Towards an EEG Based Mental Workload Evaluation Method for Construction Workers' HMD AR Use

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ABSTRACT

Augmented reality (AR), with its strong ability to enhance how a user interacts with the digital model and the real environment, has great potential to optimize the conventional construction process. Not only the design and planning phase decisions, but also the on-site job accuracy and efficiency can be improved through AR. Furthermore, the development and application of head mounted devices (HMD) provide the workers a new hands-free method to interact with digital model on the site. However, human factor aspects of HMD AR use in construction, such as human computer interaction (HCI) optimization, hardware clumsiness, and safety monitoring are still not well studied. Hence, evaluating the user's mental and physical workload can be an effective way to understand how a worker might react to this new construction mode. Since it is a new attempt to monitor the mental workload during the HMD AR use with construction activities, in this paper, we reviewed the previous studies in mental workload evaluation, and introduced a possible approach to study this problem. Different types of mental workload evaluating methods such as electroencephalogram (EEG), and NASA-TLX were discussed based on their pros and cons in this field.

INSTRUCTION

Augmented Reality (AR) technology has infiltrated into every aspect of daily life. Especially, the combination of AR and mobile devices provides a more convenient access to, and interaction with digital models and the real world. In AEC (Architecture, Engineering and Construction) industry, AR shows great potential to change the conventional working patterns. For instance, some construction companies use AR devices for evaluating design alternatives in the field, which gives their clients a more direct experience (Yoders 2018). Moreover, the development of see-through AR headsets, which enable construction workers to see the digital model in the field, brings the possibility of a brand-new approach to working at a construction site (Chi et al. 2013). However, the usability of such approach still needs validation and a critical evaluation given that construction is one of the most dangerous industries for workers. There is very limited research that looks at whether using a head wearable AR device can reduce construction workers' workload and enhance the efficiency and accuracy of the task. When workers are interacting with the system, it could be a distraction to recognize hazards from their surroundings. As a resolution to these concerns, monitoring workers' mental workload can reflect workers' mental engagement and fatigue, which can tell the usability of HMD on site. This paper reviews the current mental workload measuring approaches both in HCI and construction domains. Subjective and physiological measures are discussed based on their pros and cons, so as to find a more suitable method for this study. In this context, a possible EEG based approach is proposed to measure construction workers' mental workload with HMD AR use.

MENTAL WORKLOAD MEASUREMENT

Developing a better understanding of the workers' mental status during the construction process, which exposes their *concentration on work*, *situational awareness*, and *cognitive fatigue*, requires studying the worker's mental workload. In a setting with HMD AR, the changes in mental workload can potentially also reveal workers' reaction to this technology in the human-computer interaction mode. Generally, approaches to workload assessment can be divided into three categories: subjective, performance-based, and physiological measures (Vidulich and Tsang 2012). Among the recent subjective evaluation frameworks, NASA-TLX is the most widely used approach to measure the mental workload (Hart and Stayeland 1988). It measures the overall workload level for the whole task with six subscales: mental demand, physical demand, temporal demand, performance, effort and frustration (Hart and Stayeland 1988). Although NASA-TLX is able to differentiate the task difficulty by the aggregate or trial-average workload levels, it is not responsive to moment-to-moment changes in workload (Funke et al. 2013). In comparison, some new physiological monitoring techniques, such as EEG, functional near-infrared spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), and eye tracking systems have a stronger capability to track the real-time changes of the mental workload levels.

During the construction process with HMD AR, workers are not only required to focus on their work in hand, but also need to be aware of their surroundings, and look at the AR display. Hence, monitoring mental workload for the whole process can provide information under a high occupational stress. From this perspective, a quantitative and direct mental load measuring approach, such as EEG, would be more suitable in a construction case, and can also be easily used outside of a specific laboratory setting.

Electroencephalography (EEG)

EEG is one of the most frequently used neuroimaging techniques to monitor the activity of brain. Compared with other similar techniques, such as fNIRS and fMRI, EEG gives the advantage of higher temporal resolution and portability. In recent years, the development of wireless EEG devices equipped with through-hair sensors even requires zero preparation of the scalp (Matthews et al. 2007), which greatly simplifies the conventional process for EEG measurements.

Based on the International 10-20 System for electrodes placement for EEG test, Homan et al.'s experiment validated that EEG data acquired varies with the locations of electrodes (1987). That is, different cerebral cortex areas reflect various brain functions. Basically, the cerebral cortex consists of 4 lobes: *frontal*, *parietal*, *occipital*, and *temporal lobes*. Under frontal lobe, the prefrontal cortex is responsible for cognitive control (Miller and Cohen 2001), and the motor cortex controls the execution of movement (Kakei et al. 1999). In addition, occipital lobe receives visual stimuli and processes visual information (Grill-Spector et al. 1998). In this study, a construction activity under a HCI situation, involves both physical labor and visual information processing. Hence, the frontal lobe and occipital lobe are the most focused areas. The data collected from an EEG test are sets of time series signal, which needs to be processed through power spectral densities (PSD). The main idea is to figure out the distribution on a frequency domain, so that we can observe the power density on each certain bandwidth. This is because brain rhythms for different functions fall into different frequency bands. Generally, these are grouped as delta (1-4 Hz), theta (4-7 Hz), alpha (7-12 Hz), beta (12-30 Hz), and gamma (>30

Hz) frequency bands. All these waves, except for the delta wave used for assessing the depth of sleep (Harmony 2013), are related to motor activities and cognitive processes, and can be utilized in this study (Table 1).

Table 1. Brain Waves and Characteristics

Parameters	Frequency Bandwidth (Hz)	Reflect Functions of Brain
δ	0.5 – 4	Depth of sleep
θ	4 – 7	Working memory and cognitive fatigue
α	7 – 12	Relaxation and wakefulness
β	12 – 30	Attention and motor execution
γ	> 30	Sensory integration

Mental workload during HCI

EEG has been widely used in various HCI cases as a method to assess the mental workload. Trejo et al. (2007) employed EEG test under a HCI task mode to validate the three-state model for mental fatigue. The experiment showed the capability of EEG to detect the mental workload levels while subjects were finishing tasks using an interaction system with computer. In many other cases, researchers adopted EEG to monitor subjects' mental workload in a virtual reality simulation environment, so as to study the subjects' reaction under different cognitive conditions. Oh et.al (2015) conducted the experiment to assess pilots' mental status under different levels of challenges in a flight simulator based on the EEG test. Besides, Xie et.al (2009) also employed EEG in their drivers' fatigue detection study in a driving simulator. Similarly, Ryu and Myung (2005) combined EEG and eye tracking to measure mental workload in a dual task test under a HCI system for operator simulation. The studies above all supported the usability of EEG for measuring mental workload under a HCI situation.

APPROACH

Mental workload measurement in construction

While the mental workload measurement for human factors in other areas has long been studied, it is still a new topic in the construction research. A systematic literature review on mental workload assessment approaches conducted on three mainstream construction research journals, *Automation in Construction, Journal of Computing in Civil Engineering,* and *Journal of Construction Engineering and Management,* with separate keywords of "mental workload" and "EEG". In total, 11 articles were found that are directly relevant to this topic. In the early studies before 2016, mental workload measurement for construction workers included NASA-TLX as a self-reporting measurement method. For example, Dadi et al. (2014) examined cognitive workload for different engineering information formats with NASA-TLX. The same method was also used for a real-world masonry case (Mitropoulos and Memarian 2013), and the usability of AR devices for construction assembly tasks (Wang and Dunston 2006; Shin and Dunston 2009; Hou et al. 2015). However, in most recent researches, physiological methods, like EEG, was chosen by researchers for a more direct and quantitative observation from subjects. Chen et al. (2016) defined high mental workload as an "invisible gorilla" leading to high risk behavior. He also introduced the EEG method to assess workers' engagement and evaluate their alertness towards hazards (Wang et al. 2017, Chen et al. 2017). However, construction activities always involve intensive labor work, which can result in an inevitable artifact to the data acquired. Thus, in the study for workers' stress recognition, Jebelli et al. (2018) applied supervised machine learning approaches to remove the artifacts in EEG data and classified the stress levels (Hwang et al. 2018, Jebelli et al. 2018). The results of literature review are listed in Table 2 & 3.

Table 2. "Mental Workload" Keyword Search

Report	Purpose	Experimental Design	Approach
Wang & Dunston (2006)	Examined usability of AR HMD used in AEC project	Compared AR CAD system against a monitor for an orientation task.	NASA-TLX
Shi & Dunston (2009)	Evaluated usage of ARCam for steel column inspection	Used ARCam against Total Station to inspect steel column.	NASA-TLX
Mitropoulos & Memarian (2013)	Studied mental taskload in masonry work	Investigated 22 subjects from 2 masonry projects.	NASA-TLX
Dadi et al. (2014)	Examined cognitive load of different engineering information formats	Subjects used 3 types of information: 2D drawings, 3D CAD, and 3D printed physical model to finish a Lego size assembly.	NASA-TLX
Hou et al. (2015)	Evaluated the use of AR for pipe assembly	Subjects used AR or drawing to assemble pipes. The pipes were rated and subjects were permitted to rework on it.	NASA-TLX

The literature review above showed that mental workload assessment in construction is studied within a limited scope. Even though NASA-TLX is a well-tested method for evaluating mental workload, the emergence of more quantitative tools, such as the EPOC+ brain sensor, allows researchers to have more granularity in the assessment data. There is enough evidence in the recent literature that EEG is a promising method for construction research and has a great potential to measure construction workers' mental workload under a HCI situation.

Pilot study

This study points at testing the feasibility of the EEG based mental workload evaluation method for construction worker's HMD AR use. Hence, the study had subjects carry out wood frame assembly tasks with two information delivery types, and compared the performance metrics, such as the engagement and focus with NASA-TLX evaluation results. If the results are corresponding, then this method is supposed to be feasible for further study.

Experimental design

4 subjects with engineering knowledge background were asked to conduct two wood frame assembly tasks: one with paper blueprint and tape measure, and the other one with only a 3D model in a Microsoft HoloLens headset. Figure 1 shows the user's view through HoloLens. The left picture (a) shows the initial status, where an AR frame model is displayed on the ground, with a pile of lumbers aside. The right one (b) shows that the frame is correctly assembled

according to the model. In both task situations, the subjects were monitored by the EPOC+ brain sensor (Figure 2), which recorded their brain activity information in EEG data set. After each task, the subject was asked to finish a NASA-TLX questionnaire.

Table 3. "EEG" Keyword Search

Report	Purpose	Experimental Design	Data Analysis
Chen et al. (2016)	Monitored construction workers' mental workload	Subjects took 4 tasks: idling, ladder climbing, nut selection, bolt fastening and under 3 conditions: relax, climb, conduct installation.	Time-frequency analysis (time window & Power Spectral Density(PSD) map); Indicator: Engagement Index.
Chen et al. (2017)	Monitored construction workers' mental workload	Subjects took 4-5 minute tasks: climb up a ladder select bolts, install bolts, climb down the ladder.	Three-way ANOVA for EEG PSD data, and compared with NASA-TLX results.
Wang et al. (2017)	Monitored construction workers' vigilance and attention level	Subjects finished 6 tasks in a process: pick up material, pass obstacles (4 types), put down material.	ICA (Independent Components Analysis) and pass filters to remove artifacts.
Jebelli et al. (2018)	Measured construction workers' stress level	On-site subjects performed tasks under 3 different conditions (hazard levels). Off-site subjects performed repetitive tasks at different time after rest.	Pass filters and ICA for extrinsic and intrinsic artifacts removal. Mean PSD on beta frequency for states classification.
Jebelli et al. (2018)	Proposed a framework on artifact removal for EEG signal collected from an on-site experiment	A framework with pass filter for extrinsic artifacts and ICA for intrinsic artifacts removal. Significant difference captured for mean PSD of beta range.	Introduced various machine learning methods for classification: k-Nearest Neighbors, Gaussian Discriminant Analysis, SVM.
Hwang et al. (2018)	Measured construction workers' emotional state	On-site subjects performed tasks under different conditions (at ground, on ladder and in a confined and dimmed space). Off-site subjects performed repetitive tasks at different time after rest.	Pass filter and ICA used for data cleaning, and mean PSD for further analysis. Adopted indicator calculation for Valence and Arousal.

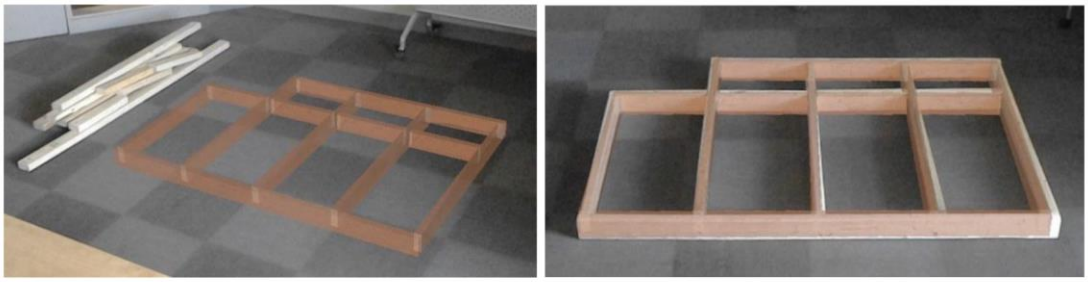

Figure 1. Screen shots from HoloLens (a) AR frame model (b) frame assembled

Figure 2. EPOC+ Brain Sensor (*https://www.emotiv.com/epoc/*)

Results

The software for EPOC+ provides performance metrics based on the raw EEG data. Table 4 shows the result of comparing the subjects' engagement score during two tasks, and Figure 3, as an instance, plots the real-time records of the engagement score for subject 2. There is an obvious difference between the results from two tasks. According to the EEG analysis results, in most cases, reading paper blueprint and doing tape measuring produced a higher mental engagement than using HoloLens. Besides, the time consumption for each task can also tell the difference in efficiency. Table 5 shows the summary for the time each subject used for the tasks. There are three out of four subjects using less time with HoloLens, and the mean value shows the same result. Based on these results, AR HMD is capable to reduce the subjects' engagement and improve their productivity.

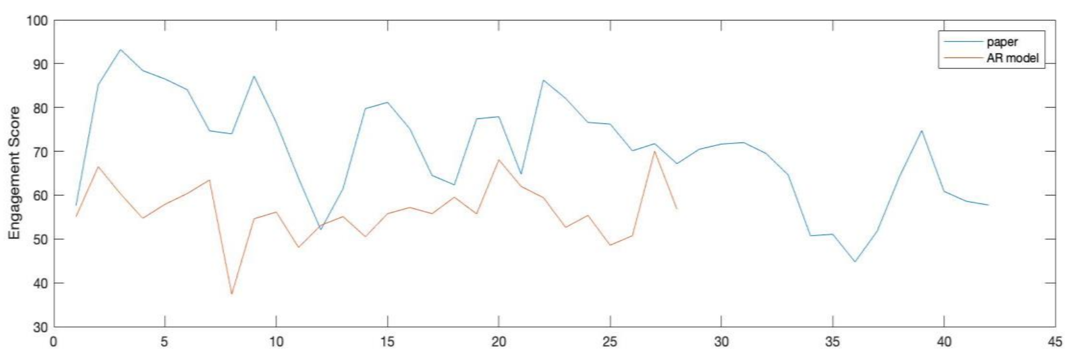

Figure 3. Plot of Engagement Score for Subject 2

Table 4. Mean Engagement Score During Tasks (scale of 0 ~ 100)

	S01	S02	S03	S04	Mean
AR model	78.06	56.46	68.36	56.49	64.84
Paper	68.05	68.02	94.63	60.87	72.89

As a reference towards the EEG based method, NASA-TLX also shows a corresponding result. NASA-TLX has six metrics for subjective evaluation: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration. From Figure 4 and Table 6, we can see that the AR model has a significant lower score mental demand than the paper drawing, which indicates that subjects felt more relax and comfortable in finishing task using HoloLens. Besides, the overall ratings also show that using AR model has a lower task demand for the subjects.

Table 5. Time Consumption for Tasks (seconds)

	S01	S02	S03	S04	Mean
AR model	216	277	450	197	285
Paper	263	505	304	571	410.75

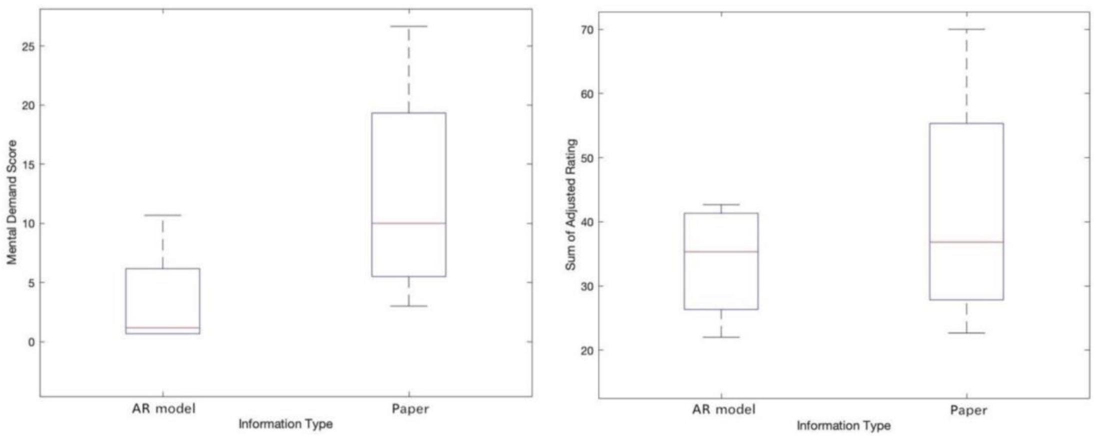

Figure 4. Box Plots (a) Adjusted Mental Demand Score (b) Total Adjusted Score

Table 6. Summary of NASA-TLX Scores (Adjusted Average Score)

	MD	PD	TD	P	E	F	Total
AR model	3.417	10.417	4.917	7.584	5.667	1.834	33.834
Paper	12.417	5.167	4.667	7.833	8.834	2.667	41.584

CONCLUSION AND FUTURE WORK

This paper reviewed different approaches utilized in mental workload measurement for HCI and construction domains. In comparison to subjective approaches, physiological measures provide a more direct and quantitative observation, with precise and analyzable results for further study. However, the literature review shows that there is still limit study in mental workload evaluation in the intersection of HCI and construction domains. In this context, a conceptual approach to measure workers' mental workload with EEG is shown to be viable. The pilot study showed the feasibility of the EEG based method to detect mental workload (engagement) difference under two situations, which helps us to study the pros and cons of HMD AR. Besides, the result of NASA-TLX also provide a corresponding conclusion, which also a validates the feasibility of the EEG based method. Nevertheless, there are still issues required to be concerned in the future. In the pilot study, we used the exist function for engagement rating, which didn't include a complete data cleaning process. Since the framing assembly task involved with an intense body movement, as the previous study proved, this can cause the artifacts and impact the accuracy of final results. Therefore, in the future study, a more complete and systematic data cleaning process needs to be added.

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