Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 50 (2016) 524 – 528

www.elsevier.com/locate/procedia

26th CIRP Design Conference

Evaluating four devices that present operator emotions in real-time

S. Mattsson[a], J. Partini[b] and Å. Fast-Berglund[a]*

[a]Chalmers University of Technology, Hörsalsvägen 7A, SE-41692 Gothenburg, Sweden
[b]CGM, Bockasjögatan 15, SE-50430 Borås, Sweden
* Corresponding author. Tel.: +46-772 36 86; *E-mail address:* asa.fasth@chalmers.se

Abstract

Industry 4.0, Internet of things and the field of Big Data, introduces challenges in terms of how to present and evaluate different types of data. An emerging field is how to use and incorporate new technology in industry in order to improve health, safety and enhance the human performance at working environment. One promising application is measuring physiological data combining it with work environment data to ensure a good working environment for the operator. A research project DIGitalized well-beINg (DIG IN) has the aim to show how operators' well-being can be measured digitally and demonstrate how data can be used and presented in real-time. Four digital devices that measure physiological data (heart rhythm, EEG, activity, temperature) were tested in 13 lab experiments to examine how operators' perceived the devices. As a further study the devices were tested during three types of activities (intuition, reasoning and physical load) and was evaluated using surveys. The evaluation included relevance of output data, industry applicability, real-time usage and general usability. Results show that the arousal and activity bracelets were best fitted and that individual experience is important.

Peer-review under responsibility of the organizing committee of the 26th CIRP Design Conference

Keywords: Operator emotion, external factors, well-being, digital devices, evaluation, experiment study.

1. Background

To manage future production systems means to successfully manage the interaction between humans and automation [2]. To create a socially sustainable production it is in addition important to keep competitiveness and avoid costly personnel turn-over and knowledge-drain. In that sense, the production system must become an attractive work place for a work force with a varying age, experience level and health issues [3]. Companies therefore need to be attentive to personnel wellbeing and subjective experience [4, 5]; or else they will risk loosing possible work force to other branches.

The rapid technology development is connected to both challenges and possibilities. Industry 4.0 (where the key words are the internet of things, big data and automation) is making a tremendous effort to transform the traditional working environment to more adjustable and personalized working environment [6], where operator needs and requirements are taken in to consideration. Challenges lies in interpreting big data using smart semantic middleware to visualize patterns, visualizing patterns, presenting trends and giving accurate information and feedback to the operator, in order to improve health, safety and well-being at working environment and so far only the vision of how that will be performed is presented [7]. Another challenge that remains is integrity, due to cyber security and inappropriate use of personal date. For Human-Automation Interaction there are many possibilities where for instance devices can reduce complexity, error and influence behavior by giving visible hints to the operator and matching the job to the person at the same time increase the job satisfaction [8].

The introduction of new technology is from a socio-technical perspective connected to many risks and often implementations introduce stress, frustration, reduced happiness and job satisfaction. To support the interaction and optimize operator performance it is important to know what the operator thinks about the system [9]. One way to take this into account is to study how the operators experience affects his or her productivity [10].

The aim of this paper is to present the results of the evaluation of the four digital devices. The evaluation was

Peer-review under responsibility of the organizing committee of the 26th CIRP Design Conference
doi:10.1016/j.procir.2016.05.013

centered on relevance of output data, industry applicability, real-time usage and general usability.

2. Measuring operator emotion

2.1. Operator emotion

During recent years studying human emotions have been come more interesting (experienced emotions and reactions) [11]. By studying how operator emotion relates to the task it is possible to study stress, frustration and boredom and thereby reducing/minimizing the number of errors that can arise due to this [10]. Individual difficulties in assessing and describing one’s own emotions have been noted by many researchers [12]. These difficulties suggest that emotions lack distinct borders, which makes it hard for individuals to discriminate one emotion from another. This indicates correlations between different emotions which researchers address by dimensional models of affect [1]. Russell proposed a structured model of affect states [13], which included the two dimensions of emotion: arousal and valence. Arousal is portrayed in an individual's activity and alertness, galvanic skin response (GSR) and by scales such as wide-awake/sleepy and excited/calm [14]. The dimensions are visualized in Figure 1 [1, 13] where arousal is on the vertical axis and valence on the horizontal axis.

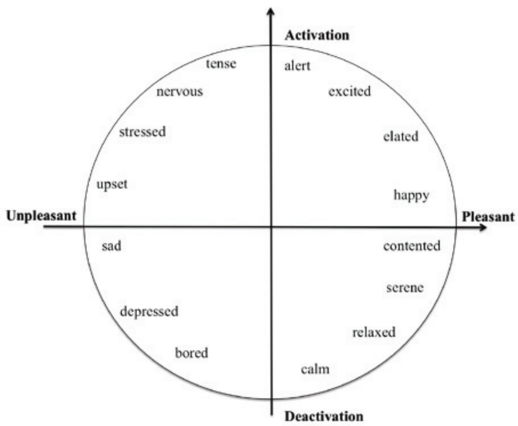

Fig. 1. Russell´s Circumplex Model of affect [1].

Changes in emotion, motivation, habits and attitude have been successfully investigated by studying the changes in the sympathetic branch of the Autonomic Nervous System (ANS) [15, 16]. This has been done by looking at Skin Conductance (SC) which is a measure of the Electro Dermal Activity (EDA) to measure human arousal, attention and cognitive effort [15]. As the sensors are both cheap and can be measured reliably [15], the method can easily be conducted. EDA does however not measure one exact emotion but instead serves as a general indicator for arousal, attention, habituation, preferences and cognitive effort [15, 16].

Since ANS signals could be due to reactions to the situation (noise in background, people walking by) and not to the task itself there is also a difference between participants being passive and active during a measurement [15, 16]. If a person is active like for instance giving a speech, the ANS results could be connected to the action of giving a speech (physiological changes while talking, producing a higher voice) and not the physiological response to the situation.

Another way of measuring ANS is to measure heart rate variability (HRV) [17, 18]. This measurement was a promising measurement to predict sudden cardiac death in 1995. Challenges with this measurement then were to now what the HRV meant and studies indicated that the meaning of the data was more complex than previously believed. Another way to study ANS signals is to measure respiratory factors i.e. breathing activities [19]. Breathing have been connected to emotions e.g. anger, anxiety, disgust and surprise. The same study showed that HRV have been connected to anger, anxiety, disgust, embarrassment as well as some positive emotions e.g. contentment, happiness and joy.

In terms of digital interaction, measures of EEG have become interesting in order to study facial expressions and vocal intonations [20]. EEG measures have also been used as a tool to differentiate positive and negative emotions [21].

2.2. Four devices

Four devices were chosen to measure operator emotion. The selection of devices was based on their possible application in industry applications (complex production). The aim was also to choose devices that measure different types of physiological data. The four devices were (Fig 2):

1. Arousal bracelet (Empatica): measuring blood volume (BVP), heart rate variability (HRV), accelerometer and scin conductance (galvanic scin response, GSR) and temperature (TMP).

2. Breathing activity (Spire): Measures breathing activity in the body by abdominals and lungs move. Three types av activities are chategorized: calm, tense and focused.

3. Activity bracelet (Sony smartband 2): Heart rate variability (HRV). The data is categorized according to three stress levels.

4. Brain activity (EPOC+): EEG through: focus, activity, interest, arousal, relaxation and stress level.

Fig. 2: The four devices 1-4 (top to bottom) and visualizations of their outputs