 2014). The majority of the peripheral models assumed that the SCR had linear and time-invariant variations. This assumption is not always true in practice (Bach and Friston, 2013). Moreover, the predictive ability of causal models must be evaluated using unbiased approaches, which has been ignored by several studies (Bach and Friston, 2013). Although many efforts have been made to develop a model-based approach, cognitive load estimation based on the signal detection and machine-learning algorithms has rarely been investigated (Bach and Friston, 2013). These considerations motivated us to generalize and extend the classifier combination approach for automatic workload recognition.

In the present study, subjects performed different levels of arithmetic task. It evoked selective attention conflicts in multiple levels of workload. The EDA signals acquired during the experiment were analyzed. The change in EDA was thought to be because of the two different physiological processes: (1) unconditional diffusion, duct filling, corneal hydration, and reabsorption, which were slow processes; and (2) a pore-opening procedure, membrane polarization, and depolarization, which were fast processes (Benedek and Kaernbach, 2010; Boucsein, 2012). Systematic analyses of the slow and fast components using the proposed decomposition methods were thought to be useful in extracting the pattern of task-related sweating. For this purpose, different decomposition techniques (Fourier, wavelet, and cepstrum transforms) and feature extraction methods were applied to extract useful information of cognitive states. The reactivity of sweat glands to different mental workload levels was characterized using new time, frequency, and time–frequency measures. To achieve a more precise description of SMNA, novel linear and nonlinear methods were used. The extracted features were combined to take advantages of all the features (feature-level combination). Principal component analysis (PCA) was also applied to accommodate within-subject variance of EDA features. To provide a more efficient cognitive load estimation system, another type of combination operated at the decision level. The outputs of the several support vector machine (SVM) classifiers were combined to make the final decision about the workload levels. Finally, the efficiency of different EDA features was evaluated and compared using a statistical test and machine-learning techniques. We also compared the performance of the combined classifier against a probabilistic neural network (PNN) classifier.

2. Materials and methods

2.1. Participants

Subjects consisted of 35 university students (23 women and 12 men) aged 19–30 ($M = 24$, $SD = 2.7$). They volunteered to participate in the study. This sample size is comparable to those used in other automatic workload estimation studies using psychophysiological signals; for example, Chen et al. (Chen and Epps, 2013), Zarjam et al. (Zarjam et al., 2013), and Yin et al. (Yin and Zhang, 2014) included 15, 12, and 6 subjects, respectively. Exclusion criteria included neurological or cardiac disorders. All subjects had normal or corrected to normal vision. Subjects were asked to refrain from physical exercise and have sufficient sleep before the study. They were told to avoid using nicotine and caffeine. All participants provided written informed consent in accordance with human research ethics guidelines.

2.2. Experimental paradigms

The study protocol and task details are illustrated in Fig. 1. The experiment was performed in the afternoon between 2 and 6 pm. The objective of the study was explained to all the subjects. The participants were subjected to a practice session that minimized experimental errors.

After training, the participants were seated in a comfortable armchair. The designed tasks were presented to the participants on a 15.6-inch monitor with a viewing distance of 60 cm. The experiment consisted of an adaptation phase, followed by five 4-min task periods. During the adaptation phase, the subjects rested for 2 min. Then, the participants underwent the mental arithmetic task. It included five levels of mental workload. Each level started with a 2-min rest period, followed by a 2-min mental arithmetic task. The rest period was used to prevent mental fatigue (Zarjam et al., 2013). There were 16 trials in each load level. On each trial, a mental addition problem was presented. The number of carry operation or digit numbers was considered as a factor determining workload levels (Imbo et al., 2007; Zarjam et al., 2013). Moreover, a fixed amount of response time was considered for all the levels. This induced greater mental load on the subject in the face of more difficult levels (Zarjam et al., 2013). This method was widely used in the previous studies and shows compatibility with other studies.

At the beginning of the trial, a central fixation interrogation point was displayed for 1 s, and two visual stimuli were then displayed sequentially. Each stimulus consisted of two numbers next to each other in Persian notation for 1.5 s. The subjects were required to selectively concentrate on one number (target number) while ignoring the other number (distractor number). The colors of the target and distractor numbers were shown in green and blue, respectively. The positions of