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Physiological Indicators for Real-Time Detection of Operator's Attention

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Attention is a safety-critical operator ability that needs to be sustained over the course of specific tasks. However, many internal factors (e.g.: cognitive underload or overload, fatigue, etc.) and external factors (e.g.: HMI quality, environmental stressors, noise, etc.), can cause attention to drift away from the task. Having real-time indicators of operator's attention could increase the safety of any human-operated system. Recent industrial deployment of driver-monitoring systems demonstrated the possible use of certain physiological and behavioural metrics as indicators of attention. However, it is unclear how sensitive and accurate these metrics are in detecting attention-related changes. This paper aims to provide a brief review of the potential real-time proxy-indicators of attention and present an experiment design to assess their suitability and sensitivity using performance metrics as a benchmark. Several variables identified in the literature are presented, each is associated with a particular aspect of attention. They are grouped into electroencephalography- , eye-tracking- , and electrocardiography- based variables. The experiment devised to test these variables involves computer-based task, designed to incur varying degrees of task load and to evoke different attentional requirements. It allows the recording of different individual performance metrics. The relationship between performance and physiological indicators will be tested and compared across different attentional requirement and task load conditions. Real-time indices of attention have important safety implications such as providing immediate feedback to the operator or predicting attentional lapses.

Keywords: Attention, Operator safety, Physiology, Real-time measurement, Electroencephalography (EEG), Eye-tracking, Electrocardiography (ECG); NASA Multi Attribute Task Battery (MATB).

1. Introduction

Attention is a crucial human capability to focus on what is assessed as important and disregard the plethora of other less- or non- relevant sensory input. The level of human attentiveness is of utmost importance when it comes to safety-critical tasks such as driving, operating machines, performing surgery, etc (McIntire et al., 2014; Warm et al., 2008). There is an abundance of psychological, neurological, and neuroscientific tests to assess this crucial human ability. One example is the Attention Network Test (Fan et al., 2002), that is designed for determining the individual differences in the efficiency of attentional networks. It is administered on a computer and can be used both in research (e.g.: Redick et al., 2006) and clinical contexts (e.g.: Johnson et al., 2008). However, when it comes to evaluating attention in real-time, during work or task performance, such tests cannot be applied, due their administering in a test-like format. There is a need for determining a method for continuous monitoring of human attention levels, in real-time, which would not require any test administration.

Most driver- or operator- monitoring systems *a priori* take certain physiological or behavioural measures such as pupil or gaze-tracking, or head movements, as real-time indicators of attention (Sigari et al., 2013; Vaca-Recalde et al., 2020; Yang et al., 2020). However, looking at a stimulus does not necessarily imply conscious cognitive processing, as supported by inattentional blindness phenomena, or the looking (perceiving) vs. seeing (attending) research (Beanland & Pammer, 2010).

Furthermore, the same measures are also used as indicators of cognitive load or mental workload (e.g., Murata, 2005), fatigue (e.g., Jap & Lal, 2011), drowsiness (e.g., Brookhuis & de Waard, 2010), and task engagement (e.g., Dehais et al., 2020). It is important to distinguish between these related, yet distinct concepts, for two main reasons. First, attention is directly related to task performance (Jiang et al., 2020; McDowd 2007), and it may be impacted by other factors in addition to the previously mentioned ones such as fatigue (Ballard, 1996; Michael, 2011). Second, detecting minute changes in operator's or driver's attention levels can allow for a timelier intervention and accident prevention compared to drowsiness detection, for instance. This is also to say that the operator may not be fatigued, drowsy, nor under high cognitive load, however, they are being distracted and therefore not entirely focused on the task. This is well illustrated in a report on a pilot study of distracted drivers, where fatigue accounted for 17% of overall specific distractions (Glaze & Ellis, 2003). For those reasons we previously argued that attention is a powerful concept to measure in real-time, and potentially superior to fatigue detection (Bjegojevic et al., 2021).

The role of what is known as top-down or goal-directed attention is essential for sustaining attention on the task and avoiding distractions (whether external or internal, such as mind-wandering). When a person is fatigued, top-down attention is more severely impacted compared to bottom-up or stimulus-driven attention (Boksem et al., 2005). Despite the fact that sustaining attention over prolonged periods of time is a critical requirement, especially in driving, there the literature has not yet agreed on an optimal method to measure attention in real-time.

The aim of this paper is to present a brief overview of the physiological measures and what aspect of attention they may be representative of (e.g., active engagement, vigilance, arousal etc.). Several electroencephalography- , eye-tracking- , and electrocardiography- based variables are identified in the literature as potential real-time proxies of changes in different aspects of attention. Furthermore, this paper provides an overview of a design of experiment aimed at determining which of those variables may be a better proxy of attention level on task, when compared with task performance metrics including reaction time and error rates.

2. Performance metrics and physiological sensors as potential tools for real-time monitoring of attention

2.1. Performance (behavioral) metrics

Reaction time and reaction time variability are often used as a behavioural measure of attention, specifically vigilance or sustained attention (Levy et al., 2018; Korber et al., 2015; Tamm et al., 2012). Reaction time tends to increase with time on task, due to the effects of mental fatigue on attention (Boksem et al., 2005). Greater reaction time variability is typically found in people diagnosed with Attention-Deficit/ Hyperactivity Disorder (ADHD) compared to control group (Tamm et al., 2012).

Errors are another behavioural measure indicative of attentional processes. Errors of omission, or the instances when we fail to react or respond to a task requirement, are considered as indicators of attentional lapses (Tamm et al., 2012). Unlike reaction time, which is measured in a continuous fashion, omissions are a binary variable (they either happen, or not). The attentional lapses can be detected through omission errors only when they coincide with a critical event that requires operator's response or reaction. Unless the reaction time is constantly measured throughout the course of a particular task, there is no way of objectively identifying the fluctuations in operator's attention over time.

2.2 Physiological sensors

Measurement of reaction time is not practical in most work settings. Therefore, there is a need for another method for continuous, objective, and unobtrusive (not interrupting the task) detection of the changes in the operator's focus. For that purpose, we have investigated three groups of sensors, including Electroencephalograph (EEG) for measuring the changes in the brain activity over time; Eye-tracker for measuring the eye movements and changes in pupil size, and electrocardiography (ECG) for measuring heart activity. The relevant metrics derived from each of these three groups of sensors are discussed respectively.

2.2.1 Electroencephalography (EEG) metrics

One of the most promising metrics derived from EEG recording that is relevant to attention detection is the Engagement index (EI). It is a metric derived from spectral power of different EEG frequency bands. It indicates the relative amount of active cognitive processing i.e., engaging with a particular task (hence the name). There are different methods of calculating this index (e.g.: $\beta/(\alpha+\theta)$; β/α; and $1/\alpha$) (Coelli et al., 2015). However, a study by Pope et al. (1995) compared the different variations of this index and has shown that beta power / (alpha power + theta power) was the best indicator of task engagement. As a ratio between the high and low frequency waves ($EI = \beta/(\alpha+\theta)$) (Mijovic et al., 2017), the increase in its value is indicative of person's higher mental engagement with the task. Another relevant EEG metric to consider is the Cognitive Load index (CLI, also known as Mental Workload Index). Some authors use this index as an indicator of attention levels and cognitive load (Mahajan, et al., 2014). Since the optimal levels of attention are achieved when the experienced task difficulty is moderate, it is important to take the subjectively experienced cognitive load into account. Cognitive Load Index is calculated as a ratio of frontal theta and parietal alpha power (Dan & Reiner, 2017).

2.2.2 Eye-tracking metrics

As discussed in our previous paper (Bjegojevic et al, 2021), several eye-tracking measures could be used as indicators of attention and mental fatigue. In that paper, we have grouped the eye-tracking measures into pupil-, blink-, and eye-movement-based variables. Many of these measures are sensitive to fatigue, since attention is directly impaired by fatigue (Williamson et al., 2011). Pupil size is a good example of this. Pupil size changes in response to many factors, including attention and cognitive engagement (Peysakhovich et al., 2015), and arousal (Bradley et al., 2008). However, it is also heavily affected by lighting conditions, so these extraneous variables must be considered, and controlled or corrected for when using this metric (Beatty & Lucero-Wagoner, 2000). Blinks are also affected by many factors including task difficulty, mental fatigue, and cognitive load (Benedetto et al., 2011). Some authors consider the metrics derived from blinks as a good indicator of sustained attention (Maffei & Angrilli, 2018). Saccadic amplitude and velocity decrease as vigilance drops (Bodala et al, 2016). Saccadic peak velocity is considered as a good index of arousal (Di Stasi, 2013).

2.2.3 Electrocardiography (ECG) or heart rate metrics

A simple sensor in a form of a chest strap can be used to detect the changes in heart activity. The hart rate variability (HRV) could be a useful measure, as it shows the changes in alertness or arousal level (Yuda et al., 2017). HRV is proposed to be used as a peripheral index of central nervous system networks underpinning goal-directed behavior (Thayer et al., 2009). The ratio between low and high frequency power of heart activity signals (LF/HF) is indicative of the ratio between the sympathetic and parasympathetic nervous system activity (Shaffer & Ginsberg, 2017). The sympathetic branch of the autonomous nervous system is responsible for the chain of physiological reactions known as "fight or flight" response activation, indicating the presence of a stressful situation, while the parasympathetic branch is a dampening system activated in the "rest and digest" or stress-free conditions (LeBouef et al., 2020).

A recent study (Lees et al., 2021) found that low frequency spectral power of heart rate variability correlated with decreased brain activity during simulated monotonous train driving. A decrease in LF as well as in LF/HF is considered as a risk factor in driving (Michail et al., 2008). Optimal arousal levels are necessary for adequate attention; therefore, heart rate variability should be considered as an important indicator of readiness to be attentive.

Table 1. Groups of variables as proxy indicators of different aspects of attention, as found in the literature.

Measurement Group	Variables	Proxy of	Reference
BEHAVIORAL / PERFORMANCE	Reaction Time (RT)	*Attention*	Maffei & Angrilli, 2018
	Omission Errors	*Attentional lapses*	Tamm et al., 2012
EEG	Engagement Index (EI)	*Active engagement with the task (Focus)*	Coelli et al., 2015; Mijovic et al., 2017; Pope et al., 1995
	Cognitive Load Index (CLI)	*Attention level / Cognitive Load*	Mahajan, et al., 2014
EYE-TRACKING	Pupil size variability	*Attention & Cognitive engagement*	Peysakhovich et al., 2015;
	Blink rate and amplitude	*Sustained attention*	Maffei & Angrilli, 2018
	Saccade amplitude and velocity	*Vigilance/ Arousal*	Bodala et al, 2016; Di Stasi, 2013
ECG	Heart rate variability (HRV)	*Arousal / Stress*	Yuda et al., 2017

To test the relationship between all these variables and their correlation with attention and performance, we have designed a lab-based study and an experimental task. These are presented in the following sections.

3. Experiment design

3.1. Experimental task

For monitoring attention levels while an operator is performing a continuous task, we designed an experiment using NASA Multi Attribute Task Battery (MATB-II), originally devised for human performance and workload research (Santiago-Espada et al., 2011). This software has several subtasks embedded that can be programmed as desired, with certain constrains. Three subtasks are used in this experiment marked in Figure 1: 1) System Monitoring (only the scales, not the lights); 2) Communications; and 3) Resource Management.

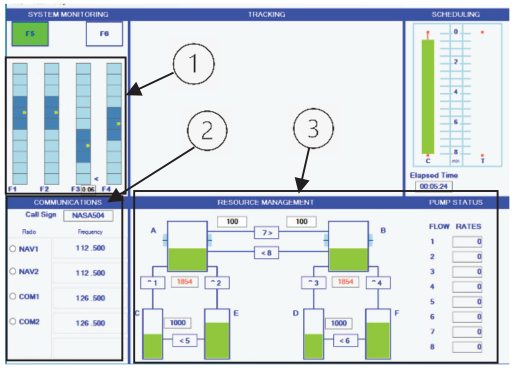

Fig. 1. Task interface with three used subtasks marked.

System Monitoring is the main or primary subtask in this study. The goal of this subtask is to keep the scales that are constantly shifting up and down in the centre of each of the four bars. It is deployed in training mode: an indicator appears pointing to the scale that needs to be clicked. This is to eliminate the decision-making aspect, therefore transforming this task into a simple reaction-time task.

Communications subtask involves audio messages that ask the operator (study participant) to select the verbally indicated radio and to change it to the specified frequency. There are four different radios (COM1, COM2, NAV1, and NAV2) and a range of frequencies that can be chosen. The subject is required to change the frequency on the denoted radio only when the audio message starts with a call sign ‘NASA 504’, which is the name of the ‘aircraft’ the participant is controlling. Otherwise, the message should be ignored.

Resource Management subtask is a fuel management system that contains six tanks (labelled A through F) and eight pumps (labelled 1 through 8). Tanks E and F contain an infinite amount of fuel, whereas the others can run out of it. Participant's task is to maintain the level of the fuel in main tanks, A and B, as close as possible to the initial level of 2500 units in each. This is done by transferring the fuel from the other tanks via clicking on the adequate pumps. This task is initiated when the pumps 2 and 4 break down (Figure 1, area number 3). Once these two pumps become red in colour, it signifies they are broken and that fuel in the main tanks needs to be maintained via all remaining pumps. Throughout the entire time this subtask is active, pumps 2 and 4 remain broken, to disable the option of direct transfer of fuel from the tanks with an infinite amount of fuel to the main tanks. The Resource Management is designed in this was to require more engagement from the study participants.

To manipulate the operator's attention, we designed four task conditions incurring different attentional demands (top-down or bottom-up attention) and different task loads (low, medium, and high) (Table 2). Different sensory modalities of the subtasks and their combinations generate different attentional requirements and contribute to the task difficulty or task load.

The first condition in order is a baseline condition involving 60 events, timed at random intervals between 2 and 8 seconds, in the system monitoring task only. It only requires bottom-up attention, as the participant is required to simply click on the scale every time an indicator appears pointing to it.

Following are three other conditions that involve one of two secondary tasks (Communications and Resource Management Task), or both. As shown in Table 2, a different type of attention is required in each of these conditions, due to the combination of subtasks. When participant's focus is shifted from the primary subtask (System Monitoring) by an auditory cue as a signal to complete a command in the Communications task, this shift in attention is controlled by 'bottom-up' processes. Having to switch the attention voluntarily and constantly from one subtask to the other, such as in conditions 3 and 4, requires 'top-down' control of attention.

The baseline condition is repeated at the end to estimate the fatigue level incurred by the vigilance nature of the task.

Table 2. Different task conditions designed to incur different attentional demands and task loads.

Condition	1	2	3	4	5
Sub-tasks	SM	SM + CO	SM + RM	SM + CO + RM	SM
Sensory modality	Vis	Vis + Aud	Vis + Vis	Vis + Aud + Vis	Vis
Attentional demand	Bottom-up	Bottom-up + Bottom-up	Bottom-up + Top-down	Bottom-up + Bottom-up + Top-down	Bottom-up
Task load	Low	Med	Med	High	Low

* SM = System Monitoring; CO = Communications; RM = Resource Management; Vis = Visual; Aud = Auditive

Half of the study participants are presented with this sequence of task conditions, designed to gradually increase in the task load and attentional demands. The other half of participants are presented with the same sequence except for the conditions 2 and 4, which are flipped, to mimic a sudden, steep increase in the load and demand (Table 3). Differences in sensitivity of performance, physiological, and subjective measures to the rate of change in task load have been observed in another study using MATB software (Muñoz de Escalona et al., 2020.)

Each of the conditions lasts about 5:30 minutes and their transitions are seamless, so to the participant the task appears continuous.

Table 3. Experimental groups and task condition sequences.

Experimental group	***Condition sequence***
1	1 - **2** -3 - **4** - 5
2	1 - **4** - 3 - **2** - 5

3.2. Variables

Three groups of physiological measurements are considered in this study as potential proxies of the changes in attention: electroencephalography (EEG), eye-tracking, and electrocardiography (ECG). Along with the physiological variables, behavioural measures are recorded, including reaction time (RT), task performance (errors and accuracy), as well as subjective assessment of participant's focus (attention), tiredness (fatigue), and task difficulty (task load or cognitive load), in a form of Likert-type scale from 1 to 10.

3.3. Equipment

For recording the brain activity during the task, a semi-dry wireless EEG (mBrainTrain) with 24 channels and sampling frequency of 500Hz is used. The electrodes are embedded in a cap adhering to the international 10-20 system of electrode placement (Howman, 1988). The cap utilizes sponges immersed in saline solution for conducting the brain signals.

Eye-movements and pupil size are recorded with a wearable eye-tracking device (Core, PupilLab). The eye-tracker has two eye-facing cameras with a sampling frequency of 200Hz, and a world-facing camera that records the video of what participant is facing. To accurately detect the wearer's gaze, the eye-tracker requires a quick calibration first.

A chest strap (Polar H10) is used to detect the heart activity. It has an electrode sensor embedded in a rubber band that is strapped under participant's chest in contact with the skin.

All equipment is safe to use and is cleaned after each individual use.

3.4. Experimental procedure

The experimental procedure is as follows: the participant is presented with a video containing detailed task instructions, followed by a short quiz and a practice session, to ensure that the task requirements are fully understood.

After the equipment is set up and calibrated, one minute of baseline physiological activity is recorded. Before the start of the task, as well as at the end of it, participants are asked to provide a self-assessment of their focus and tiredness levels on a scale from one to ten. This is repeated throughout the task, once per each condition, along with the subjective task difficulty assessment. A similar on-line approach of fatigue self-assessment was used in another study combining performance, subjective, and physiological measures (Muñoz-de-Escalona & Delgado, 2020).

4. Planned Analyses

The correlation between behavioral / performance, physiological, and self-assessment data will be tested. Average RT and standard deviation of RT in each condition will be used as indicators of attention level in each condition. Also, the intercorrelations between various physiological variables will be tested. The variables which achieve highest correlations with proxies of attention will be further evaluated in a follow-up study in a more naturalistic environment.

Having a valid and reliable moment-to-moment estimation of attention would have numerous applications such as designing of a feedback device that informs the operator when their attention is decreasing, in collaborative robotics design, driver monitoring systems, etc. Also, it could allow for prediction of the drop in operator's attention level which would greatly enhance accident prevention.

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