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Benchmarking of tools for User eXperience analysis in Industry 4.0

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Abstract

Industry 4.0 paradigm is based on systems communication and cooperation with each other and with humans in real time to improve process performances in terms of productivity, security, energy efficiency, and cost. Although industrial processes are more and more automated, human performance is still the main responsible for product quality and factory productivity. In this context, understanding how workers interact with production systems and how they experience the factory environment is fundamental to properly model the human interaction and optimize the processes. This research investigates the available technologies to monitor the user experience (UX) and defines a set of tools to be applied in the Industry 4.0 scenario to assure the workers' wellbeing, safety and satisfaction and improve the overall factory performance.

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Keywords: User experience; Human Factors; Industry 4.0, Production system design, Human Interaction.

1. Introduction

Industry 4.0 indicates the current trend of automation and data exchange in manufacturing technologies. It includes cyber-physical systems (CPS), the Internet of Things (IoT) and cloud computing to create what has been called a "smart factory". Within modular structured smart factories, CPS monitor physical processes and create a virtual copy of the physical world to make decentralized decisions on the basis of the collected data and the created knowledge [1]. Over the IoT, such cyber-physical entities can communicate and cooperate with each other and with

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humans in real time, and both internal and cross-organizational services are offered and used by the participants of the value chain. In the context of Industry 4.0, manufacturing will become smart and adaptive thanks to collaborative and flexible systems able to solve the problems arising during the process and execute the best actions [2]. Such scenario offers new and interesting development for the modern companies but contemporarily creates a greater system complexity, with an enhanced human-machine interaction that requires highly variable and changing tasks as well as new demands [3]. Indeed, workers will be faced with a large variety of jobs ranging from machine control to process monitoring, until verification of production strategies. As a result, although industrial processes are more and more automated, human performance is still the main responsible for product quality and factory productivity, and too high human workload risks to be the real bottleneck of the smart factory [4]. Only reducing human errors and improving the workers' capability to make strategic decisions and to be flexible problem-solvers can guarantee a higher system efficiency and factory productivity, with less cost and less resources' consumption.

The Industry 4.0 framework allows the physical systems to be digitalized by Internet of Things in order to communicate and being interoperable each other. Thanks to a virtual copy of the physical world through sensor data, information can be contextualized to have self-adapting systems able to intelligently adjust the production patterns for difference scopes [5]. Machines, devices, until the entire production systems can be one if those "things", virtualized and managed by the Industry 4.0 approach. However, factories are not only made up of machines but also of human beings (i.e., workers) cooperating with the machines and each other in various ways: executing tasks, controlling the process, loading or unloading the machines, interacting the machine interfaces, etc. So in the smart factory also people could be seen as "things" to be monitored and connected with each another and with machines. Indeed, although the increasing level of automation of production lines, humans still continue to have a central role in factories and are the main responsible for successful factory productivity and high product quality [6]. According to the Industry 4.0 paradigm, the factory system could support workers' in task execution, data interpretation, and context-aware making decision to carry out their job more safely and more comfortably, which allow reducing time and improving quality. Furthermore, in the last few years new methods of investigation of humans' behaviours and feeling have been developed based on physical and physiological measurement, to guarantee a more objective way of investigation. In general, monitoring tools like heart rate (HR), electrocardiogram (ECG), electroencephalogram (EEG), electro-dermal activity (EDA) and others are used mostly in medical research to investigate diseases or other disorders [7]. Nowadays, thanks to the miniaturization and cost reduction of most of those technologies, their adoption is growing also in design and engineering contexts for behavioural analysis and stress monitoring.

This paper provides an extensive analysis of existing technologies to monitor workers' behaviours, actions and feelings in industrial applications in order to enhance system productivity. In particular, the paper focuses on the analysis of the so-called user experience (UX) that refers to the analysis of humans' behaviours and perceived experiences while interacting with machines, systems and products during their job. Traditionally, the workload and the level of stress of workers are measured by direct observation, users' interviews and questionnaires. However, such methods provide a late assessment of the working conditions and are strongly influenced by the subjectivity of the involved users. Late assessment allows problems' evaluation, but does not support a human-centred integrated design of both product and processes, to substantially improve the process performance. The aim of this paper is to inquire how human monitoring tools can be used to evaluate physical and mental workload of workers and how to correlate such data with the design of the working environment in order to achieve better working conditions and more efficient workflows. In particular, such tools could be adopted for real-time monitoring and smart product-process re-design to improve the factory performance. The main findings of the research are:

1) a set of human factors' monitoring tools for UX analysis,
2) an experimental set-up for UX analysis to be easily adopted in in smart factories, and
3) a preliminary industrial case study, where the above-mentioned set-up is adopted.

2. The research background

The concept of human-centred manufacturing is not new but raised in 1990s [8]: it places human beings with their skills, behaviours, creativity and potentiality, at the centre of the activities carried out by technological systems, and focuses on how humans interact with technology, questioning how and why technology may be of service in supporting human work. However, in early 1990s technologies were not mature enough to easily include workers into factory design and management. Today, two important factors push towards the development of the human-centred manufacturing: the miniaturization and cost reduction of the monitoring technologies, and the Industry 4.0 framework. Indeed, according to Industry 4.0 paradigm company architectures are evolving to effectively receive data about the production plants. Such data can be collected from machines, but similarly also from human beings and be merged with system data [19]. The consolidated amount of data can create unique factory knowledge able to drive process configuration and smart adaptation of manufacturing systems, according to the humans' behaviours and stress conditions.

Human factors have been recognized as a fundamental aspect in industrial engineering, so that ergonomics is always more often considered in industrial system design. However, traditional approaches are based on the late assessment of ergonomic performances, rather than on their proactive analysis able to effectively support system design and workers' decision-making. The analysis of human factors in manufacturing focuses on the inclusion of human factors in production system design by in order to understand human behaviours and performance interacting with socio-technical systems, and the application of that understanding to design of interactions [9]. Despite the increasing interest of the scientific community in the "human" dimension, its investigation is still poorly explored in manufacturing. Recent studies dealt with the analysis of human factors in industry by monitoring the strength predictions, metabolic rate predictions, reach assessments, and time predictions [10] or by investigating the cognitive and comfort [11].

In order to create a reference framework for user monitoring in the context on Industry 4.0, the research considers those physiological parameters that can be used for the UX analysis, relying on the previous literature. One of the most common methods used in medical, fitness and working contexts is heart monitoring. Nowadays, it is quite simple and cheap thanks to the simplicity of measurement and low cost sensors. In particular, the measurement regards heart rate (HR) and heart rate variability (HRV). Previous researches showed the correlation between HR and HRV with the mental workload and drowsiness. For instance, HR has been used as the simplest indicator of drivers' workload [12], while Mulder [13] showed that a decrease in HRV indicates an increase in the mental effort. It has been demonstrated also that both intense physical and mental workload may increase HR and decrease HRV at the same time [14]. Also electro-dermal activity (EDA), also known as galvanic skin response (GSR), is quite used in UX assessment. It consists of the measurement of flow of electricity through the skin of an individual that causes continuous variation in the conductance of the skin. In an under stress condition, skin conductance is increased due to increase in moisture on the surface of the skin, which increases the flow of electricity [15]. Electro-encephalography (EEG) is the most commonly used method to brain activity measurement due to low intrusive equipment and low cost. Studies showed the correlation between brain activity and stress [16]. Electromyography (EMG) shows electrical activity produced by active muscles, and its assessment is quite used for stress detection. Respiration measurement has been used to assess levels of stress but generally in conjunction with other physiological measures [17]. Among all the other technologies, eye tracking based on pupillometry and electrooculography is nowadays widely diffused, due to the increased performance of eye-trackers, the more ergonomic devices (i.e., glasses) and gradually cost reduction. The most frequently used parameters are eye gaze, eye blinks and pupil dilatation, which provide information on an individual's attention source and stress [18]. Due to its complex nature, it has been found that UX can be well investigated only by the combined measurement of multiple parameters, to achieve a reliable evaluation of both physical and mental stress in an objective way. However, industrial applications requires to be less expensive, not too much intrusive, and robust enough to be wired in industrial environment. As a consequence, the number of parameters has to be optimized according to the specific measurement objectives.

3. The human factors monitoring tools

The device selection started from the analysis of the new Industry 4.0 paradigm and the demands of companies on UX assessment. An industrial survey were conducted to ask to more than 200 Italian companies their interest in human factors analysis and UX assessment in the context of Industry 4.0 revolution. The 80% of interviewed companies declared their interest in monitoring also the workers at the shop floor and to monitor their interaction with machines, interfaces, and control systems. Three main purposes were highlighted by the survey:

1) to improve the process control and avoid process delay as well as machine downtime (75% relatively);

2) to ensure the workers' safety and to prevent excessive physical and mental workload, with consequent absence form work (68% relatively).;

2) to better control the process performance and improve the process planning quality, taking into account also the workers' actions, reactions, needs and demands (55% relatively).

Finally, human factors monitoring has the potential to be integrated into the evolved smart factory architecture, to effectively receive data about the production plants. Such data can be collected from machines, but similarly also from human beings and be merged with system data [19]. The consolidated amount of data can create unique factory knowledge able to drive process configuration and smart adaptation of manufacturing systems, according to the humans' behaviours and stress conditions. On the basis of the industrial survey and the technological benchmarking, a set of parameters to be monitored was defined as shown in Fig. 1.

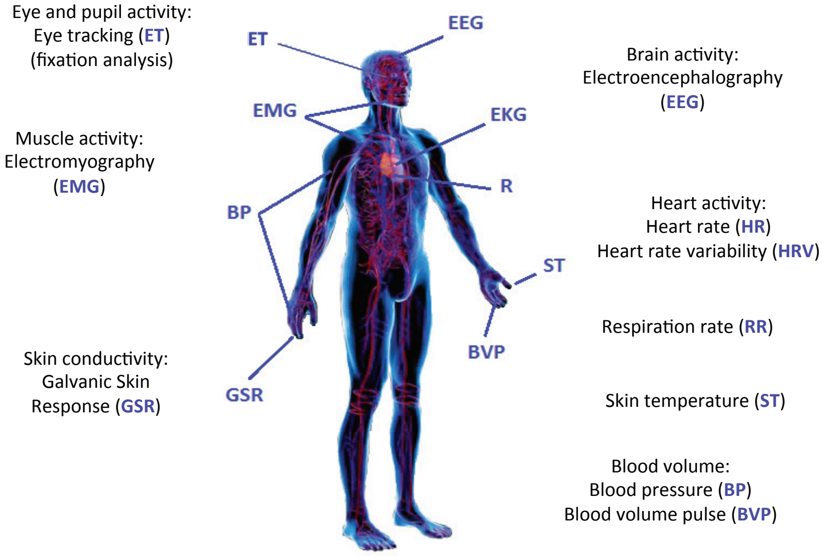

Fig. 1. Selected parameters for human factors monitoring in industry 4.0

Subsequently, for each parameter the available technologies were analysed and compared according to different features: usability, intrusiveness, robustness of the collected data, use in an industrial context, flexibility, data collection and post-processing, and costs. As a result, the most proper tools were selected to create a preliminary testing set-up. Some parameters were neglected due to different reasons: BVP, BP and EMH were considered not useful when HR and HRV are monitored; GSR correlation with stress is still too vague to be adopted for industrial purposes; EEG was considered useful but not easily adopted in an industrial context and the less intrusive technologies are still quite expensive. For the present research, two devices were selected: a high-quality eye tracking systems (i.e., Glasses 2 by Tobii) and a multi-parametric wearable sensor (i.e., BioHarness 3.0 by Zephyr). As far as eye tracking, the obtained data are considered extremely useful to monitor the human-system interaction and to correlate the eye-related data with human stress, mental workload and emotions. On the basis of the analysis of fixation duration and pupil dilatation [20], also an index of cognitive activity (ICA) can be defined and gaze variability can easily detect low attention and stressful conditions [21]. Furthermore, eye tracking technology has several advantages: the camera records user point of view, it can be used on both real and virtual environments, and collected data can be integrated with EEG data to have a more compressive cognitive workload analysis. Obviously, results depend on the users' head movements and mental load have to be interpreted according to the specific field of application. Moreover, the multi-parametric wearable sensor allows to directly record human behaviours and physiological data, is cheap and poorly obstructive. In particular, it measures a set of useful parameters such as HR and HRV, which were found to be the most important markers to identify human stress in various conditions such as mental task, high physical workload, stressful driving and other common daily activities [22]. Furthermore, it measures also the breathing rate (BR) and the skin temperature (ST) to provide a more complete analysis of the health workers' conditions, and the body activity (BA) and body stooping (S) by means of accelerometers and gyroscopes to define the posture assumed by the workers and the physical comfort. Finally, workers' video recording allows adding useful information about the actions executed and the surrounding environments. An external camera is used and data are synchronized with the head view obtained by the eye tracker camera. Table 1 shows the selected parameters and technologies for the present study.

Table 1. Selected tools for UX analysis in industry 4.0

Monitored physiological parameters	Tool typology	Selected tool	Collected data
Eye tracking (ET) (eye fixations)	Eye Tracker	Tobii Glasses 2	Gaze plot, Heat maps
Heart Rate (HR)	Multi-parametric wearable sensor	Zephyr BioHarness 3.0	HR diagram
Heart Rate Variability (HRV)			HRV diagram
Breathing Rate (BR)			HR max
Skin temperature (ST)			BR diagram
Body activity (BA)			Activity diagram
Body stopping (S)			Stooping on x-y-z axes
-	Camera	GoPro Hero 3	Videos of workers and the surrounding environment

4. The UX analysis framework for industry 4.0

In order to generate a reliable UX analysis, the selected tools were used in a combined and synchronized way in order to have data correlation. They were adopted both on real environments and on virtual simulation environments. A reference framework has been defined to support process optimization in Industry 4.0 based on UX analysis, as shown in Fig. 2.

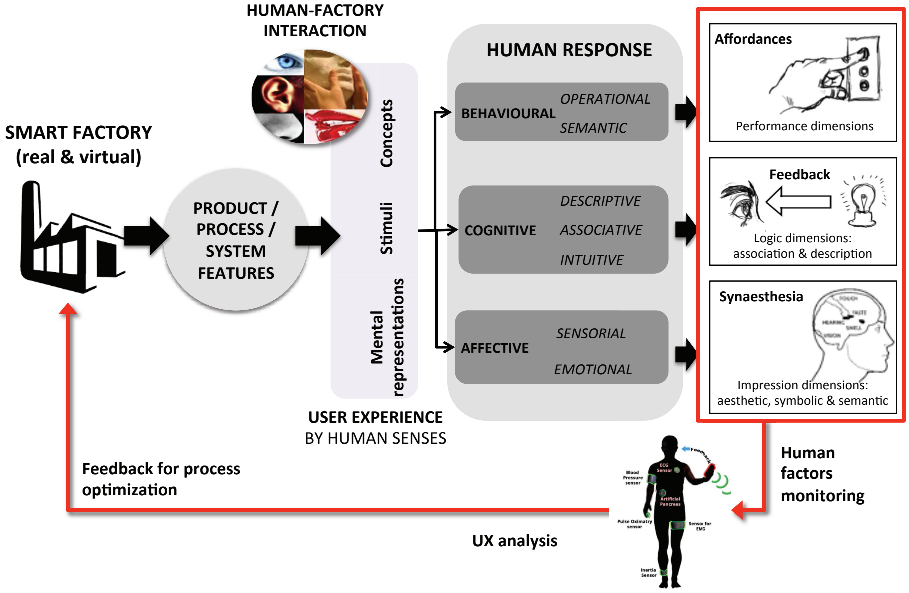

Fig. 2. UX analysis framework in industry 4.0

The factory is monitored by real and virtual assets, characterized by product / process / system features, which are experienced by the workers by their human senses. According to the Norman's model of interaction [23], the human response generated by the system features (e.g., graphical interfaces, physical interfaces, supporting devices, tasks to be carried out), depending on the product and process characteristics, can be divided into three levels: behavioural, cognitive and emotional. Such responses are intrinsically combined, but they can be simplified in terms of physical and cognitive workloads, which are determined by system affordances and synaesthesia, as well as the feedback received by the workers during tasks execution. Such response can be objectified and measured by the selected tools for human factors monitoring. Such information can drive the factory process optimization.

5. The industrial case study

5.1. The case study

The case study has been developed in collaboration with CNH Industrial, a global manufacturer of agriculture and industrial vehicles, with more than 64 manufacturing plants and 50 research and development centers in 180 countries. Its production is divided in 12 brands, from tractors to trucks and buses, as well as powertrain solutions for on-road and off-road and marine vehicles. The case study focused on the UX analysis for its workers during assembly operations along tractors' manufacturing process, in the Italian sites of Modena and Jesi. Monitoring the workers' physical and mental workload allowed to understand how comfortable they are working and how stressful the interaction with the production machines as well as the supporting devices (e.g., tackles) and the process control system interface was. The defined set of devices was adopted to monitor workers acting both on physical assets and on virtual assets, considering that in the future smart factory some interactions will be carried out also on digital representations of the real world. The workers were equipped with the eye tracking system (Tobii Glasses 2) and worn the biosensor (Zephyr BioHarness 3.0). An external camera recorded their actions. Within the virtual environment, workers were also tracked by an optical tracking systems made up of 8 Vicon infrared cameras to create their "digital twin" to put into the virtual scene for further process simulations.

5.2. Preliminary results

During the experimental testing, the above-mentioned set-up was used to monitor the UX of real workers during assembly tasks' execution. The workers were equipped with the eye tracking system and the biosensor, while their actions were recorded by an external video camera and a set of infrared cameras for optical motion capture. Fig. 3 shows the experimental set-up and the preliminary data collected. The workers' action can be monitored by video recording analysis (VIA) as well as eye tracking data elaboration, with the creation of gaze plots and heat maps for the most significant "views". An expert processed the collected data to create significant maps according to the UX analysis objectives. In the meanwhile, the biosensor monitored the physiological data, in particular HR, HRV, BR, activity analysis and posture analysis, based on accelerometers' and gyroscopes' data. For the specific case shown in Fig. 3, the analysis goal was related to the understanding of the assembly sequence and the identification of criticalities in the product design affecting the assembly process. Such criticalities can be defined by the correlation among the eye tracking results highlighting confused eye navigation paths and stressful conditions, as well as the analysis of the collected physiological data demonstrating high level of physical and mental workload. Different analysis sessions were carried out; each of them was 20 minutes long.

Preliminary tests allowed verifying the feasibility of UX analysis on by the defined technological set-up. Even though wearable devices are used, they are proved to be poorly intrusive and workers were able to carry out their job without any significant obstacles. Data were collected correctly during the analysis sessions and results could be easily synchronized. Specific time steps were further investigated with a more detailed data post-processing.

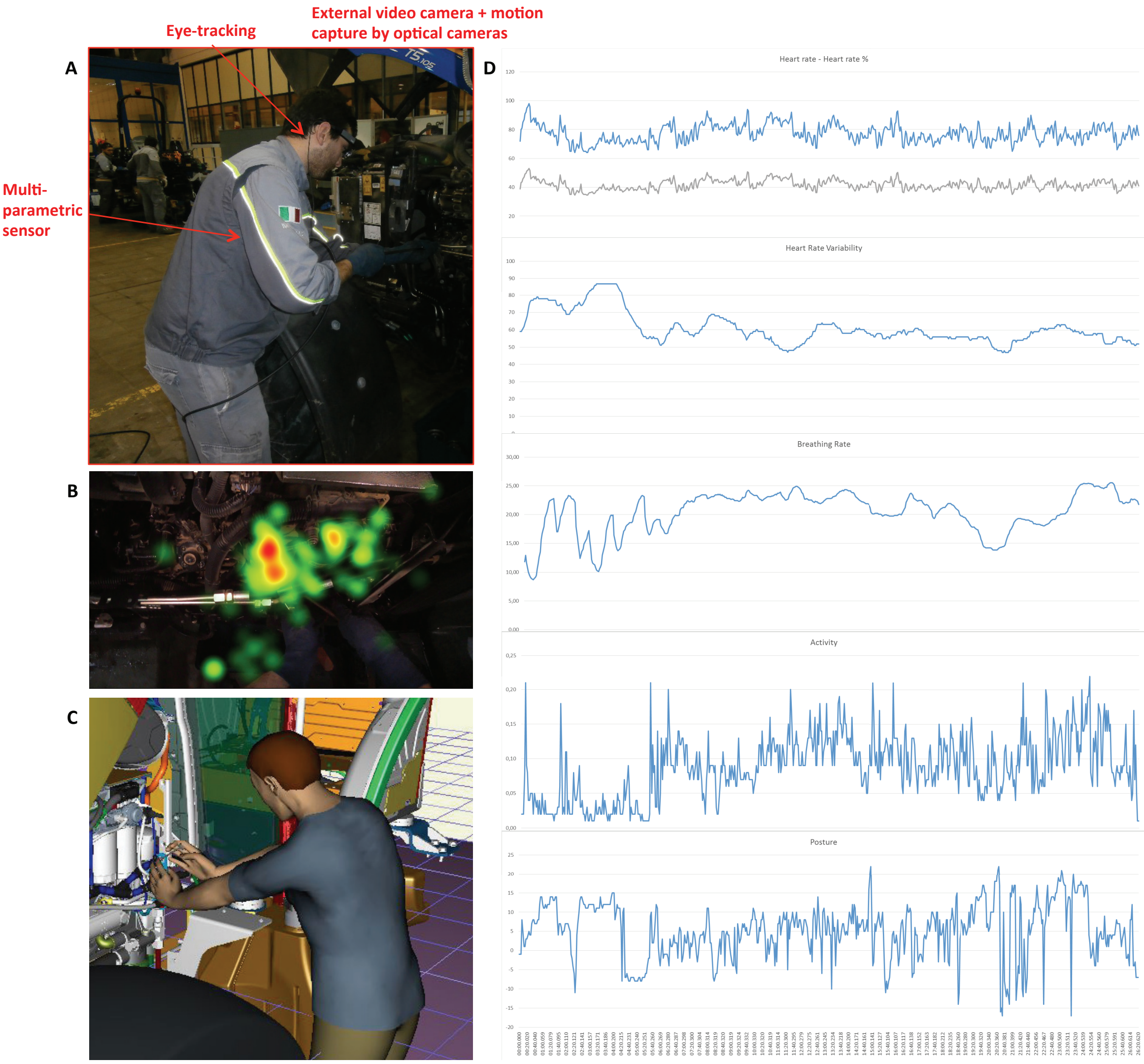

Fig. 3. UX analysis for the case study: the monitored worker (A), the eye-tracking heat map (B), the worker digital twin obtained by optical motion capture (C), the physiological data collected during task execution referring to HR, HRV, BR, activity and posture (D)

6. Conclusions

The paper focused on the analysis of the user experience (UX) during job execution in the context of Industry 40 a proposed a reference framework for the human factors monitoring to be applied on workers in the factory environment. The paper defined a set of human factors' monitoring tools for UX analysis and an experimental set-up for UX analysis to be adopted in smart factories to measure the physical and mental workload and the level of stress of workers in a more objective way with respect to the traditional practices. A preliminary industrial case study was arranged to check the set-up validity and to collect data on real workers. Experimental testing demonstrated that the set-up could be validly used for workers monitoring and to provide human-related data. Detailed analyses can be carried out by proper data post-processing. Future works will be focused on the definition of a structured protocol for data correlation and interpretation to detect specific critical issues of the factory process and to define process optimization rules.

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