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Research paper

A novel cepstral-based technique for automatic cognitive load estimation

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ABSTRACT

The development of a reliable algorithm with low computational requirement is a challenge in cognitive load estimation. To address this challenge, this paper presented a view towards the novel application of cepstrum analysis in workload estimation. The proposed method used minimum number of physiological signals. It integrated amplitude and phase information of electrocardiogram (ECG) signals while reducing feature sample size. A set of cepstral-based ECG features, such as dynamic cepstral warping (DCW), differential energy density, and differential statistical features was proposed for designing a new cognitive load estimation system. The features were processed by principal component analysis and support vector machine in order to discriminate different levels of an arithmetic task. The discriminating capability of the method was evaluated using the ECG recording of 22 healthy subjects.

The proposed algorithm achieved high average accuracy of 92.27% and 90.34% for the workload levels determined by the variation in the digit numbers and in the number of carry operations, respectively. In the case of combination both variables, the average accuracy of 90.48% was obtained. Furthermore, comparing between complex and real cepstral measures revealed better performance of the complex measures. These findings indicated the role of phase information in the ECG-based cognitive load estimation. Integrating dynamic and static characteristics of the cepstral coefficients in a multivariate approach improved the performance of the system. It performed significantly better than popular ECG features. The proposed approach provided a trade-off between performance and computational complexity of the estimation system.

1. Introduction

An automatic workload estimation system can be used for cognitive overload prevention and neuropathological assessment of the central nervous system [1]. Hence, it has attracted the attention of scientific community in the recent years. Subjective measures and physiological signals have been widely used in estimation of cognitive workload [2]. However, there is an increasing interest in the use of physiological signals, such as electroencephalogram, electrocardiogram (ECG), Galvanic skin response, electrooculogram, heart rate, and heart rate variability [3,4]. This interest has three different reasons 1) The physiological signals are eminently suitable to capture the continuous and real-time changes in the cognitive states [3]. 2) They are very sensitive to cognitive fluctuations [2]. 3) These measures are less influenced by intentional conduct.

The development of a reliable workload estimation algorithm with low complexity and high performance can make it ideally suited to meet the requirements of closed-loop error prevention systems. Such a system can be used in different workplaces and conditions, such as medical and emergency departments, air traffic control, and driving [3]. However, typical problems in the development of such system include individual differences in the physiological signals and high computational requirements of the estimation algorithms. The cognitive workload refers to the interaction between task demands and individual characteristics [2]. Hence, the psychophysiological patterns vary substantially across subjects. Moreover, these signals are associated with the other sources of mental activity [1]. To address these problems, this paper proposed a subject dependent method based on the cepstral measures. It also utilized minimum number of psychophysiological signals to reduce the computational complexity.

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The ECG is a nonlinear biological time series. It is a low cost and noninvasive cardiac screening tool. The analysis of the ECG signals has become one of the most interesting techniques in the cognitive load estimation [2,5]. In this context, power spectrum and statistical features have frequently used to discriminate different mental workload levels [6]. A growing number of psychophysiological studies have suggested that the statistical measures of the ECG signals are significantly influenced under different task situations [6–9]. Moreover, it has consistently been found that heart rate and ratio of the low frequency over the high frequency (LF/HF) increase during high level of mental load [9,10]. In these studies, a decrease in the heart rate variability has also been observed. While, a great deal of effort has been made to develop cognitive load estimation system using frequency features; cepstral-based workload estimator has not been investigated. Cepstral method provides a framework to approximately model the spectral information of the signals. It can offer more effective representation of spectral envelopes of the quasi-periodic signals compared to the original spectrum analysis [11]. Compactness, source-filter separation and orthogonality have long been recognized as three major advantages of the cepstrum analysis [12,13]. This approach is well-suited to the homomorphic deconvolution problem and quasi-periodic signal modeling [11,14]. In mathematical terms, the ECG signals can be represented by a convolution of heart beat rate with the basic ECG wave form [14]. Hence, the cepstral analysis can provide a simple way to decouple such convolution [14,15]. This approach transforms nonlinear relationship into linear ones [16]. Consequently, a linear filtering in the transform domain can be applied. The cepstral analysis of the ECG signal has been found a variety of applications in areas such as physical activity recognition, ECG classification, apnea detection, and respiratory rate extraction [15,17–19].

These considerations motivated our study, where a new cognitive load estimation algorithm was developed based on the harmonic analysis of the ECG signals. In order to meet quasi-periodic characteristics of the ECG signal, these signals were subjected to the cepstral analysis. Then, the abilities of dynamic programming approach and statistical measures were explored to discriminate the workload levels. This nonlinear method could provide an appropriate framework to extract frequency pattern from the ECG signals. The main contribution of this paper was to propose new application of cepstral based features for cognitive load estimation namely, dynamic cepstral warping (DCW), differential energy density(DED), differential variance(DV), differential skewness(DS), differential kurtosis(DK), and differential spectral flatness(DSF). The new workload estimation algorithm coupled the homomorphic deconvolution capabilities of the cepstral analysis with static and dynamic capabilities of the proposed features. One of the problems related to the physiological signals was a large amount of physiological data. Therefore, an intensive and time-consuming processing method was required for ECG-based workload estimation. In this paper, the cepstral analysis converted the ECG signals into a set of cepstral coefficient. Small subset of cepstral coefficients could be used to represent and recognize the oscillation or excitation characteristics of the signals [20]. A clean spectral band could also be obtained by eliminating undesired coefficients [20]. Hence, this approach could overcome the problem of high sampling rate of the physiological data. Furthermore, it was applied to reduce feature variability associated with additive or convolved noise. For this purpose, 15 real and 15 complex cepstral coefficients were analyzed from every ECG window at every trial. Then principal component analysis (PCA) was applied to accommodate within-subject variance of the features. Finally support vector machine (SVM) were used as a classifier to estimate different workload levels. Moreover, in a comparative study, the performance of the real and complex cepstral features across different task conditions was compared.

2. Materials and methods

2.1. Data recording and task paradigm

The data were comprised of the ECG recording of 22 healthy university students (5 men and 17 women; M_{age} =23.73, SD = 2.55, range = 19–28 years). All participants volunteered to take part in the study. Human research ethical approval was obtained from all participants. The data was collected at computational neuroscience laboratory. Color vision deficiency, brain, and heart disorders were used as the exclusion criteria. For further assessing the ability to distinguish between blue and green colors, all the participants were required to select green targets among blue distractors in the pre-task testing. They were also asked to refrain from physical exercise and to avoid using nicotine and caffeine at least 24 h prior to the experiment. The participants were told to have sufficient sleep the night before the study. All the subjects had a pre-task training session to make sure that they understood the procedure. After 2 min adaptation phase, the subjects performed five levels of a mental arithmetic task over the course of four minutes on each level (20 min in total for task sessions). The designed task evoked selective attention conflicts in different workload conditions. In the proposed study, the number of carry operations or digit numbers in the addition problems were manipulated to induce different workload levels [3].

The experimental sequence and the examples of the addition problems are illustrated in Fig. 1. As shown, every workload level began with a 2 min rest session. Each rest session was followed by a 2-min arithmetic task. During each workload level, 16 trials were presented. Each trial started with a central fixation point (1s). The task stimulus consisted of two numbers (target and distractor numbers) next to each other. The numbers were presented in subject's native language. The target and distractor numbers were represented in green and blue color, respectively. The subjects were required to total the target numbers as quickly as possible. The target's position was varied over trails in a randomized order. After a retention period of 1s, the subjects were presented with a series of four possible answers in blue and green colors. The subjects were required to attend the numbers while ignoring their colors. A time limit of 2 s was considered for answering each addition problem. When the subjects responded or this time elapsed, a new trial was started. The subjects were instructed to respond by pressing the up, down, left, or right arrow keys corresponding to the correct answers. They were asked to respond with minimum physical movements. Each difficulty level followed by a short break to assess the subjective stress and experienced workload. For this purpose, a self-report questionnaire was utilized.

A 16-channel ADInstruments PowerLab system paired with Chart 5 software was used for physiological data recording. A continuous data acquisition process was conducted during each workload level. Four types of physiological signals were recorded in each level: electroencephalogram, electrooculogram, galvanic skin response, and ECG. However, only the ECG signals were analyzed in this study. The ECG data were collected from two bipolar electrodes in a lead II configuration. The data were sampled at 1000 Hz. In order to remove line noise, the data were filtered using digital notch filter at 50 Hz.

2.2. Workload estimation system

The block diagram of the proposed cognitive load estimation system is depicted in Fig. 2. It relied on the preprocessing, feature