Proceedings of the 2020 Winter Simulation Conference
Q. Zhu, J. Du; T. Roeder, and R. Thiesing, eds.

NEURAL FUNCTIONAL ANALYSIS IN VIRTUAL REALITY SIMULATION: EXAMPLE OF A HUMAN-ROBOT COLLABORATION TASKS

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ABSTRACT

Human-robot collaboration has gained its popularity with the fast evolution of the Industry 4.0. One of the challenges of HRC is human-robot interface design that adapts to the personalized needs. This paper presents a method of using Virtual Reality (VR) simulation as a testbed and data collector for examining and modeling personal reactions to different human-robot interface designs. To obtain real-time leading indicator of human performance, this study focuses on the neural functional analysis in VR. An integrated system is presented using eye-tracking and force input data as event makers for Neuroimaging technique, i.e., Functional Near Infrared Spectroscopy (fNIRS). The real-time hemodynamic responses in subjects' brains are analyzed based on the general linear model (GLM) for modeling neural functional changes under different levels of haptic designs. Our results indicate that the neurobehavioral data collected from the VR environment can be used directly as a personalized model for human-robot interface optimization.

1 INTRODUCTION

Human-robot collaboration (HRC) is a defining technology of the Industry 4.0 (Rüßmann et al. 2015). With the fast technological development, robotic applications have penetrated in various operational areas in the construction industry such as, turtlebots for construction site scanning (Asadi et al. 2018; Vickranth et al. 2019), autonomous brick-laying robots (Pivac and Wood 2012), unmanned aerial vehicles (UAVs) for detecting environment (Roberts et al. 2017; Kim, Park, et al. 2019), humanoid robots in daily industrial operations (Hasunuma et al. 2002) and teleoperation robots collaborating with human workers in construction workspaces (Kim, Goyal, et al. 2019). One of the long-lasting challenges faced by HRC, especially robotic teleoperation, is human-robot interface design, i.e., how the feedback from the robotic system to the human operator should be designed and optimized to enable a better performance (Burdea and Zhuang 1991; Al-Mouhamed et al. 2008). Human perception about the HRC workspace is highly affected by the created sensations on the operator's end via human-robot interface; literature has identified that perceptual modalities of human beings such as visual, auditory and haptic feedback, all play a critical role in generating proper sense of the workspace and eventually affect the teleoperated task performance (Sallnäs et al. 2000; Chen et al. 2007; Boessenkool et al. 2013). But it shall be noted that the optimal human-robot interface can be varying case by case, person by person, requiring a sophisticated method for soliciting and modeling individual preference and requirements.

This paper presents a method of using Virtual Reality (VR) simulation as an effective tool for examining the neurobehavioral implications of different human-robot interfaces in robotic teleoperation. Particularly, in this study we focus on the optimal design of haptic feedback that reproduces the physical interactions in intensive motor tasks. A VR simulation is created to simulate industrial operations, such as pipe maintenance and valve manipulation tasks. A haptic device (force feedback) is used to simulate the resistance (e.g., torque) on the human operator end, with varying magnitudes. The performance of the human operator is tracked as the basis for adaptive haptics design. To be noted, for a faster adaption of the

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haptic interface, we focus on tracking the neural functions of the participants as they are leading indicators of the final task performance. As such, we use Functional Near Infrared Spectroscopy (fNIRS) (Ferrari and Quaresima 2012) that monitors the hemodynamic responses in different cortexes of interest, including prefrontal cortex and premotor cortex. The neural data is then analyzed to assess the functions (such as attention) of human operators. The challenge with neural data tracking is event makers, i.e., the mark precisely when a triggering event occurs and ends (e.g., when turning a valve starts and ends). This is because the hemodynamic responses of humans are usually slower than the triggering events, and can last for 10-30 seconds(Huppert et al. 2006). As a result, the time points and duration of each event must be documented precisely. The traditional way for event marking relies on a heavy manual process of the researcher, which introduces potential errors. We propose a multimodal neurophysiological tracking system where the eye tracking data and motion analysis data can be used as the automated event makers. The remainder of this paper introduces the experiment for the proof of concept.

2 THEORETICAL AND TECHNICAL BACKGROUND

2.1 Functional Near-Infrared Spectroscopy (fNIRS)

Recent technological advances, especially the development of portable device, have allowed neuroimaging to be used in various disciplines that interested in human mental and physical behaviors (Di Rienzo et al. 2016). Neuroimaging analysis has been already used for studying cognitive processes in multiple engineering domains such as decision making (Goucher-Lambert et al. 2017) and hazard detection (Thirunavukkarasu et al. 2016), attributed to its advantages of measuring the individual's cognition directly rather than the subjectivity an imperfection that comes with observational studies or questionnaires. Particularly, Functional near-infrared spectroscopy (fNIRS) has started to draw attention as a novel and invaluable tool to study and monitor tissue oxygenation changes in the brain non-invasively (Bunce et al. 2006; Du et al. 2020). The attributes of fNIRS like portability, movement tolerability, and safety of use have made it particularly suitable for investigating brain function (Pinti, Tachtsidis, et al. 2018). Comparing to other available neuroimaging techniques relying on neurovascular coupling such as functional magnetic resonance imaging (fMRI)(Ochsner et al. 2002) and positron emission tomography (PET) (Andreasen et al. 1996), and those based on the electromagnetic activity of the brain such as electroencephalography (EEG) (Ray and Cole 1985) and magnetoencephalography (or MEG)(Halgren et al. 2000), fNIRS is more robust for monitoring cortical hemodynamics during motor tasks or tasks involving walking given its advantages of low sensitivity to body movements and the systems' portability (Pinti, Tachtsidis, et al. 2018). These features of fNIRS make it suitable for tracking worker's brain activities with heavy body motions during regular operations. Previous studies have proven that hemodynamic responses in the prefrontal cortex (PFC) measured by fNIRS can be used to quantify and classify mental workload (Herff et al. 2014) , and is also linked to decision making (Ramnani and Owen 2004). Both metrics are essential factors influence workers' performance in complex tasks involving working memory, knowledge and motor skills. According to (Leff et al. 2011), motor stimuli increase the oxygenated hemoglobin and decrease the deoxygenated hemoglobin in the motor cortex, which contains the primary sensorimotor cortex (PSMC) and the premotor cortex (PMC). The activation signals from this area can be used to evaluate behaviors like movement planning, control, and execution, which are related to physical operation as valve rotation. As a result, in this research, the prefrontal and motor cortex activities measured by fNIRS are used to study the mental workload of the worker during the task.

2.2 Event Marking and Recovery For fNIRS Data Analysis

Most neuroimaging studies rely on block design, which is more effective in the lab environment but often fails in a more naturalistic setting. Compared to block design, the event-based design can overcome the drawbacks such as poor estimation- extracting the time course for a type of event (Boynton et al. 1996). Therefor event-based designs are preferred for certain types of experiments that look at responses to unpredictable or uncontrollable events. But it is also noted that event-based design ignores specific neural responses, including transients at the block transitions and sustained activity that begins and ends with the performance of the task (Petersen and Dubis 2012). To tackle these problems, the mixed-design experiment including both block and event-based activity is recently used as a better representation of most experiments (Pinti et al. 2017). Unfortunately, only a few studies have been shown effective in using this approach because of the lack of control in an independent variable or known occurrence of stimulus (Shealy and Hu 2017). In addition, the event marking and recovery processing is still difficult and time-consuming as most studies rely on a heavy manual process such as video analysis to label the start and end points of each event (Pinti et al. 2015; McKendrick et al. 2016). This asynchronous event recovery method could also result in synchronization problems between fNIRS data and event recorders. Therefore, a new design framework that can automate the event marking for faster or even, real-time neuroimaging analysis is needed. The following section presents a VR system and experiment for the proof of concept.

3 SYSTEM DESIGN AND EXPERIMENT

3.1 Analytical VR System Overview

Since our VR system integrates real-time neural analysis functions, we call it "analytical VR". The analytical VR system aims to provide an immersive environment of the realistic working environment and recover events from the behavioral data for fNIRS data. In the experiment, we simulated a teleoperating valve manipulation task with different levels of robotic force feedback magnitudes. The human operator worn a VR headset to display the first-person view (FPV) from the remote robot. We used a force feedback device, Novint Falcon (Martin and Hillier 2009) to reproduce the sensed force from the virtual robot, and control the arm of the remote robot. The architecture of events data recovery system is illustrated in Fig.1. The behavioral data of the participants during the experiment was recorded via two input functions in Unity. The first one was the metadata collection, which collected data directly from controllers and eye tracker. The controller system incorporated the HTC VIVE controllers recorded the body motions of the participants, and the Novint Falcon controller recorded the hand positions when the participants were manipulating the valves via the remote robot. All the data was recorded by the format of (x, y, z), the location of the sensor mapped in the virtual space. The data recorded from eye tracker (HTC VIVE PRO) included pupil size (radius) and gaze position (x, y, z) in the virtual space. The second type of data was processed data collection. When the system detected that the hand or gaze position collided in the predefined area, a special event label was marked. All data was recorded by the system automatically at the frequency of 90 Hz. To synchronize the data between fNIRS device and Unity system, an initial timestamp with the same standard was used. Then by timestamps, the events recorded from Unity system can be easily located in fNIRS data.

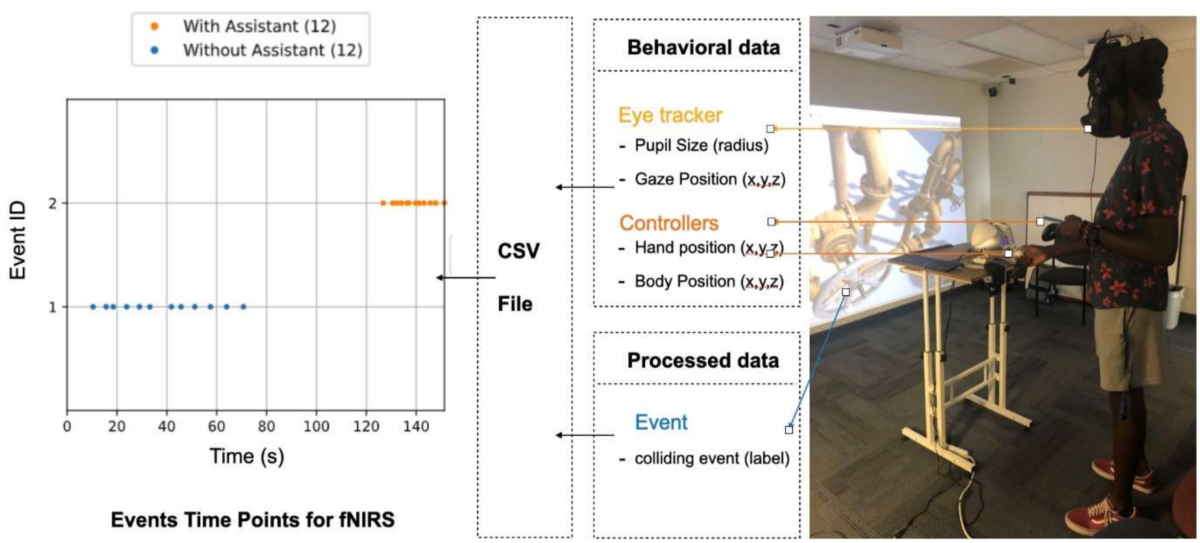

Figure 1. The architecture of the analytical VR system with events data recovery.

3.2 Experiment Design

The experiment designed for the test case incorporated both motor and knowledge tasks under two conditions: *realistic* force feedback that reproduces exactly the same torque the remote robot uses to manipulate the valves (15 lbs./ft), and *mediated* force feedback that simulates a less torque (7.5 lbs./ft), shown in Fig.2. The participants (n=30) were required to memorize the sequence of operating 12 valves (memory or knowledge based), and then turn five rounds with the proper force given to the remote (virtual) teleoperation robot (motor based). The goal of the human-robot interface (haptics) design is to ensure that human operators engage more in planning and memory retrieval tasks (i.e., prefrontal cortex) activities. Our previous findings (Qi et al. 2020) indicate that the neural functional change is a strong indictor of both task performance of perceived mental load of human operators. As a result, we focus on identifying and tracking neural activities. The challenge to neural data tracking is that the participants often engage in dual tasking status, i.e., looking around instead of focusing on the valve during the valve manipulation task. In order to evaluate how the pure valve rotating operation affects neural activities under the two different conditions, a more specific event recovery and marking method should be used for fNIRS data analysis. Here, we propose to use both hand and gaze positions to recover the pure operating events.

Before the experiment, the participants were seated and asked to adjust their hair to affixing the wireless fNIRS device. We used a wearable 24-channels fNIRS system (Oxymon, Artinis Medical Systems, Zetten, The Netherlands) to evaluate activation levels in the prefrontal cortex and motor cortex. Fig.3 shows a schematic design of the fNIRS probes and channels used in the experiment, which contains eight detectors and ten emitters, capturing twenty-four channels for both left and right frontal lobes, including PFC and motor regions. As shown in Fig.3, red dots indicate the sources (emitters), green dots are detectors, and blue lines are the channels. A black shower cap was used to fully cover the participant's head to ensure that the environmental light would not contaminate the fNIRS signals. Care was taken to ensure that all emitters and detectors were not affected by the VR google when the participant was wearing the VR headset. Once the fNIRS sensors, shower cap and VR device were positioned, the fNIRS devices started data collection.

Then the participants were asked to fill background questionnaires and the FRCT test before wearing the VR headset and being introduced to the experiment procedure. The experiment consisted of seven sessions: (1) Training: participants were asked to finish a training session which helped them learn how to use our teleoperation system to manipulate the valve. (2) Memory session i: memorizing the operating sequence of 12 valves in 3 minutes. (3) Teleoperation session i: operating valves in the given sequence and for the required number of rotations (randomly in one of the two conditions). (4) Memory session ii: same requirements as review session i but with a different sequence. (5) Teleoperation session ii: same requirements as review session i but in the other force feedback condition. The sequence of the two performance sessions was shuffled to rule out any potential learning effects.

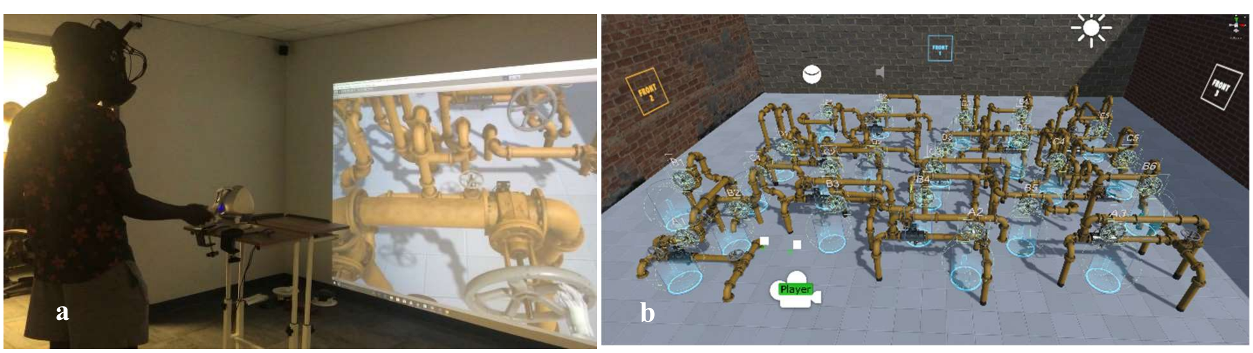

Figure 2. The designed experiment. (a) valve operating event; (b) working environment.

4 DATA ANALYSIS

4.1 Data Pre-Processing

First, fNIRS data was filtered and cleaned. For each participant, raw light intensity fNIRS data (18 optodes * 2 wavelengths per optode) were sampled at 10 Hertz. For pre-processing, the signals were low-pass filtered with to remove the influences from physiological changes (heartbeats, breath, Mayer waves and very low frequency oscillations(VLF) (Pinti, Scholkmann, et al. 2018). Then the motion artifacts were identified and removed through the algorithm hmrMotionArtifact from the HOMER2 NIRS processing (Huppert et al. 2009) to improve signal quality. Participant data containing motion artifacts in three channels or more were removed from the analysis (9 were removed) (Peña et al. 2003). The changes in the concentrations of oxygenated (oxy) and deoxygenated (deoxy) hemoglobin (Hb) were calculated by absorbance change of 730 and 850 nm wavelengths for each channel according to the Modified Beer-Lambert Law method (Delpy et al. 1988). The changes in oxy-Hb values were used as indicators of changes in regional cerebral blood volume as oxy-Hb(HbO2) is the more sensitive indicator of changes in cerebral blood flow (CBF) (Hoshi et al. 2001).

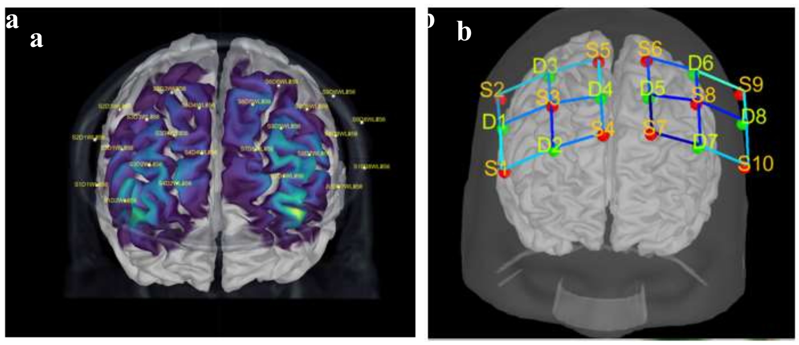

Figure 3. fNIRS channels configuration. (a) Sensitive areas; (b) schematic layout

4.2 Recover Events From Gaze Tracking And Motion Data

According to the force data transferred from Novint Folcon, the system recorded the time stamp when the participant started and ended operating the valve for each trial. However, as discussed earlier, while participants were performing valve manipulation, they could also be engaged in other mental activities such as looking around the environment and planning out the next action. As a result, the eye-tracking data was also used to recover the attention-related events during the operating period. We define the focused operating event as following: When a participant is operating the valve and his/her gaze is also fixed at the valve, we assume that he/she focuses only on motion coordination. In this way, we can filer out the influence of other stimuli such as dual tasking. All the annotated time points were exported as a csv file by the system automatically. The extracted time points of two events (operating valve with mediated/realistic force feedback) during the experiment are shown in Fig. 4. Moreover, the data was used to create a design matrix that would be used in General Linear Modal (GLM) for fNIRS data analysis for neural functional classification. We used the standard SPM hemodynamic response function and included a first-order polynomial drift to design our event matrix. The visualization of the design matrix is shown in Fig.4.

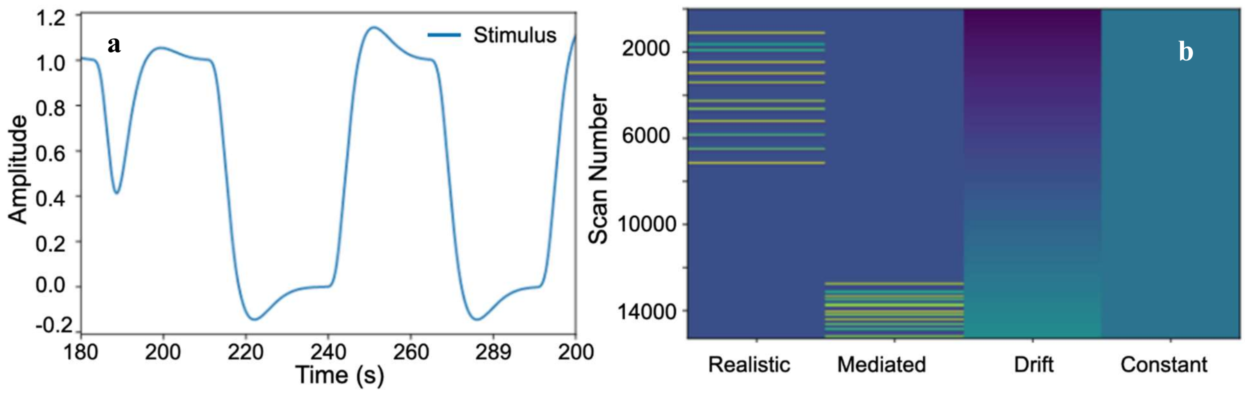

Figure 4. Visualization of the GLM design matrix. (a) GLM solution with stimulus (forced valve operating in non-assistant condition) (b) Visualization of events matrix.

4.3 GLM Analysis

The General Linear Modal (GLM) is commonly used in fNIRS data analysis because of its advantages of stronger statistical power than other methods (e.g. block averaging) (Pinti, Scholkmann, et al. 2018). In fact, the GLM offers more complexity and rules out information related to noise or other non-experiment related factors. It also provides a more objective comparison between experimental conditions with different statistical testing methods(Monti 2011). The GLM can be expressed for fNIRS as Eq (1):

$$Y = X\beta + \varepsilon \tag{1}$$

where Y is the observation fNIRS signal matrix which contains time points and fNIRS channels; X is the design matrix that incorporates the repressors with a priori knowledge about the expected model of the activated hemodynamic response (e.g. canonical hemodynamic response function HRF); β indicates the estimated weight that each repressor to the observed response (Y); ε is the error matrix, including the independent error or additional residual /noise term. To estimate β values, ordinary least squares (OLS) estimation method was used. The estimated parameters β̂ are calculated as Eq (2):

$$\hat{\beta} = (X^T X)^{-1} X^T Y \tag{2}$$

The estimated parameter β̂ are used to be a representation of how well or poor the fNIRS signals fit the idea response. The larger the value is, the greater activation in certain channel.

5 RESULTS

Fig. 5 shows an example of pre-processed HbO2 activation signals (24 channels) extracted from one of the participants during the valve operating experiment. The separation lines are event markers automatically extracted from the gaze tracking and motion tracking data (as described in 4.2). From the data, we found the operating events in both conditions were related to HbO2 increments of most channels. However, the details of the activation in each channel were not clear. It is hard to compare the brain activity difference in different experiment conditions from this analysis.

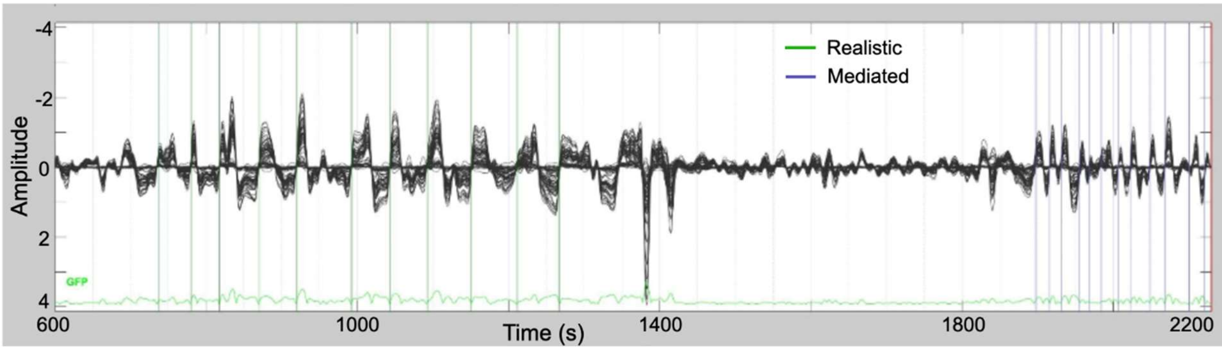

Figure 5. fNIRS signals after pre-processing with events labels.

We applied GLM to compare the relative difference between the prefrontal cortex and premotor cortex as a marker for personalized interface design. The idea is that a haptic interface design that leads to relatively higher prefrontal cortex activation level is preferred as it relates the right retrieval of the operation procedure and sequence memory. Fig. 6a illustrates the GLM analysis on one of the marked event. As mentioned before, the β values represented the activation levels of HbO2 of each channel. Table 1 shows the results of the estimated β values of 24 channels in both conditions. The β values can be used as the feature for interface optimization in further analysis. In the same way, we compared the activation levels of the prefrontal cortex of all 30 participants (Fig.6b). The Wilcoxon signed-rank order analysis shows that participants engaged in stronger prefrontal cortex activities with mediated haptic device, suggesting that in general a mediated haptic feeling encourages more preferable neural function. However, we also noticed that the results indicate individual differences (several cases showing the opposite), indicating that the haptic interface design shall be personalized.

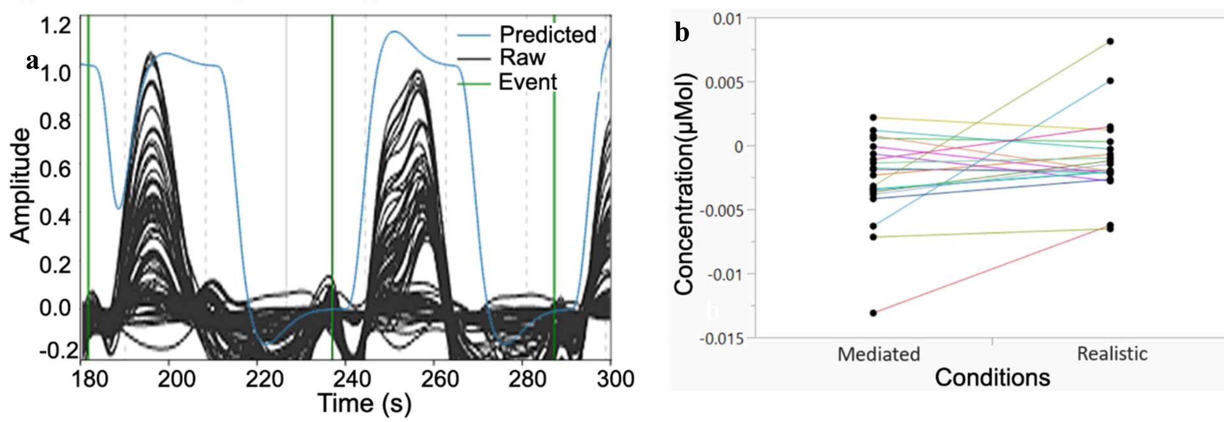

Figure 6. GLM analysis results. (a) GLM analysis on marked events (b) relative activation levels of prefrontal cortex of 30 participants.

Table 1. The estimated β values of 24 channels in both conditions.

Channels	Realistic	Mediated	Channels	Realistic	Mediated
S1D1	1.40704233e-7	1.4776771e-7	S6D5	3.47664216e-7	3.6485437e-7
S1D2	2.39274106e-7	2.3795255e-7	S6D6	3.31277771e-7	2.5788651e-7
S2D1	1.64273091e-7	1.2152032e-7	S7D5	3.76309264e-7	4.3842814e-7
S2D3	1.34040946e-7	3.7591079e-8C	S7D7	3.69247744e-7	3.9286947e-7
S3D1	1.40433062e-7	1.1719338e-7	S8D5	2.44740924e-7	3.5257961e-7
S3D2	2.59291034e-7	2.1377746e-7	S8D6	1.9775862e-7	2.5931064e-7

S3D3	1.70590724e-7	1.1582783e-7	S8D7	1.73134252e-7	2.8141878e-7
S3D4	1.90708196e-7	1.3893009e-7	S8D8	2.76384505e-7	2.891638e-7
S4D2	2.79929275e-7	2.175811e-7	S9D6	9.38885831e-8	1.3726255e-7
S4D4	2.09481583e-7	2.0834453e-7	S9D8	1.47352406e-7	1.5069201e-7
S5D3	1.71751935e-7	5.4957727e-8	S10D7	1.94037439e-7	1.7339521e-7
S5D4	2.07444849e-7	1.4078258e-7	S10D8	2.62158231e-7	1.5455624e-7

6 CONCLUSIONS

Given its advantages in dynamic and complex workplaces, human-robot collaboration has gained its popularity in multiple industrial applications areas. One of the challenges is the design of human-robot interface that enables better human functions and performance. We present a Virtual Reality simulation-based method to extract neural functional data for personalized human-robot interface design. A VR pipe maintenance model was created to simulate robot teleoperation tasks. The haptic interface was manipulated to check what levels of haptics (realistic versus mediated) can trigger higher activation level in prefrontal cortex, which is believed to be related to higher level cognitive process for job planning and memory retrieval. To tackle the even marking and recovery difficulties, we tested an automated approach of using gaze tracking and motion analysis. The automated marked event time points were used to divide data into blocks for GLM analysis of fNIRS data. The results show that (1) the automated gaze and motion based event marking and recovery method is effective, and (2) VR-based neural functional analysis can facilitate the design of human-robot interface.

ACKNOWLEDGMENTS

This material is supported by the National Science Foundation (NSF) under grant 1937053. Any opinions, findings, conclusions, or recommendations expressed in this article are those of the authors and do not reflect the views of the NSF.

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