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Evaluating four devices that present operator emotions in real-time

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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.

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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

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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.

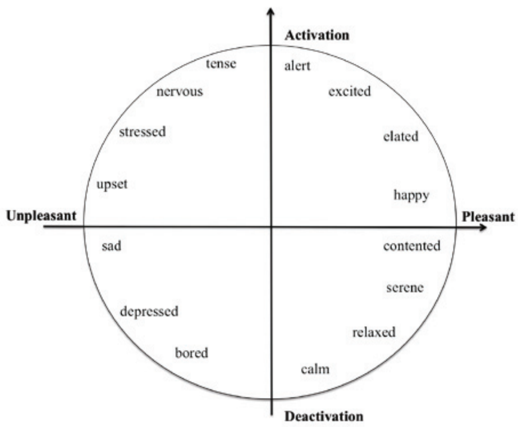

Fig. 1. Russell´s Circumplex Model of affect [1].

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

3. Evaluation

Evaluation comprised 13 experiments and 5 user studies. The user studies included describing participants' first impression of the device and then (one week later) using it while practicing three types of activities (intuition, reasoning and physical load). The aim of the experiment was to find our which device was preferred and why by participants and the aim of the user studies was to get a more detailed view of what participants thought about using the devices and what emotion was connected to the activities.

3.1. Lego experiment

As a first step, 13 experiments were carried out to test how the operator perceived the devices and the presentation of the physiological data that was shown in their own soft-ware. The operators assembled eight lego gearboxes and were affected during the first four assemblies by changes in the physical environment. The experiments were carried out at Chalmers Smart Industry lab (CSI-lab) and the sample included the following groups:

- Three age groups: <30, 30>x<40, 40+ distributed evenly
- 30 percent females and 70 percent men
- 5 novices, 4 average and 4 experts in assembling that specific gear box.

The last device (brain activity, EPOC+) was not included in the experiment

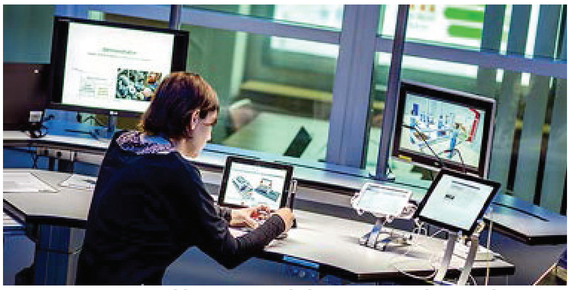

Fig. 2. Assembly station at Chalmers Smart Industry Lab

After the experiment participants watched the output from the software and were asked which device and physiological data they thought was the most and the least relevant, and why. The experiment results showed that data from device 1 and 3 was most relevant for the participants. However physiological data from device 3 and 2 was rated by participants as the least relevant. When asked why the preferred and not preferred a device participants stated that their choice was based on how they perceived themselves. For instance one participant said that she normally does not sweat (and was in general very cold) but that she was very used to recognizing change in her heart rate, which is why she preferred device 3 (activity bracelet). Some participants that preferred physiological data presented from device 1 stated that all devices could be interesting in the long term but that nr 1 seemed more relevant due to its detail level.

3.2. User studies

Five students took part in the user studies testing the devices. First impressions were captured in a survey studying the exterior and the initial perception of the devices. Then three activities were performed and an additional survey was filled in. The survey included questions regarding how well participants' emotion fitted with the devices output data. The three activities *intuition, reasoning* and *physical load* were chosen due to that intuition is often used in assembly [22], that complex problem solving (reasoning) might show different values (cognitive load) [15, 16]. *Physical load* was included due to that production work have been perceived as complex due to both cognitive and physical load [23].

Results showed that the devices were best fitted to participants' own emotions (experience of the activity) during the *physical load* activity. Next best was *reasoning* and the least best was *intuition*. During the *reasoning* activity participants read/wrote theory or did cognitively demanding schoolwork. They stated that they felt focused during that activity and calm during the *intuition* activity. During the *intuition* activity participants were checking Facebook and watching Youtube clips.

Device 2 (breathing activity) was the least sensitive to the activities in general but showed good correspondence to *reasoning* and *physical load* activity. Device 3 was the only device participants considered using both at home and at work.

In general participants thought that the devices showed corresponding results between measured emotion and experienced but that it sometimes did not fit at all. One participant stated that it seemed like the device (number 3) were more connected to physical activity than to cognitive stress or load.

3.3. Summary of results

The evaluation is summarized in Table 1.

Table 1: Evaluation of four devices measuring emotion in real-time

Device	Relevance of output data	Industry applicability	Real-time usage	General usability
1. Arousal bracelet	Requires further tests to understand what the data means	Feels like it could brake easily	Sensitive	Feels technical
2. Breathing activity	Unreliable and not relevant	Robust but would get dirty quickly	Takes time before registering data	Easy to use (the mobile app was very user friendly)
3. Activity bracelet	Reliable		Sampling frequency should be higher	Easy to use and discrete
4. Brain activity	The different factors does not give more data than the other devices	Complex to prepare and use, not robust		Usable and easy but set-up time was high

4. Discussion

The aim of the paper was to evaluate four digital devices that measure operator emotion in real-time. It was seen that the output data were reliable for the arousal and bracelet but that more studies are needed to investigate what the results mean and how individual threshold values could be set. Regarding industrial applicability only the activity bracelet seemed appropriate. Regarding measuring emotion in real-time the activity bracelet should have an increased sampling rate. All devices, except the arousal bracelet were seen as easy to use (which could be due to that they are commercially developed).

The evaluation also showed that different activities could give more reliable answers than others. To some extent the devices seemed better fit to measure *physical load* and *reasoning* than *intuition*. However, this could depend on the choice of task. In the user studies the participants used the Internet and did not perform assembly tasks, which could be one reason for why the correspondence was not high (however, participants stated that the task they chose felt appropriate to measure the *intuition* activity).

5. Reflections

Measuring emotion is complex since the physiological measures are connected to several activities (both cognitive and physical) [15, 16] and therefore more research is needed to further study how and if emotion can be measured in real-time in an objective way.

The results can be used to suggest how devices could be used in an industrial or semi-industrial application. It is interesting to regard how the different types of data could be visualized. There is a big potential in this since the device in itself is not expensive. If data can be connected to threshold values (for each individual) it can give a signal to the operator e.g. when it is time to take a break. A demonstrator should present data according to the operators' preferences and should include a function that notifies the operator when a threshold is breached and suggest to him/her an action. This could strengthen the work towards social sustainability and increased well-being at the workplace [3-5].

There are many opportunities and risks connected to studying new technology. In a comparison of activity and pulse bracelets a journalist writes that the devices present different output data (although stated that they do measure the same data) [24]. Probably the difference was due to the quality of the bracelets and that different devices could be better for some operators/persons. This was also seen in previous measurements were the arousal data had different amplitudes depending on the persons electro dermal sensitivity and body temperature [25, 26]. In a production context the gathered physiological data should be made visible only to some people, considering threats to their integrity.

Future work includes identifying interesting cognitive and physical activities and analyzing how those activities could be measured. Due to that digitalization suggests that more technical devices will be connected to each other it is also possible to combine measurements from several devices (seen in [27]). The first step is to identify interesting tasks and then their emotion signatures need to be investigated.

6. Conclusions

This study provides a first step to see if commercial devices can be used in industry. Results indicate that the arousal and activity bracelet are best fitted for further use and that it is important to take into account what activities are tested during an evaluation. An important finding was that experiment participants chose the most relevant device depending on how they experienced themselves. The study therefore points towards that individual experience are important when studying what devices could be used to study emotions in real-time.

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