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Detection of temporal changes in psychophysiological data using statistical process control methods

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ABSTRACT

We consider the problem of detecting temporal changes in the functional state of human subjects due to varying levels of cognitive load using real-time psychophysiological data. The proposed approach relies on monitoring several channels of electroencephalogram (EEG) and electrooculogram (EOG) signals using the methods of statistical process control. It is demonstrated that control charting methods are capable of detecting changes in psychophysiological signals that are induced by varying cognitive load with high accuracy and low false alarm rates, and are capable of accommodating subject-specific differences while being robust with respect to differences between different trials performed by the same subject.

1. Introduction and motivation

Modern systems produce a great amount of information and cues from which human operators must take action. On one hand, these complex systems can place a high demand on an operator's cognitive load, potentially overwhelming them and causing poor performance. On the other hand, some systems utilize extensive automation to accommodate their complexity; this can cause an operator to become complacent and inattentive, which can also lead to deteriorated performance [30,31]. An ideal human–machine interface would be one that optimizes the functional state of the operator, preventing overload while not permitting complacency, thus resulting in improved system performance.

The objective of this paper is to advance the methods for monitoring and detection of changes in operator's functional state (OFS), defined as the momentary ability of an operator to meet task demands with their cognitive resources. A high OFS indicates that an operator is vigilant and aware, with ample cognitive resources to achieve satisfactory performance. Low OFS, however, indicates a non-optimal cognitive load, either too much or too little, resulting in sub-par system performance [29]. In the context of this work, OFS is associated with cognitive load experienced by the operator; with this caveat in mind, we will use both terms interchangeably.

OFS is often measured indirectly, e.g. by using overt performance metrics on tasks. Another indirect measure is the subjective estimate of mental workload, where an operator narrates his/her perceived functional state while performing tasks [32]. However, indirect measures of OFS are often infeasible in operational settings as performance metrics are difficult to construct for highly-automated complex systems, and subjective workload estimates are often inaccurate and intrusive [24,26,32].

OFS can be measured more directly via psychophysiological signals such as electroencephalogram (EEG) and

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electrooculography (EOG). Numerous studies have demonstrated these signals' ability to respond to changing cognitive load and to measure OFS (see, among others, [1,6–9,27,28]). Moreover, psychophysiological signals are continuously available and can be obtained in a non-intrusive manner, pre-requisite for their use in operational environments.

Reviews on methods for measuring OFS can be found in, e.g. [16,30,32]. Most of these approaches use data mining and pattern recognition techniques to classify mental workload into one of several discrete categories. For instance, given an experiment with easy, medium and hard tasks, and assuming that the tasks induce varying degrees of mental workload on a subject, these methods classify which task is being performed during a given epoch of psychophysiological data. The most common classifiers are artificial neural networks (ANN) and multivariate statistical techniques such as stepwise discriminant analysis (SWDA). ANNs have proved especially effective at classifying OFS as they account for the non-linear and higher order relationships often present in EEG/EOG data; they routinely achieve classification accuracy greater than 80%.

A question that has received much less attention in the literature is that of real-time or on-line detection of *temporal changes* in OFS or, equivalently, in an operator's psychophysiological signals. Such a capability is essential for development of closed-loop adaptive control systems that will aid human operators in time-critical decision making. In this paper we present a new technique for detection of changes in OFS that uses the methods of statistical process control to monitor psychophysiological signals in real-time. We demonstrate that control chart methods are capable of detecting changes in psychophysiological signals that are induced by changes in cognitive load with an accuracy exceeding 80%, and can accommodate subject-specific differences while being robust to between-trial variations.

The paper is organized as follows. The next section describes the dataset used in this study, and Section 3 discusses the processing of the psychophysiological signals and their statistical properties. In Section 4 we outline the control charting methods used to monitor the psychophysiological data, and in Section 5 evaluate the suitability of the various control charting methods to monitoring psychophysiological signals, and analyze their effectiveness in detecting changes in OFS due to varying levels of cognitive load.

2. Dataset and data processing

The dataset used in this study originated from experiments conducted at Wright-Patterson Air Force Base in 2007. Data was available for three subjects (A, E, and F), each of whom performed two 14-min trials (denoted as A01, E02, etc.), which consisted of supervising four unmanned aerial vehicles (UAVs) on a simulated bombing mission. The simulation was designed to present the subjects with tasks of three levels of difficulty: low (LL), medium (ML), and high (HL). The LL was the baseline state and encompassed most of each trial. During a trial, the tasks of medium and high difficulty (ML and HL) were presented four times each, in a random order, each lasting approximately 20 s. Every trial began in the LL, and each period of ML or HL was followed by LL, thus allowing time for the subject to recover. The experimental design assumed that varying task loads induced corresponding levels of cognitive load on the subject. It is important to emphasize that since the tasks involved monitoring four UAVs executing a bombing mission, the tasks were very visual in nature and were expected to engage the visual processing centers of the brain; see [32] for the complete experimental task design and details.

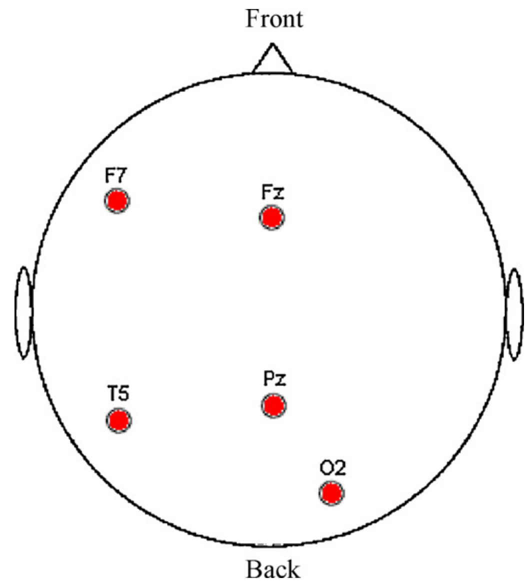

Fig. 1 – EEG electrode diagram.

The data collected for each trial consisted of eight psychophysiological channels of electroencephalogram (EEG), electrooculogram (EOG), and electrocardiogram (ECG) recorded at a sampling frequency of 200 Hz. The EEG channels were recorded from five electrodes: F_7, F_z, P_z, T_5, and O_2, affixed to the subject's scalp according to the 10/20 International electrode system shown in Fig. 1. Vertical and horizontal EOG data, termed VEOG and HEOG respectively, were collected for two purposes: primarily, as a measure of cognitive load, and secondly, to eliminate blink artifacts in the EEG signals. Finally, one channel of ECG was collected to measure heart rate. In the present analysis, only the EEG and EOG data were used.

The data was pre-processed by an online adaptive filter that eliminated blink artifacts, which were especially prominent in the F_7 and F_z electrodes, whose proximity to the eye rendered them most susceptible to contamination (see Figs. 1 and 2). The adaptive filter incorporates the VEOG and HEOG signals, s_t^v and s_t^h, as reference inputs to de-contaminate an EEG signal, say, s_t, for every time moment t. The corresponding artifact-free signal $\hat{s}_t$ is obtained as

$$\hat{s} = s_t - \hat{s}_t^v - \hat{s}_t^h,$$

where $\hat{s}_t^v$ and $\hat{s}_t^h$ are the filtered VEOG and HEOG reference signals, respectively:

$$\hat{s}_t^v = \sum_{m=1}^{M} h_m^v s_{t+1-m}^v, \quad \hat{s}_t^h = \sum_{m=1}^{M} h_m^h s_{t+1-m}^h,$$