Real-time mental workload assessment with low intrusiveness for assembly processes: Limits and preliminary results

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Edited by
Livan Fratini,
Luca Settineri

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Editors

Livan Fratini[1] and Luca Settineri[2]

[1]Dipartimento di Ingegneria, University of Palermo, Palermo, Italy
[2]Dipartimento di Ingegneria Gestionale e della Produzione (DIGEP), Politecnico di Torino, Torino, Italy

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Real-time mental workload assessment with low intrusiveness for assembly processes: Limits and preliminary results

Riccardo GERVASI[1,a *], Matteo DE MARCHI[2,b], Luca MASTROGIACOMO[1,c], Dominik T. MATT[2,d] and Fiorenzo FRANCESCHINI[1,e]

[1]Department of Management and Production Engineering, Politecnico di Torino, Turin, Italy

[2]Faculty of Science and Technology, Free University of Bozen-Bolzano, Bolzano, Italy

[a]riccardo.gervasi@polito.it, [b]Matteo.DeMarchi@unibz.it, [c]luca.mastrogiacomo@polito.it, [d]Dominik.Matt@unibz.it, [e]fiorenzo.franceschini@polito.it

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Abstract. The real-time assessment of mental workload emerges as crucial in Industry 5.0 for optimizing human performance and wellbeing when interacting with complex systems. However, balancing diagnosticity and sensitivity with low intrusiveness in such assessments remains challenging. According to ISO 10075, mental workload is a broad concept encompassing several observable phenomena (e.g., monotony and mental fatigue), each requiring special attention. This paper explores current techniques for real-time assessment of mental workload in manufacturing and presents preliminary results from a case study in an assembly line. The case study integrates physiological metrics (i.e., heart rate variability, electrodermal activity, and eye-tracking) collected by non-invasive biosensors with task performance metrics to highlight benefits and limitations of a low intrusive real-time assessment setup. The need to use more metrics to reliably identify the operator's psychophysical state is also highlighted.

Introduction

The transition to Industry 5.0 aims to achieve a human-centric approach in industrial systems by encouraging seamless interaction between humans and complex technological systems, such as collaborative robots. Cognitive ergonomics plays a key role in this paradigm, addressing how mental processes affect the interaction between operators and autonomous systems and trying to adapt the work environment to the cognitive abilities and needs of the human operators involved [1]. There are some pioneering works in the literature that present real-time assessment frameworks and setups [2], however they often require the adoption of biosensors that can be invasive and limiting for an operator in a manufacturing context, especially in assembly processes. The objectives of this paper can be summarized by the following research questions: (i) *How intrusive are current methodologies for real-time monitoring of mental workload in a manufacturing context?* (ii) *What limitations may arise by using a nonintrusive setup?*

To address these questions, an overview of current methods related to real-time assessment of mental workload will be presented, highlighting intrusiveness and diagnosticity. A preliminary case study of an assembly process will also be presented, in which noninvasive methodologies for studying the mental processes involved are implemented to explore advantages and limitations of a noninvasive setup.

Cognitive ergonomics and real-time evaluation methods

Cognitive ergonomics deals with the interaction between a human being and the elements of a system by studying the mental processes involved (e.g., perception, attention, memory, reasoning, and emotion), with the ultimate goal of designing systems in line with users' cognitive abilities and mental representation. A topic closely involved in cognitive ergonomics is the evaluation of aspects related to mental workload, which is a domain that analyzes the mental-level effects of external factors (e.g., environment, task) on human beings [3]. In the context of cognitive ergonomics, it therefore becomes crucial to identify and mitigate the negative effects related to mental workload. The following subsections will describe the negated effects related to mental workload according to ISO 10075 [4], as well as methodologies for evaluating these effects in real time showing potentials, limitations and tradeoffs in terms of invasiveness.

Negative effects related to mental workload

According to ISO 10075 [4], mental workload refers to a domain which encompasses concepts and constructs related to the relationship between external factors (i.e., stressors) and the resulting mental processes for exposure to them, modulated by an individual's internal characteristics (e.g., age, gender, skills, attitudes, health).

The work environment is composed of various stressors that together constitute a certain "load", called *mental stress*, that mentally affects an individual [4]. Some examples of stressors are task requirements (e.g., task content, duration), physical conditions (e.g., noise, climatic conditions), social and organizational factors (e.g., conflicts, group factors), and societal factors external to the organization (e.g., cultural standards, economic situation).

The exposure to *mental stress* induces mental processes that can lead to facilitating/positive effects or impairing/negative effects. The immediate impact within an individual resulting from *mental stress* is called *mental strain* and it is moderated by the individual's characteristics and actual conditions [4]. Depending on the duration and frequency of exposure to a given mental stress, short- and long-term effects may occur. Short-term effects (both positive and negative) are characterized by being transient, in that they can be eliminated by a change of task or by rest. Table 1 presents an overview of the short-term effects outlined in ISO 10075. Repeated exposure to certain conditions can lead to effects (both positive and negative) that persist for long periods or are chronic [4]. For example, burnout is a long-term negative effect that can be achieved after repeated exposure over time to conditions that lead to short-term negative effects such as mental satiation. On the other hand, skill development is a positive long-term effect that is achievable with prolonged and repeated exposures to certain conditions. Consequently, to create a healthy work environment from the perspective of cognitive ergonomics, it is first necessary to identify the presence of short-term negative effects in order to mitigate or eliminate their causes.

Real-time evaluation methods

In the context of cognitive ergonomics, there are several techniques for assessing mental workload-related effects which can be divided into mainly three categories: self-reporting methods, performance measures, and psychophysiological measures [5]. The term "real-time" refers to the process of collecting, processing, and interpreting data at short intervals — typically within seconds or minutes — so that a system can detect changes immediately as they happen. Real-time monitoring of mental strain can enable dynamic adaptation, allowing timely corrective interventions (e.g., rest breaks, task changes) or proactive management through support systems such as cobots. In a real-time setting, the intrusiveness (i.e., the extent to which it interferes with the performance of the primary task and the operator comfort) of an assessment method plays a key role in collecting information in a naturalistic manner in a dynamic context (e.g., assembly processes).

Self-reporting methods rely on subjective evaluations, mostly though questionnaires, providing direct insight into an individual's perceived workload. Example of widely used self-reporting methods are the NASA-TLX and SWAT [5]. Although these methods allow operator perceptions to be collected, these methods are often not suitable for real-time monitoring, as they usually require the operator to interrupt the process.

Performance measures are objective indicators that monitor performance aspects in a given task and are used to indirectly assess mental workload [5]. Examples of commonly used performance measures are task completion time, cycle time, error rate, reaction time, and accuracy. The extremely low intrusiveness of these methods makes them suitable for real-time monitoring, however, performance-only measures are often not very sensitive to changes in mental strain and in identifying affective states.

Table 1. Short-term effects according to ISO 10075 [4].

Type of effect	***Consequence of mental strain***	***Description***
Felicitating/ Positive effect	*Warming-up effect*	Phenomenon characterized by a decrease in the effort needed to perform an activity shortly after it begins, compared to the effort initially required.
	Activation	Internal state that leads to increased mental and physical activity. Varying levels of activation can occur based on the duration and intensity of mental strain, with an optimal range where activation levels yield the highest functional efficiency.
	Learning	Process driven by experiences that results in enduring changes in an individual's behavior, plans and attitudes.
Impairing/ Negative effect	*Mental fatigue*	Internal state characterized by a temporary reduction in mental and physical functional efficiency (e.g., feelings of tiredness and/or increased likelihood of errors). It can be eliminated through rest.
	Monotony	Gradually developing state of reduced activation, typically associated with drowsiness and diminished performance, responsiveness, and adaptability. It commonly arises during repetitive, prolonged, and uniform tasks. Although not immediately, recovery from this state occurs after changes in the task or environment.
	Reduced vigilance	State characterized by decreased activation and diminished detection performance during monitoring or inspection tasks that involve limited variety. Recovery from this state occurs after changes in the task or environment.
	Mental satiation	State of nervously unsettled, strongly emotional rejection of a repetitive task or situation in which the experience is of "marking time" or "not getting anywhere". It is often associated with unchanged or increased activation and adverse emotion or mood (feelings of tiredness and/or decreased performance, and a tendency to withdraw).
	Stress response	State within an individual characterized by increased mental (concerning both cognitive and emotional components) and/or physical activation resulting from the negative interpretation of *mental stress* (e.g., perceived as threat or hindrance to one's goals or values).

Psychophysiological measures are particularly well-suited for real-time evaluation settings and provide objective insights into mental workload by monitoring an individual's psychophysiological signals and responses linked to mental strain [6]. Electroencephalography (EEG) and functional Near Infrared Spectroscopy (fNIRS) monitor brain activity, allowing for accurate detection of activations of different brain areas associated with different functions (e.g., motor area, emotional area, cognitive area) [7,8]. Although EEG provides extensive information about mental processes, it is very sensitive to artifacts commonly found in a manufacturing context [5]. In addition, EEG often requires head-mounted electrodes that can be intrusive to the operator and cause discomfort. Electrocardiography (ECG) and photoplethysmography (PPG) are two techniques for monitoring hearth activity, which is influenced by the autonomic nervous system and, consequently, by an individual's physical and mental process [9]. One heart parameter often observed is heart rate variability (HRV), which represents the variability present in the time intervals between systolic peaks (i.e., NN-intervals). The lower the HRV, the lower the individual's ability to adapt to imposed physical or mental stresses, translating into greater strain. Two commonly used measures of HRV are the standard deviation of NN-intervals (SDNN) and root mean square of the successive differences of NN-intervals (RMSSD) [5]. Acquiring information about the heart's activity can be noninvasive, as there are specific wearable biosensors in the form of bracelets, smartwatches, and chest bands that do not hinder an operator's activity. Electrodermal activity (EDA) monitors changes in skin conductance due to the sweat gland activity, which is directly influenced by the sympathetic nervous system arousal [9]. Consequently, through EDA, physical and mental activations can be accurately monitored. EDA can be decomposed into two components: skin conductance response (SCR) and skin conductance level (SCL). SCR consists of rapid fluctuations in skin conductance that usually occur in response to emotional or arousing stimuli (i.e., phasic activity). SCL, on the other hand, consists of slower fluctuations that reflect the continuous activity of the sympathetic nervous system (i.e., tonic activity). Facial expressions analysis can also provide useful clues on the operator state and can be performed non-invasively though external cameras [10]. Eye tracking is a useful method for gathering information on visual attention and its related mental strain, relying on the analysis of fixations, saccades, and pupillary dilation [11]. Eye tracking can be performed noninvasively, either through special external cameras or wearable glasses.

Preliminary case study

To investigate the potential and limitations of a noninvasive setup for real-time assessment of cognitive ergonomics, a preliminary case study will be presented and analyzed.

A 100-minute repetitive assembly process of a diaphragm water pump (Figure 1) was recreated at the Mind4Lab laboratories of the Politecnico di Torino. This process was intended to elicit mental states of monotony, mental satiation and mental fatigue in the operator. The assembly process can be decomposed in the following steps:

1) *Assembly of the pump head*. Flange F1 is inserted inside flange F2, and diaphragm D1 is attached to flange F1 with three screws (V2). Next, the component CV is inserted with the diaphragm D1 into the slots provided, and finally the cover (C) is placed on the flange F2, securing it with three screws (V2).
2) *Joining with the engine block*. The rubber support (RF) is attached to the engine block (EB) with the two screws (V1). The previous assembly related to the pump head is taken and fitted to EB, finally securing it with three screws (V3).
3) *Finalization of the pump*. The diaphragm D2 is inserted into the cover housing (C) and then the pressure switch (PS) is fixed with two screws (V4). Assembly is completed by fitting the filter (FIL) and the two adapters (AF1 and AF2).

During the assembly process, the operator wore two noninvasive biosensors: a pair of Tobii Pro Glasses 3 eye-tracking glasses and the Empatica E4 wristband (Figure 2). These biosensors were used to obtain information on fixations, pupil dilation, EDA and HRV. The assembly cycle time of each assembled product was tracked as a performance indicator. The assembly cycle time of each assembled product was also tracked. Unstructured feedback from the operator was collected every 20 minutes by asking what sensations he or she was experiencing. This information was used to verify the onset of the expected mental states in the operator and a match in the observed patterns in the evolution of psychophysiological and performance indicators.

Preliminary results

This section will present, as an example, the results of one participant (25-year-old male) drawn from a group of participants who had no previous experience in assembling the case study product. After explaining the structure of the study, how to assemble the pump and mounted the biosensors on the participant, the 100-minute assembly process began. Table 2 shows the unstructured feedback collected at various points in the process every 20 minutes without interrupting the process. EDA was decomposed using the MATLAB tool Ledalab [12], while eye-tracking

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indicators were extracted through the software Tobii Pro Lab. As HRV indicator, RMSSD was obtained from the NN-intervals extracted by the Empatica E4 internal algorithm.

Table 2. Unstructured feedback of the participant collected during the assembly process.

20th minute	***40th minute***	***60th minute***	***80th minute***	***100th minute***	***Overall feedback***
"Fine, all smooth"	"Bored"	"Tired, alienated, bored, slow on some activities, faster on others"	"Somewhat stressed, more distracted, mentally tired, monotonous activity"	"Increasingly stressed"	"Tedious and boring experience, I feel tired and less responsive."

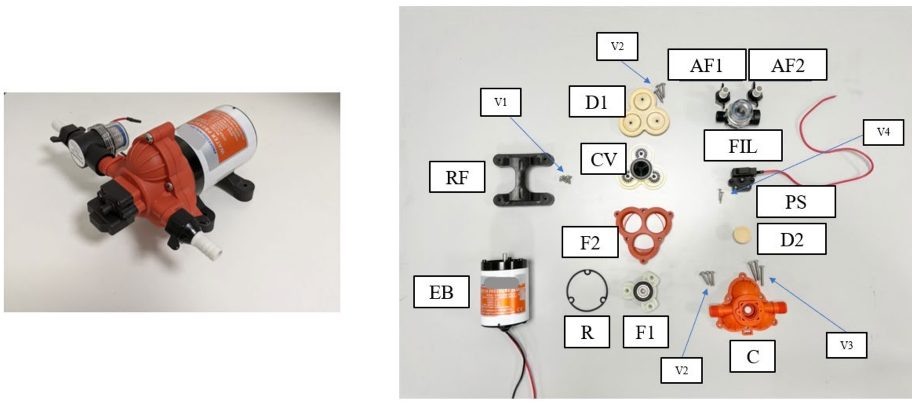

Figure 1. The diaphragm water pump and its components.

Figure 2. The implemented noninvasive biosensors: Tobii Pro Glasses 3 and Empatica E4 wristband.

Figure 3 shows the evolution of the psychophysiological indicators and performance in terms of assembly cycle time. Psychophysiological indicators were calculated every 30 seconds considering a time window of 240 seconds, to ensure sufficient data for each type of signal and reduce noisy fluctuations. It can be observed that:

- By the 20th minute, the SCL and SCR were quite stable with low values, which can be associated with a calm state, in line with the participant's feedback. The number of fixations at the beginning increased and then decreased, which can be associated with an initial activation due to a learning process. This effect can also be seen in pupillary dilation, which starting from high values, a decrease is observed gradually, showing a decrease in mental strain. Regarding HRV, from the RMMSD a slight gradual increase is observed associated with a gradual relaxation. The effect of warming-up and learning is also visible in performance, with a consistent decrease in assembly cycle time.

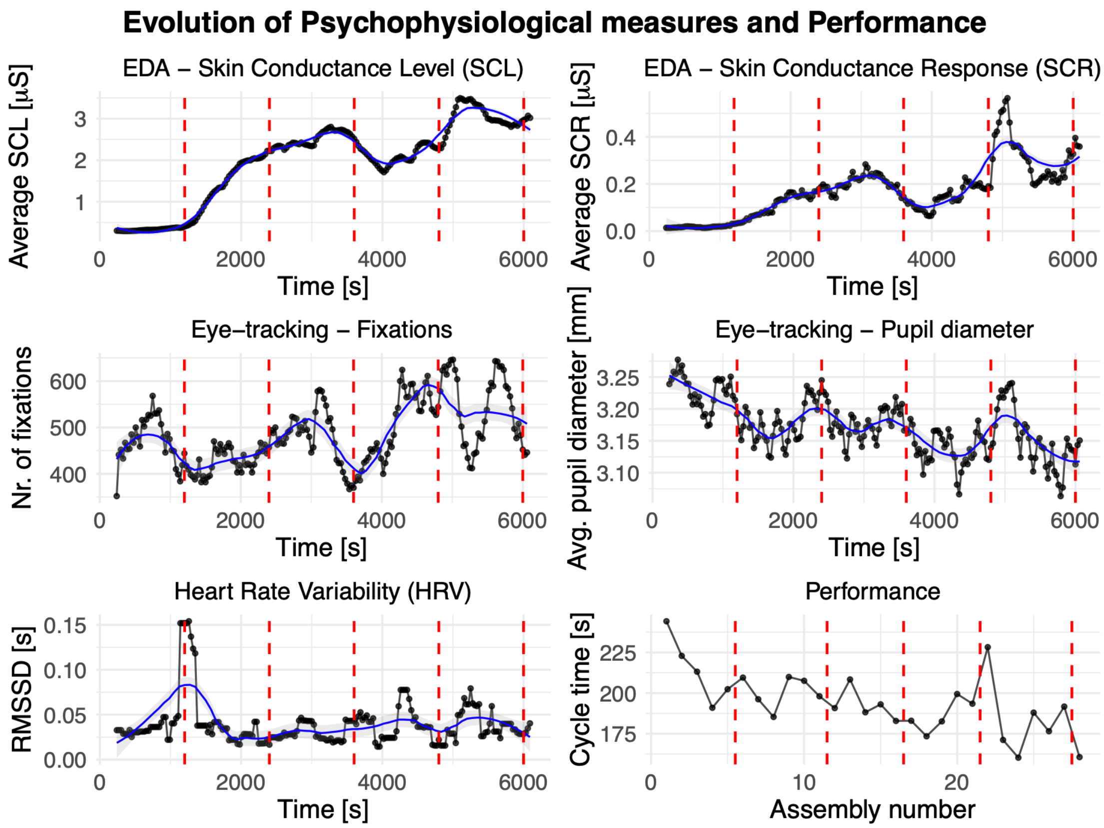

Figure 3. Evolution of psychophysiological indicators and performance for the selected participant. The dashed red lines represent the moments when unstructured feedback was asked to the participant.

- By the 40th minute, perceived boredom seems to be reflected in more unstable signals (i.e., number of fixations and pupil diameter). SCL and SCR increase stably, while RMSSD decreases slightly, suggesting increased activation attributable to physical activity. Assembly cycle times fluctuate slightly but still remain lower at the beginning of the process.
- By the 60th minute, SCL and SCR still increase, indicating increased physiological activation probably due to physical exertion, and then begin to decrease slightly. Pupillary diameter continues to fluctuate, while the number of fixations at first increases and then decreases significantly, indicating a reduction in attention. RMSSD remains fairly stable, while assembly cycle times tend to decrease slightly. The observed patterns are partially matched by feelings of fatigue, alienation and boredom attributable to mental satiation.
- By the 80th minute, the participant feels somewhat stressed, more distracted, mentally tired, symptoms of mental satiation. SCL and SCR grow slightly, presenting fluctuations. As the number of fixations increases, pupillary diameter decreases slightly and has several fluctuations, attributable to more distraction seeking stimuli. RMSSD also exhibits more fluctuations and there is a decrease in performance with an increase in assembly cycle time. These increased fluctuating activations and decreased performance are in line with the mental satiation state.
- By the 100th minute, the participant feels more stressed, indicating mental fatigue. This state is reflected in an increase in SCL and SCR with noticeable fluctuations in the latter.

More fluctuations continue to be evident in the RMSSD. Notable fluctuations are also evident in the number of fixations, while instead the pupillary diameter increases rapidly initially and then slowly decreases. There is also a worsening of performance, especially in the 22nd assembly, where due to an error the assembly cycle time increased and resulted in particularly observable activations in the SCR, pupillary diameter and number of fixations.

Table 3 provides a summary of the observed signal patterns associated with the different mental strain effects present in the exploratory case study. In addition, a comparison of the observed patterns with the expected qualitative patterns based on expert evaluation and literature is reported, showing a fair correspondence [11,13,14]. Only a discrepancy can be observed for the monotony state in SCL and SCR, which were observed to be increasing mainly due to physical activation, but the observation of fluctuations in eye-tracking metrics and performance were helpful in identifying the phenomenon. In addition, it emerges how the use of multiple signals becomes necessary to ensure the reliability of identification of the operator's psychophysical state, since individual signals can also be influenced by other factors.

Table 3. Summary of observed signal patterns associated with the different mental strain effects present in the preliminary case study. Expected patterns based on experts and literature are reported in brackets.

Legend: ↗ Increasing; ↘ Decreasing; → Stationary; ↝ Fluctuating.

Mental strain effect	***EDA***		***Eye-tracking***		***HRV***	***Performance***
	SCL	***SCR***	***Nr. of fixations***	***Avg. pupil diameter***	***RMSSD***	***Cycle time***
Activation	↗ (↗)	↗ (↗)	↗ (↗)	↗ (↗)	↘ (↘)	↘ (↘)
Learning	→ (↘)	→ (↘)	↘ (↘)	↘ (↘)	↗ (↗)	↘ (↘)
Mental fatigue	↝ / ↗ (↝)	↝ / ↗ (↝)	↝ (↝)	↘ (↘)	↝ (↘)	↝ (↝ /↗)
Monotony	↗ (↝ / ↘)	↗ (↝ / ↘)	↝ (↝ / ↘)	↝ (↝ / ↘)	↝ (↗)	↝ (↝ /↗)
Mental satiation	↗ (↗)	↗ (↗)	↗ (↗)	↝ (↝)	↝ (↘)	↝ (↝ /↗)

Discussion and Conclusions

Monitoring cognitive and mental aspects in real-time in dynamic environments, such as manufacturing, requires the use of non-invasive and unobstructive methodologies, so that information about the operator can be obtained in the most naturalistic manner possible without introducing discomfort. Among the various methodologies, psychophysiological signals offer an interesting opportunity to monitor in real-time the mental and emotional processes involved in a work environment. Different signals offer different perspectives on the nature of physiological activations, providing a broad overview of a person's psychophysical state. However, there is often a trade-off between invasiveness and diagnosticity.

The example case study implemented a noninvasive setup consisting of two wearable biosensors in the form of commonly used accessories: a bracelet and a pair of glasses. Preliminary results showed the importance of considering more than one psychophysiological signal to fully understand the operator's psychophysical state. EDA provided information on activations of both a physical and mental nature, while eye-tracking metrics allowed better identification of moments of learning, relaxation, and distraction. The combination of these two methods, together with performance monitoring, allowed different mental states (e.g., learning, activation, monotony, mental satiation, and mental fatigue) to be distinguished, finding evidence in participants' unstructured feedback. HRV, particularly RMSSD, was not useful in distinguishing the various mental states. However, the main general limitation that emerged is the not immediate understanding of the valence of the operator's affective state. Valence allows one to distinguish between positive (e.g., relaxation or engagement) and negative (e.g., boredom or nervousness) affective states and interpret the origin of psychophysiological activations. In the case study, valence information was inferred by jointly analyzing the context, time spent in the process, performance, and patterns of psychophysiological signals. The results presented should be treated in exploratory terms, as generalization of the observations that emerged will be possible following larger experimental campaigns. However, these initial results help to formulate an initial hypothesis on signal patterns that might be observed in a systematic study. In addition, it should be noted that different subjects may have different initial signal baselines that should be considered when analyzing data across multiple subjects. Future work will focus on comparing the current setup with more comprehensive and invasive setups (e.g., with EEG) to check whether significant differences in information emerge for assessing operator state in an assembly process. In addition, a systematic experimental campaign will be carried out on a large sample of subjects, supported by a quantitative analysis to better explore the consistency of signal patterns.

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