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Metaverse Creates New Opportunities in Healthcare

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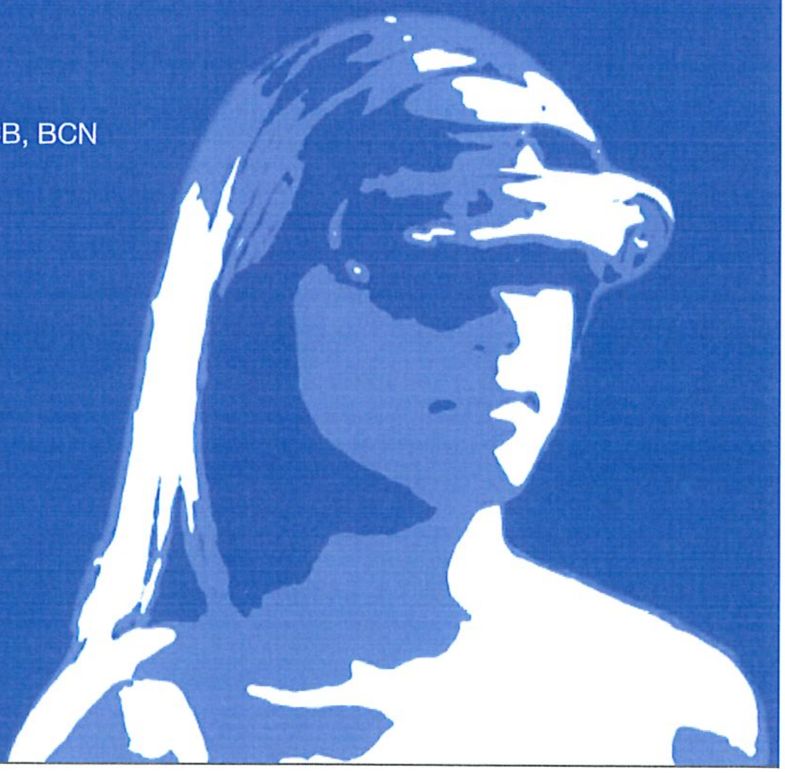

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Cyberintervention on plant workforce's mental activity for safety

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Abstract. Stress is recognized as an important health and safety indicator in work environments as it can both endanger workers and hinder companies' workflow. HRV is recognized as a good psychophysiological indicator of personal stress and can also be detected with innovative wearable electrocardiogram (ECG) bands which allow us to obtain recordings in real-life situations. This work proposes an innovative procedure for the assessment and a subsequent intervention against stress, using an AI approach for the detection of unhealthy stress status followed by a VR heart rate variability biofeedback treatment to address it. The procedure consists of assessing personal data and stress and tiredness levels of workers, and then collecting their ECG data through the cardio band Zephyr BioHarness during a standard workday. Researchers will shadow the participants without interfering, labeling each activity according to a predefined scale in clusters of homogeneous behaviors. After preliminary analysis, the data will populate a database to be used to train an AI with the goal to detect patterns related to stress and find out which HRV components are best at predicting stress. To compare our on-field recordings, we will also use data from open-source databases, with physiological registration of stressful situations. This procedure was tested on 11 plant workers during a standard job day.

Keywords. Mental Activity, Stress, ECG, HRV, Company Productivity

1. Introduction

Chronic stress can lead to cognitive dysfunctions, cardiovascular diseases, depression, and death, and it is related to injuries and accidents [1–3]. Apart from health and safety issues, in work environments, stress causes performance reductions [3] that hinder workflow and reduce companies' productivity and profitability.

Many studies correlate stress to changes in Heart Rate Variability (HRV) values, detected by ECG; in detail, in the frequency domain, the decrease in the High Frequency (HF) values and the increase in the ratio between Low and High Frequency (LF / HF) were proven to be significantly related to stress levels [2,3].

Wearable wireless devices for health monitoring are becoming increasingly accurate and reliable, and therefore a popular prevention tool used in healthcare. This is also due to their low-cost availability and the possibility to be used outdoor and in motion [1].

Thanks to the reliability of recent smart devices, we decided to exploit this kind of technology in a novel approach: we measured psychophysiological ECG data of a group of plant workers along with recording the type of activity they simultaneously carried out during their day job.

Our general objective is to investigate potential correlation between ECG activation, psychological status, and type of activity performed.

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For this purpose, we put in relation psychophysiological data obtained in a real-world context with changes of environment and activity in the daily workflow and the workers' psychological condition to assess their status during their day job.

Our ultimate aim is to create a useful tool for workers that could improve health and safety, and help people avoid dangerous mental states such as extreme stress or tiredness.

In the present study, we propose a procedure for the simultaneous assessment of ECG activation, psychological status, and type of activity. To test the feasibility of such an investigation, we have carried out a preliminary registration in a real-life condition with a sample of 13 plant workers.

2. Method and Tools

Our proposed procedure includes a 15-minute meeting in which we explain the aim of the study to the subjects, collect the minimal significant set of their personal data, along with information about their stress and tiredness levels in brief questionnaires in accordance with data protection and privacy regulations.

The questionnaires consist of 7 items administered before and after the recordings using a Likert scale from 1 to 10, and 4 yes/no questions about personal situations that could raise stress levels:

- How physically tired do you feel right now?
- How mentally tired do you feel right now?
- Right now, how much do you need to sleep or rest?
- Right now, how is your energy level?
- Right now, how physically nervous do you feel?
- Right now, how tense are your muscles?
- Right now, how stressed do you feel?/During your job, how stressed have you felt?
- Did you have any physical discomfort today?
- Have you experienced a non-ordinary and potentially stressful situation in the last month?
- Do you often have difficulty sleeping?
- Have you felt stressed or unable to manage daily events/unforeseen events?

The Zephyr BioHarness BH3 band [4,5] is a gold standard tool for multiparametric monitoring of ECG, HRV, and respiration signals, designed for sport activity and therefore suitable for data collection in a work environment. Participants are asked to wear it and, after the beginning of data collection, have a 2-minute baseline recording while resting.

Data need to be collected over at least two and half hours, depending on the duration of the shift and the subject's activities that day. Data are collected on the field while workers are carrying out their standard and planned activities. Meanwhile, researchers observe the work of those involved without impacting normal workflow, and register which activities are performed by each worker and at what time. At the end of their activities, involved workers repeat the 2-minute baseline recording and the stress and tiredness questionnaire.

Recorded ECG data are automatically saved and time referenced in the local memory of the Zephyr BioHarness. All the collected data are anonymized in compliance with all labor and governmental laws and regulations.

Thirteen plant workers took part of a preliminary test of our procedure aimed to investigate the feasibility of the procedure.

3. Data processing and preliminary results

Recorded workers' activities needed to be successively labeled in terms of predefined homogeneous behaviours as identified in Table 1, with one indicator for the category of activity (mental, physical, stand-by, rest) and one for the activity's relevance (strategic, operational, stand-by, rest).

Table 1. Activities are described in terms of type of activity (physical or mental) and relevance (strategic or operational). Stand-by activity 3/7 and Rest break/Coffee break 4/8 always coincide.

Code	Type of activity	Description
1	Predominantly mental activity	Activities of control, supervision, and all those activities that involve reasoning in order to make a decision
2	Predominantly physical activity	All the operational activities that can be included in an "automatic" decision which is neither reasoning nor decision-making. (e.g. walking, lifting weights)
3	Stand-by activity	Not a break from work, but a temporary lack of activity during the performance of one's duties
4	Rest break / Coffee break	An effective break from work activities (e.g., coffee break)
Code	**Type of activity**	**Description**
5	Strategic activity of significant importance	Activities that involve decision-making by a person who plays a key role in the company, not easily replaceable
6	Operational activity	Non-strategic operational activities carried out by a person holding a non-strategic role
7	Stand by activity	Non-strategic operational activities carried out by a person holding a non-strategic role
8	Rest break / Coffee break	An effective break from work activities (e.g., coffee break)

ECG data are retrieved from the Zephyr's internal memory and examined through Matlab, digital signal processing modules, and SinusCore.

Each labelled epoch will be synchronised and linked to the psychophysiological recordings and to the results of questionnaires; this data will be used to populate a multimodal database. It will be important to precisely define which variables would be included in the single dataset and to choose which variables will be included in the minimum dataset in order to sufficiently obtain precise predictions with the lowest computational cost of the models used.

4. Discussion

Our experience suggests that this procedure is feasible and could lead to interesting evaluations of workers' stress conditions.

Moreover, some pre-analysis were performed: data was analyzed in terms of key statistical indicators over time (average, variance, correlation) with different preliminary hypotheses, and some qualitative evidence has arisen during the meetings with the workers.

The main difficulties were found in the following of the subjects by the experimenters: the routes in the plants were complicated and partially dangerous. Consequently, the subjects often talked to us, explaining the functioning of the instruments around and of the job. This could also be linked to the novelty of the experience for them.

We believe that the realistic working conditions are sufficiently maintained, especially during the core activities. However, different kinds of activity tracking methods could be considered (e.g., video equipment, automatic geospatial tracking,...) to minimize bias due to the researcher's presence.

Another important point is that the shift of the single subject needs to provide different kinds of activities with different levels and kinds of engagement and stress.

Future steps will focus on the data analysis and will proceed in the following way: recorded physiological data, divided in epoch and linked to the labels of worker's activity and level of stress, will populate a database which will be used to set up an AI/ML approach.

To increase the amount of data, we will request access to 3 open-source multimodal databases in which researchers link psychophysiological recording to activities categorized by arousal and valence [6] (stress is described as a high arousal and negative valence status). These are:

- MAHNOB HCI-TAGGING (recording data from eye tracker, ECG, 32-channels EEG, skin conductance, respiration, and skin temperature) [7]
- DEAP (recording data from 32-channels EEG, skin conductance, Blood Volume Pulse, ECG, respiration, skin temperature, electrooculogram, and electromyography of the zygomatic and trapezius muscles) [8]
- DECAF (recording data from magnetoencephalography, electrooculogram, ECG, trapezius electromyography, and infrared facial videos) [9]

The integration between our recording and the open-source database will follow three methodological logics:

- Machine learning on the open-source database then application of the best performer algorithm to our on-field recording database
- Machine learning on our on-field recording database then application of the best performer algorithm to the open-source database
- Mixing the open-source database with our on-field recording database, dividing it in two homogeneous groups – one for machine learning and one for evaluation

Machine learning will start with a preliminary estimate of maximum accuracy and will therefore take place as suggested by Orrù et al. [10] through supervised black box regression models – more accurate but not easily interpretable, such as, for example, Tree Ensembles (Random Forest, Gradient Boosted Trees) and Deep Neural Networks.

Secondly, we will implement a training through supervised white box regression models (i.e., Linear Regression, Decision Trees, GAMs) performed directly through stratified 10-fold cross validation (removing 20% of the data for the next test and performing fold and training on the remaining 80%) in order to ensure maximum replicability of the study. The results of the various models will then be compared and evaluated to determine which ones show greater precision. The implementation of this phase will take place via Azure Machine Learning or equivalent systems.

A further step would be to collect a wider dataset spanning over different organizations, seniority tiers, and assigned tasks. This will be used to improve the AI capability to recognise unhealthy stress statuses.

A proposed step is the design of a user-friendly smartphone application collecting physiological data, analysed through a remote processing service, giving real time feedback. With this application, we will also provide a virtual reality immersion experience to train people who find themselves in stressful situations.

As in Blum et al., [11] we will use a virtual nature environment to administer immersive HRV biofeedback based on slow-paced breathing as it has shown good results in terms of relaxation, relaxation self-efficacy, decrease of mind wandering, and conservation of attentional resources (making it suitable for work environments).

5. Conclusion

The procedure suggested and carried out appears feasible and could lead to implementations which could improve workers' health and safety and could boost productivity and profitability in plants. Additionally, we suggest that this kind of procedure be tested and applied in different fields and conditions.

Main innovations are the use of real-life recording for creating the AI dataset and the early detection of dangerous stress levels. More studies will lead to the definition of the minimum time series needed to understand the stress level and give real time feedback to the user.

Furthermore, the use of wearable ECG sets and smartphone-based VR represent an innovative but viable and cost-effective solution for a small-medium enterprise.

Similar systems would be also applied to other mental states such as boredom, sleepiness, or flow performance.

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