Measurements of Mental Stress and Safety Awareness during Human Robot Collaboration - Review

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Human-robot collaboration is an emerging research area that has gained tremendous attention in both academia and industry. Yet, the feature that human and robot sharing the workplace has led to safety concerns. In particular, the psychological states of human teammates during human-robot collaboration remains unclear but is also of great importance to workplace safety. This manuscript briefly reviewed possible direct and indirect measures that can be used to evaluate workers' mental stress and safety awareness during human robot collaboration. It was concluded that each measure reviewed in this paper has its validity and rationality, and a combination of different methods may provide a more comprehensive and accurate assessment.

INTRODUCTION

In recent years, the concept of human-robot collaboration (HRC) has been widely adopted in a variety of industries. In HRC, a human worker and a robot share the workplace and work together in a collaborative way. HRC takes advantage of the flexibility of human and the endurance of robots to substantially improve the productivity (Villani et al., 2018). A robot adopted in human-robot collaboration is typically referred as a collaborative robot, or a co-robot. Because a co-robot is designed to work alongside workers, multiple engineering features (Michalos et al., 2015), such as limited end effector speed (International Organization for Standardization (ISO), 2016), torque sensors (Heinzmann & Zelinsky, 2003), and flexible exterior material (Pang et al., 2018) have been implemented in co-robot design in order to physically ensure human workers' safety.

Co-robots also have psychological influences on human workers besides physical collision as human workers tend to treat their robot teammate as a social entity (Sauppé & Mutlu, 2015). Therefore, it is important to ensure that co-robots are human-friendly and psychological acceptable (Kokabe et al., 2008). Human-friendly means that the co-robots are both safe and in good performance, and psychological acceptable means robots should meet the functional expectations of human workers. To achieve these goals, co-robot motions need to be perceptible, comprehensible, and predictable without imposing mental stress. For example, in common industry practice, the movement trajectory criterion is set to minimize the integral of end effector jerk (derivative of acceleration) or to minimize the total execution time (Gasparetto & Zanotto, 2008). Such trajectories appear unpredictable to and confuse workers at the early phase of the movement (Dragan et al., 2015), and possibly impose mental stress on workers.

Another important psychological aspect of workers during HRC is safety awareness. Safety awareness is a concept derived from situation awareness and emphasizes workers' perception, comprehension, and projection of the safety-related elements and events at work (Stanton & Piggott, 2017). To date, a variety of studies have been conducted in different fields such as aviation and ground transportation and proved situation awareness is of great importance to system safety (Kaber & Endsley, 1998). In HRC, safety awareness refers to workers' understanding of potential hazards related to location, activities, and status of co-robots. From the hazard control perspective, safety awareness is just as important as engineering approaches, because it serves as a redundancy in safety mechanism. For example, when a worker quickly walks toward a co-robot, depending on the walking speed, the automatic obstacle avoidance function of the co-robot may not have enough time to retract its end effector for avoiding the approaching worker. Serious injuries can still occur if the worker is not aware of the existence of a co-robot in the shared workspace. Accident records of Occupational Safety and Health Administration (OSHA) show that multiple fatal and non-fatal injuries related to robots can be partially attributed to workers' low safety awareness (e.g., *OSHA Accident Report 202475737*, 2009).

Some studies have shown that higher stress level was significantly associate with lower level of safety awareness (Sneddon et al., 2013). As workers may be stressful and or have low safety awareness during HRC, it is important to understand workers' psychological states for improving the safety conditions during HRC. To date, a number of approaches have been proposed and applied in literatures on quantifying human psychological state. The main approaches include direct measurements and indirect physiological measurements. The direct methods are those that can quantify or qualify the operator's psychological states directly through self-reports, questionnaires or observations. Indirect measurements are those that estimate operator's psychological states based on their performance or physiological data obtained by special sensors or devices. In this manuscript, we reviewed and summarized different methods for measuring the mental stress and safety awareness that have been adopted or can be applied in HRC.

METHODS TO MEASURE MENTAL STRESS

Direct measurements

Self-report is the most commonly used direct method of psychological estimate. One can design a questionnaire based on psychological knowledge and then compute the stress index by the results. Or et al. (2009) examined effects of moving speed and size of industrial robot on operators mental workload. The effects on workers were then estimated by subjective questionnaires. It was noted that when operators encountered a larger robot or a robot with a higher end effector speed, they perceived a significantly higher mental workload. One limitation of the direct measures is that participants may answer the questions in a way that they think the researchers want them to answer. Another issue is that to some extent the participant's responses depend on his or her mood on the day of the experiment (Bethel et al., 2007). The self-reports were commonly used as reference to build connection between participants' subjective stress levels and the objective physiological data.

Indirect measurements

Indirect measurements to estimate mental stress are mainly divided into psychological signals and facial expression recognition.

The major systems in human body that respond to the mental stress are the autonomic nervous system (ANS) and hypothalamic-pituitary-adrenal (HPA) axis. HPA is a neuroendocrine system that adjusts response to stress, but the response is slow and not intuitionistic. Therefore, ANS response is more suitable for examining worker mental stress (Park & Kim, 2018). Common physiological signals for ANS include blood pressure, cardiac response, electrodermal activity (EDA), Electroencephalogram (EEG), and electromyographic (EMG).

Cardiac response. Heart Rate Variability (HRV) has an effect in determining the role of the human autonomic nervous system fluctuations. Increased sympathetic nervous system activity results an acceleration of heart rate while an increases parasympathetic nervous system activity causes a decrease of the heart rate. Under mental stress, it is commonly observed that the parasympathetic activity of the heart decreases and the sympathetic activity increases. Rani et al. (2002) exploited this feature of heart rate variability to detect stress. They used video games to induce stress and acquire the electrocardiogram (ECG) waveforms, and then both Fourier Transform and Wavelet Transform were used to process the signals. These signals were then adopted to infer the stress condition based on the level of activation of the sympathetic and parasympathetic nervous systems using fuzzy logic.

Electrodermal Activity (EDA). The change of skin electrical properties is referred as electrodermal activity (EDA). EDA is affected by the sweat secreted by eccrine sweat glands (Safta & Grigore, 2011). Eccrine sweating is known as emotional sweating, which is a kind of sympathetic nervous activity involved with mental stress. EDA is divided into exosomatic measurement and endosomatic measurement (Bari et al., 2018). Exosomatic methodology mainly includes Skin Conductance Response (SCR), Galvanic Skin Response (GSR) and Skin Resistance Response (SRR). Endosomatic methodology mainly includes Skin Potential Response (SPR), Galvanic Skin Potential (GSP) and Skin Potential Level (SPL) (A. Affanni & Chiorboli, 2014). Most research use GSR or SCR to analyze mental stress based on EDA. Dehais et al. (2011) examined the effect of the different types of robot trajectories on galvanic skin conductance response. The results suggested that a strong GSR was observed when a participant was surprised to a quickly approaching robot.

SPR signal is more difficult to obtain because it needs complicated and high-cost instrumentations (Antonio Affanni et al., 2018). However, endosomatic methodology exhibits a faster response to stress stimuli than exosomatic methodology, which make exosomatic methodology more suitable to measure mental stress in time. Arai et al. (2010) investigated mental stress of workers when they are working together with a moving robot by measuring the SPR. The results showed that when an operator felt high mental stress at a condition the robot moved too near to them or the moving speed was too fast, the rate of occurrence of spike of SPR was greater.

Electroencephalogram (EEG). EEG is an imaging technique that detect the electrical activities generated by brain (Teplan, 2002). EEG signal is an effective signal to represent the changes in autonomic nervous system. To gain useful information, the decomposition of EEG signals in some frequency bands are extracted using band filter (alpha (8-13 Hz), beta (14-30 Hz), theta (4-8 Hz) and delta (0.5-4 Hz)) (Saidatul et al., 2011). The increased or decreased level of brain activities in frequency band often reflects the level of mental stress (Yang et al., 2010). Al-Shargie et al (2016) utilized arithmetic task as stress stimuli to induce different levels of mental stress and classified the stress based on the EEG signals. The results demonstrated that participants were appeared less attentive and could not relax under high level of stress based on the analysis of alpha and beta rhythm power values. In general, the studies revealed EEG was an effective method to detect mental stress and right prefrontal cortex played a leading role in mental stress.

Electromyogram (EMG). The electromyogram (EMG) measures the electrical activity related to muscle contraction level. In stressful situations, the EMG activity in some muscles increases compared to non-stressful situations. Wijsman et al. (2013) measured EMG signals generated by upper trapezius muscle in three different stressful conditions. The results have shown that amplitude of the EMG signal during stress situations was much higher than rest situations. The relative time with gaps decreased during stress conditions because fewer gaps would occur during stressful situation than during rest. The results suggested that EMG was a useful method to detect stress. Orguc et al. (2018) adopted an EMG-based facial gesture recognition system that could classify different jaw movements. They used discrete wavelet transforms to extract features and a support vector machine to classify jaw movements at different stress level.

Facial expressions. From the psychology perspective, facial expression is a highly reliable measure to infer mental stress (Mauss & Robinson, 2009). There are two mainly techniques to measure emotional facial expressions (Höfling et al., 2020). One is recording the activities of specific muscles with EMG, as mentioned in the previous section. The other technique is by applying computer vision algorithms to face images to infer human stress levels in real-time (Mollahosseini et al., 2017). For example, an intelligent tutoring system uses facial expressions of a student to decide whether a student is confused and needs more practice or is ready to proceed to more difficult concepts. Lerner et. al (2007) experimentally revealed the facial expressions corresponded with the biological stress response. The participants were required to perform stress-challenge tasks, during which the facial expressions as well as several other physiological signals and subjective emotional experience were evaluated. As the results have shown, the facial expression of fear was positively associated with stress whereas the facial expression of anger and disgust were negatively associated with stress.

Bueno et. al (2013) proposed a method of emotional interaction between a robot and a human. The robot could recognize the human emotion changes based on Neural Evolution Algorithm and Active Appearance Models and then performed adaptive actions to mitigate workers' negative emotions.

Multimodal measurements

Although each physiological indicator to measure mental stress has its validity and rationality, there are two main concerns that need to be considered when these methods are applied. One is the large individual difference in physiological response, and the other is that the same physiological signal may be triggered by a range of psychological states. (Kulić & Croft, 2003). For these reasons, some studies sought to compare the stress level derived by different method and infer mental stress in a multimodal way.

Pourmohammadi at el. (2020) classified stress level by detecting the EMG signal of right and left erector spinal muscles and the right and left trapezius muscles and ECG signal. ECG signal was applied as a reference to evaluate the efficiency of EMG signals for stress detection. The results indicated EMG and ECG signals together could successfully classify stress into multiple levels with a satisfactory accuracy. It has also been shown that the EMG signal of the right trapezius muscle recognized stress better than other muscles.

Rani et al. (2007) focused on jointly detecting and recognizing stress through ECG, blood volume pulse (BVP), pulse transit time (PTT), SCR, skin temperature and EMG signal form both corrugator supercilii muscle (eyebrow) and masseter muscle (jaw). The results were compared with the participant's self-reports psychological state. The physiological data were classified using fuzzy logic along with decision tree learning. It was concluded that this approach was able to detect affective state reliably.

METHODS TO MEASURE SAFETY AWARENESS

Self-report measurements

Safety awareness can be evaluated through questionnaires or reports, which are direct approaches to determine a person's situation awareness regarding safety. The most commonly applied measures are Situational Awareness Rating Technique (SART), Situation Awareness Global Assessment Technique (SAGAT) and Situational Present Assessment Method (SPAM). As a subjective method, SART outcomes are easy to obtain as the queries are genetic. SART measures one's situation awareness from ten dimensions, each of these dimensions has seven points rating scale. Both SAGAT and SPAM are objective measures, which provide unbiased estimation of an operator's situation awareness (Endsley, 2019). The queries for SAGAT and SPAM are special designed according to the situation, and the questions can be scored correct or false objectively and are asked during live missions.

SART questionnaire is provided after the trial, and it is based on a subjective estimation of situation awareness of the operator. Da Merwe et. al (2019) developed a VR mediated HRC framework for non-professional operator. They compared operator's situation awareness and attentional demand under the full information and preprocessed information context based on the answers of SART questionnaire. The results suggested that there was no significant difference of operators' situation awareness between the two information contexts. However, attentional demand scores were significantly greater for the full information context.

SAGAT is a popular freeze probe technique. A task is interrupted when the SAGAT is applied, and participants are required to answer the questions regarding the current situation. Unhelkar et al. (2014) evaluated human worker's awareness of mobile robotic assistant in task environment through SAGAT. The designed questions were about the features of robotic assistants and human assistants. The results showed that participants were significantly more aware of the tray's color after a delivery was performed by a robotic assistant. In contrast, the background environment was noticed better by participants after a delivery was performed by a human assistant. This suggests that the robot may have a transitory distracting effect that degrades situation awareness, even after the robot left the participant.

SPAM questionnaire is performed in real time but with no freeze while the participants carry out their operational tasks. Yeo et al. (2017) used four parameters obtained from SPAM to measure situation awareness and workload in an air traffic control context. The percentage of correct response and the latency of the response were two parameters to measure the situation awareness while time taken to be ready and the number of ready responses were used as workload measures. It is suggested to conduct nine situation awareness probes at a six-minute interval.

Although the self-report methods are easy to apply, there are also some limitations (Zhang et al., 2020). SART is subject to memory decay since participants must complete the questionnaire at the end of the task (Gatsoulis et al., 2010). SAGAT requires interrupting tasks, which limits its application in case the task cannot be stopped (Sneddon et al., 2013). SPAM requires participants to answer questions while performing tasks, which could have a negative affect on the participant's performance. Furthermore, the obtained data from SPAM may suffer from bias because participant's attention may be oriented to the relevant situation awareness elements due to the questionnaire (Salmon et al., 2006).

Physiological measurements

There are only a limited number of studies examining using physiological measures to infer situation awareness. Eye tracking was most commonly used physiological measures and account for the majority of the relevant literature. Another commonly used physiological method is EEG.

Eye tracking. Eye tracking is an approach to measure situation awareness unobtrusively in an environment where multiple tasks exist. The situation awareness can be estimated by locating human gaze. Dini et al. (2017) developed a methodology to measure situation awareness from gaze interaction with objects of interest in the context of human robot handover events. Their research question was whether SAGAT or SART questionnaire could be replaced by 3D-gaze tracking. The results showed that fixation distribution analysis significantly served the purpose to measure situation awareness. Besides, the look rate, average dwell time and turn rate were all features considered in the frame. Although not all the metrics had significant correlations with situation awareness, discriminative features were selected to predict situation awareness and made successful estimations.

Electroencephalogram (EEG). Brain wave activities in beta band are related to active thoughts and problem solving (Yeo et al., 2017). It has been demonstrated by some studies that there is a negative correlation between the workload and situation awareness while positive correlation exists between the situation awareness and performance (Dini et al., 2017; Schuster et al., 2012). EEG is widely deployed to examine the pilot or driver's brain activities during their driving tasks and what correlations built between the brain activities and situation awareness (Borghini et al., 2014). Catherwood et al. (2014) recorded participants brain activities with EEG during loss of situation awareness. They required participants to identify target pattern or “threat” in urban scenes and then changed the target to enforce a loss of situation awareness. By analyzing the EEG data obtained from different brain areas, it is concluded that there was a co-activity in visual and high-order perception regions during loss of situation awareness. Luca Kästle et al. (2021) proposed a novel analytical methodology to correlate EEG signals to situation awareness. Participants completed the situation awareness test in Psychology Experiment Building Language (PEBL). PEBL is a psychological assessments framework contains a situation awareness test based on SAGAT technique. EEG data was collected throughout the whole test process. After processing the EEG data, the features were extracted and classified into high and low situation awareness categories. A correlation was found between the beta and gamma frequency bands and situation awareness.

CONCLUSIONS

As HRC is flourishing in recent years, there is an urgent need to better understand human workers’ physiological states when they are working with their robot teammates. This manuscript provides a brief review regarding the possible methods for assessing mental stress and safety awareness during HRC. According to our literature review, each method mentioned above for evaluating operators’ mental stress or safety awareness has its validity and rationality. In general, most experiments that have been carried in HRC scenarios employ both indirect physiological measurements and direct self-report measurements, which give us a depiction of psychological states from different dimensions. Some methods have been proved effective and feasible to measure mental stress and safety awareness but are lacking in the application in human robot collaboration. Future work is needed to explore the effectiveness and efficiency of these techniques based on other measurements as references. This review may provide insight into alternative methods to assess mental stress and Safety awareness. For example, a combination of different methods may provide a more comprehensive and accurate assessment of mental stress or safety awareness in HRC tasks.

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