Cognitive Work Protection - a new approach for occupational safety in human-machine interaction

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Abstract. Previous occupational safety concepts in human-machine interaction scenarios are based on the principle of spatial separation, reduction of collision force or distance monitoring between humans and robots. Collaborative robot systems and semi-automated machines are working closely with people in more and more areas, both spatially and functionally. Therefor a new approach for occupational safety in close human-machine collaboration scenarios is presented. It relies on a real-time EEG measurement of human workers with brain computer interfaces and a subsequent adjustment of the robot system based on the detected cognitive states.

Keywords: Occupational safety, human machine interaction, brain computer interfaces

1 Introduction

According to a study by the International Federation of Robotics, the number of industrial robots sold in 2016 was 16% higher than in the previous year. Annual sales growth of 10% on average is expected until 2020 [1]. In addition to the possible increases in efficiency and productivity made possible by the growing number of robots in working environments across countries, the protection and safety of the employees involved must always come first. Accidents at work not only have serious consequences for those affected but are also a cost factor that should not be neglected for the companies involved and the economy in general. The main causes of accidents at work are human behavior errors based on carelessness, stress or hecticness [2]. Especially in close cooperation with industrial robots, this is triggered by complex motion sequences, unpredictable changes in position and speed or unexpected starting of the robots [3]. Current safety strategies to avoid work accidents in human machine interactions are based on a strict spatial separation between the robot and the work area of the human operator. However, collaborative work scenarios that are characterized by a very close human-machine interaction are increasingly coming into focus. Collaborative robot systems and semi-automated machines will work closely with people in more and more areas, both spatially and functionally. Particularly in these situations, special attention must be paid to the protection and safety of people. Classical safety strategies can no longer be applied for these collaborative work scenarios. The close physical cooperation between man and machine requires adapted and reliable occupational safety concepts.

Another aspect is the problem of under- or overstraining at the workplace. According to stress reports of recent studies, already in 2012 about 18 percent of employees felt that they were either professionally or quantitatively underchallenged at their work. About 23 percent of those questioned suffered from work overload [4]. However, mental health problems can arise from permanent under- or overchallenging. In order to master the unavoidable change in work requirements in a socially acceptable manner, new methods are therefore necessary to optimally design the working conditions for the individual person.

In this paper we present a new approach to increase occupational safety in collaborative working scenarios, including the potential to optimize the individual working conditions in a rapidly changing environment. It is based on cognitive measurements of human workers which are analyzed and used to optimize the co-working situations with robots with the aim to avoid work accidents. Following a design science methodology [5], we first demonstrate the relevance of such an approach followed by a conceptual solution which acts as the artifact and a subsequent discussion and evaluation.

2 Related Work

Especially in the field of human-robot interaction, the aspect of occupational safety and security is of great importance. Current approaches for collaborative robot systems are mainly focused on aspects of force and power limitation as well as speed and distance monitoring [3], [6]. On the one hand, there are approaches to minimize the collision force in a potential human-robot contact. On the other hand, technologies were developed to detect persons entering the safety area of the robot to initiate appropriate safety measures of the robot [7,8]. The analysis and use of cognitive states to control and influence physical objects (such as robots) is an approach that has been less considered so far. Most of the current research relates to medical applications [9,10,11]. Especially in the industrial sector, i.e. in production or manufacturing, other requirements arise which have not yet been addressed to this extent. The electroencephalogram ("EEG") is a representation of electrical brain activity measured at the head surface and detected by means of metal electrodes and a conductive medium [12]. The EEG has so far mainly been used for the detection of neurological diseases in medicine, for the investigation of brain functions in research as well as in the context of therapy and rehabilitation. Further applications can be found in the field of brain-computer interfaces, i.e., the use of EEG signals to decipher mental states (fatigue, stress, etc.) and the improvement of human-machine interaction based on them [13,14,15]. The mental states can be analyzed in the EEG using the P300 or changes in the frequency bands. At a high workload, changes in the alpha and theta frequency bands are observed, e.g. increases in theta activity in the frontal brain area and reduction of alpha activity in the parietal area [16,17,18,19,20,21,22]. However, individual studies report increases in alpha activity [23, 24], which can be attributed to a general large variance of individual differences [25]. With onset of fatigue, however, activity in both frequency bands is increased [26,27,28,29,30,31]. In the case of the P300, a reduction in amplitude can be observed both with a high workload and with onset of fatigue [32], [14]. Errors in robot behavior or faulty human-robot interaction can be measured in the EEG as error-related potentials and detected in real time using machine learning methods [33,34,35]. The error-related potential can also be used as implicit feedback from humans (e.g. encouraging learning) in robot learning approaches [36].

Based on recent research a next step in the direction of implementing functional solutions within realistic industrial applications is needed to prove that cognitive work protection using physiological data is applicable and a strong contribution to worker's safety.

3 Technical Developments and Feasibility of the Approach

Our approach for occupational safety in close human-machine collaboration scenarios is feasible due to technical developments of the used core components that have come up over the last few years. This applies in particular to the fields of **EEG data analysis methods**, **digital platform technologies and robotic control**, as well as **smart devices** (e. g. in terms of wearables).

By means of the introduction of machine learning methods [37] and advanced signal processing techniques (e. g. [38]) **EEG analysis** is now possible in almost real time and more importantly cognitive states and intentions of humans can be detected or inferred in single trial [39]. This development is the basis for applying brain computer interfaces (BCIs) in real world settings, such as done by embedded Brain Reading (eBR) [39]. Further, the improvements in EEG recording and analysis techniques that allow EEG analysis and analysis of other physiological data recorded under non-static conditions such as walking and running [40] or cycling [41, 42] did also enabled the integration of psychophysiological data into the control of robots such as exoskeletons [15]. Thus, due to the combination of both developments it is no longer required that persons wearing EEG recording equipment are not allowed to move at all while recording the data in often shielded lab environments [43]. Instead, free movements in cooperation with robotic systems in real world settings is now possible [36].

On the other hand, the development of embedded processing hardware and advanced embedded software solutions [44] does even enable the implementation of small recording as well as analysis techniques that already incorporate advanced real-time EEG processing [45] and even classifier training or adaptation on embedded devices [55].

Despite improvements in hardware and data analysis techniques the integration of physiological data into the control of robots or its usage for the improvement of human-machine interfaces required new concepts for deep integration and failure free usage of highly uncertain data such as EEG data. New concepts were developed that allow to infer on the context of interaction to make use of low level information from EEG data to infer on high level intentions of a user or to automatically detect markers in the EEG based on the current activity of the supported person that can be used to infer on the cognitive or mental state of the user [46]. The latter one is even possible without using a secondary task to measure workload [14].

Finally, advances in **EEG sensor systems** regarding usability and costs lead to a widespread use of EEG data in gaming and entertainment (e. g. [56,57,58]). Similar to the development of mobile cell phones this development is a major driver for solutions in the field of low cost and easy to use EEG sensor systems that are of need for our proposed application.

Digital platforms are new marketplaces by which the exchange of goods, services and other added value can be organized and realized using digital technologies. They enable interactions and transactions between interested participants and objects (e.g. machines, networks, institutions, etc.) [47], [48]. In this context "digital technologies" such as standardized interfaces, user and role administration, service catalogs, database technologies, intelligence and analytics software components serve as enabler and technological framework for the running of this connecting technology. These technological developments lead to a widespread use of digital platforms in the production as well as in the service sector [47]. Within the Industrial IOT scenario, platforms have the potential to realize the holistic framework of a "smart factory", in which **centralized robotic control scenarios** can be established as well [49]. In the field of data intelligence and analytics, big-data scenarios in particular can be implemented e.g. as predictive analyses and real-time data processing [50].

The use of **smart devices** such as **wearables** reflects the current development of the "quantify yourself" trend, which mainly focused on tracking and analyzing data from everyday activities such as sports, weight control, sleeping activities and other habits [51]. Technologically, applications can be deployed on the wearable that establish an interface to other decentralized services thus analyzing data in real-time. Besides sports and clinical approaches [52], new approaches arise in field of occupational safety e.g. for personalized construction safety environment using techniques like physiological monitoring; environmental sensing; proximity detection; and location tracking [53].

Regarding those technical developments, the combination of the components leads to the conception of the following holistic approach.

4 Cognitive Work Protection

The first goal of our approach (Fig. 1 shows the holistic design) is to measure the cognitive condition, for example the stress level or the workers' ability to concentrate, and thus to optimize interaction with robots and machines in real time with a view to increased safety. The second objective is to reduce accidents at work that occur in cooperation between humans and robots and to promote the physical and mental health of employees.

Starting point of our approach are EEG measurements of employees during the operation of machines or in cooperation with robots. The electrical activity of the brain is determined by electrodes that measure the voltage fluctuations at the head surface. The focus is on the electrode design and the ergonomic design of the sensor system. The system is optimized for a minimum number of sensors that are able to detect the desired cognitive states. For this purpose, the brain and thus head regions are identified which have the highest information content when determining the various cognitive states.

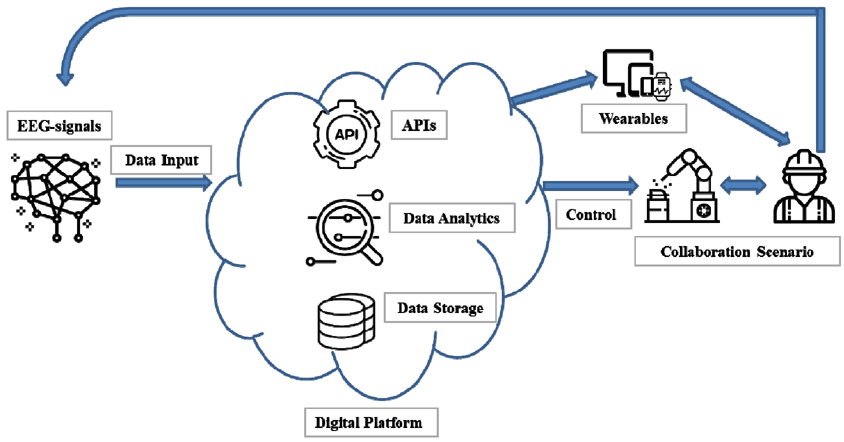

Fig. 1. Design representation of the holistic framework

The electrodes based on flexible polymer substrates are installed at the identified head- and electrode positions in safety goggles and thus integrated into the safety equipment that is required in any case. Based on the identified electrode positions, optimal electrode flexibility and shape is identified by various prototypes and tests on person. These optimal electrode shapes should ensure reliable hair penetration and head contact as well as high long-term wearing comfort.

The measured brain waves are recorded in real time and transmitted via a wireless interface to a central digital platform. The data is processed there by means of automated analysis methods. Based on data preparation, characteristics are generated and patterns are classified using methods of machine learning and artificial intelligence. Thus, online measured EEG patterns can be assigned to certain cognitive states. EEG analyses can be performed in regards to time and frequency. Regarding the timing sequence, changes in natural potentials generated by the brain can be detected. An example of this is the potential P300 attributed to the attention of a test person; with an increasing workload, the amplitude of the signal decreases. A higher latency of the potential can also occur. To do this, the data is first filtered in time and then a spatial filter (e.g. xDAWN) [38] is trained, which reduces the amount of data and extracts important characteristics. Then the extracted characteristics are classified with a classifier like a support vector machine [54]. If the target signal changes, the processing chain can no longer correctly classify this signal, which can then be an indication of an overload or distraction of the subject. Furthermore, there are different frequency bands in the EEG. The activity in the respective frequency bands allows conclusions to be drawn about the mental state of the subject. To use this online, the energy of the respective band is measured under normal stress or no stress on the subject. This can be done by spectral analysis, for example. The determined rest values are then continuously compared with the current values in the application in order to be able to evaluate any differences directly. Error related potentials [33,34,35,36] are generated in the brain when a subject perceives something unexpected, such as a robot behaving incorrectly. These potentials can be classified with a comparable processing chain to that of the P300.

The information about the employee's cognitive states is then used for two different functions: to optimize interaction with robots and machines and to provide feedback for the employee himself. Based on the determined cognitive state of the employee, a rule-based control of the robot is realized. For example, the higher the measured stress level of the employee, the lower the speed of the robot. The robot is also controlled in real time and is connected via wireless communication to the digital platform [47,49].

Within the feedback system, the real-time results of the EEG analysis, i.e. the information about the cognitive state, are visualized and made available to the employee via mobile devices. This ensures that the employee is permanently informed about his own data. This is realized via various visualization components (pie charts, alerts etc.) and haptic signals (e.g. vibration alarm). On the other hand, algorithms are included to identify patterns in continuous EEG measurements and to generate recommendations for optimizing working conditions. For example, with the help of a time series or classification analysis, which are usually found in Business Intelligence and Analytics components, mental state developments such as fatigue in time can be anticipated and thus recommendations can be displayed early via text windows and alarms (e.g. via wearables [51,52,53].

In order to ensure adequate data protection, the design of the system has to ensure that only the employee himself receives information about his EEG measurements. The resulting recommendations for improving working conditions are also only made available to the employee in a first step.

5 Discussion and Future Research

The Cognitive Work Protection approach has the potential to change the way occupational safety is realized in human-machine interaction scenarios. Compared to classical approaches it allows a close collaboration and real collaborative work between humans and robots. It is the first approach to directly detect the main reasons for work accidents - namely stress, fatigue, inattention - and to trigger countermeasures in a proactive way.

Besides occupational safety, the presented approach offers the possibility to improve the general working conditions in particular with respect to work overload and boredom. As discussed, this can be realized by providing recommendations for improving the working conditions to the employees themselves. In a next step however, the method can also be used for a company-wide management of human resources. Employees could be assigned varying tasks depending on their skills and level of satisfaction. For example, employees that typically feel unchallenged performing the same tasks every day could be dynamically assigned to frequently changing tasks, while the workload of employees feeling overstrained could be reduced. In this scenario, the presented approach therefore not only reduces work accidents and improves the working conditions of employees, but also has the potential to increase a company's productivity through managing human resources in an optimal way.

Despite the great potential of the approach, there are also challenges that need to be overcome for practical applications. From a technical point-of-view the main challenge is to construct a reliable and comfortable EEG measurements sensor system that does not interfere employees in their work. Current advances in EEG sensor systems show promising results in this regard and hint to a realistic possibility for a practical realization. The second and most important challenge comes with the fact that EEG sensors determine highly sensitive data in the human working environment within which the employee is in a relationship of dependence. In this regard, urgent questions arise which are of an ethical, social and legal nature and which must be sufficiently addressed before a practical realization.

In our future research, we plan to address these challenges and drive the development of a Cognitive Work Protection system, that is accepted by employees and employers alike. Therefor we will develop a prototype that can be tested and evaluated regarding usability, security and privacy issues.

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