Semi-Autonomous Continuous Robotic Arm Control Using an Augmented Reality Brain-Computer Interface

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Abstract

Noninvasive augmented-reality (AR) brain-computer interfaces (BCIs) that use steady-state visually evoked potentials (SSVEPs) typically adopt a fully autonomous goal-selection framework to control a robot, where automation is used to compensate for the low information transfer rate of the BCI. This scheme improves task performance but users may prefer direct control (DC) of robot motion. To provide users with a balance of autonomous assistance and manual control, we developed a shared control (SC) system for continuous control of robot translation using an SSVEP AR-BCI, which we tested in a 3D reaching task. The SC system used the BCI input and robot sensor data to continuously predict which object the user wanted to reach, generated an assistance signal, and regulated the level of assistance based on prediction confidence. Eighteen healthy participants took part in our study and each completed 24 reaching trials using DC and SC. Compared to DC, SC significantly improved (paired two-tailed t-test, Holm-corrected $\alpha<0.05$) mean task success rate ($p<0.0001$, $\mu=36.1\%$, 95\% CI [25.3\%, 46.9\%]), normalised reaching trajectory length ($p<0.0001$, $\mu=-26.8\%$, 95\% CI [-36.0\%,-17.7\%]), and participant workload ($p<0.02$, $\mu=-11.6$, 95\% CI [-21.1,-2.0]) measured with the NASA Task Load Index. Therefore, users of SC can control the robot effectively, while experiencing increased agency. Our system can personalise assistive technology by providing users with the ability to select their preferred level of autonomous assistance.
Abstract—Noninvasive augmented-reality (AR) brain-computer interfaces (BCIs) that use steady-state visually evoked potentials (SSVEPs) typically adopt a fully-autonomous goal-selection framework to control a robot, where automation is used to compensate for the low information transfer rate of the BCI. This scheme improves task performance but users may prefer direct control (DC) of robot motion. To provide users with a balance of autonomous assistance and manual control, we developed a shared control (SC) system for continuous control of robot translation using an SSVEP AR-BCI, which we tested in a 3D reaching task. The SC system used the BCI input and robot sensor data to continuously predict which object the user wanted to reach, generated an assistance signal, and regulated the level of assistance based on prediction confidence. Eighteen healthy participants took part in our study and each completed 24 reaching trials using DC and SC. Compared to DC, SC significantly improved paired two-tailed t-test, Holm-corrected α<0.05) mean task success rate (p<0.0001, µ=36.1%, 95% CI [25.3%, 46.9%]), normalised reaching trajectory length (p<0.0001, µ=26.8%, 95% CI [-36.0%, -17.7%]), and participant workload (p<0.02, µ=-11.6, 95% CI [-21.1,-2.0]) measured with the NASA Task Load Index. Therefore, users of SC can control the robot effectively, while experiencing increased agency. Our system can personalise assistive technology by providing users with the ability to select their preferred level of autonomous assistance.

Index Terms—Shared control, brain-computer/machine interface (BCI/BMI), augmented reality (AR), steady-state visually evoked potential (SSVEP), assistive robot.

I. INTRODUCTION

A brain-computer interface (BCI) allows a person to control a computer or external device using recorded brain activity [1], bypassing natural neuromuscular pathways to help people with paralysis perform activities of daily living [2], [3]. Compared to invasive BCIs, noninvasive electroencephalography (EEG) systems carry a reduced safety risk but suffer from lower information transfer rates (ITRs) [4] and a cumbersome setup.

Exogenous EEG-BCIs that use steady-state visually evoked potentials (SSVEPs) require few recording electrodes, little or no user training/training data, and have relatively higher ITRs [1]. SSVEP-BCIs present the user with flickering stimuli that correspond to system actions. The BCI decodes which stimulus the user is attending to and hence which action they want the system to perform. A limitation of this paradigm is that the interface presenting the visual stimuli may divert the gaze of the user from their task [5], which can be hazardous if the BCI is used to control a robotic arm or wheelchair. This issue can be overcome by overlaying the stimuli on a video feed of the task, shown on a monitor [5] or a head-mounted display in video see-through (VST) augmented reality (AR). The stimuli can also appear to be placed in the environment using a semi-transparent screen in optical see-through (OST) AR [6].

OST-AR SSVEP-BCIs have been used to control robotic arms [7]–[10], humanoid robots [11], [12], a robotic wheelchair [13] and a quadcopter [14]. Typically, these systems [7]–[9], [11], [12] rely on a goal selection paradigm, where the BCI is used to select an action that the robot then executes autonomously. This is an example of traded control (TC), where the control authority is discretely traded between the user and the robot [15]. Alternatively, in direct control (DC) systems, the BCI is used to continuously control robot movement in the joint [10] or task space [13], [14].

One drawback of TC is that during autonomous operation the system cannot leverage human intelligence and the situational awareness of the user is reduced [16]. More importantly for any assistive technology like BCIs, while improving task performance, TC may fail to improve the sense of independence of the user. When participants with a spinal cord injury used non-BCI interfaces (e.g., a trackball) to control a robotic arm for pick and place tasks [17], TC was found to be significantly more efficient than DC but there was no significant difference in user satisfaction between the two modes. In fact, DC generated slightly higher mean satisfaction scores and, when interviewed, participants indicated being satisfied with being in control during the more interactive DC mode.

To provide BCI users with the ability to control robot motion continuously without diverting their gaze, we developed a system where SSVEP stimuli were displayed around the robot end-effector using OST-AR, similar to a monitor-based system [5]. Our polyhedral stimuli [18] dynamically tracked...
end-effector motion, allowing the user to focus on the task rather than being positioned in a grid in the field of view (FoV) [10], [13]. Since the low ITR of EEG-BCIs makes it difficult to effectively control the many degrees of freedom (DoFs) of the robot, we adopted a semi-autonomous shared control (SC) framework [19]. Similar to other robot control BCIs, we shared control at the operational level [20]–[22] by controlling end-effector translation. In combining user and autonomous control, the system aims to reduce the impact of BCI errors by leveraging contextual information (e.g., environment geometry or user fatigue). The output control command can be generated by contextual fusion, gating or regulation [23]. However, since gating represents a discrete switching of control authority, we and [15] label these systems TC [24]. Our system linearly fused the BCI input with an autonomous assistance command, where the proportion of assistance was regulated by the confidence of the robot in predicting the goal of the user [19]. We previously developed and tested a proof-of-concept of this SC system [25], where healthy participants controlled a robotic arm to reach objects in the environment using a noisy joystick that simulated a four-command BCI. Compared to DC, SC was likely to improve reaching efficiency but at the cost of more failures. To improve the performance of SC in the current study, we developed a new model for the control policy of the user and modified the relationship between robot confidence and assistance. We evaluated the SC AR-BCI in a task where participants used the system to control a robotic arm to reach objects in a 3D environment. We hypothesised that compared to DC, SC would improve task success rate and reaching efficiency, as well as reducing participant workload, which was assessed using the NASA Task Load Index (TLX) questionnaire [5], [25]–[27]. The main contributions of our work are twofold: (1) an AR-BCI for continuous control of a robot using moving stimuli and (2) a prediction-based SC system for reaching tasks. The combined system can allow users of a low-ITR interface to manually control robot motion, aiming to increase their agency while maintaining high levels of task performance.

II. METHODS

The experiment took place in an electromagnetically shielded room. Each participant took part in one 1.5 h session, made up of five blocks: \( OR_{A} R_{B} R_{A} R_{B} \), with a 1-3 min rest period between each block. The session began with a block of observation trials (\( O \)), where participants observed the motion of a robotic arm while attending to stimuli presented via an AR headset. This was followed by four blocks of reaching trials (\( R_{k} \)), where they controlled the robot to reach objects in the environment using the AR-BCI (Fig. 1). Reaching trials required participants to touch the goal orange object with the ‘finger’ end-effector while avoiding the remaining grey objects using either direct control (DC) or shared control (SC). \( R_{A} \) and \( R_{A} \) were assigned to DC and SC, respectively, for half of the participants and reversed for the rest. Participants completed the NASA-TLX questionnaire that described the workload they experienced when using each control mode after blocks four and five. The data from all sessions is available at doi.org/10.26188/25734054.

Fig. 1. View of the experiment through the AR headset. Five flashing stimuli (1) are displayed around the robot end-effector (2, behind middle stimulus). Attending to any of the outer stimuli will cause the end-effector to move in that direction and attending to the middle stimulus will cause it to move forward. The stimuli are continuously updated to maintain their position relative to the end-effector. In reaching trials, the participant needs to touch the orange object (3), with the end-effector, while avoiding the other three grey objects (4) located on the shelf (5).

The observation task was used to quantify the ability of the BCI to correctly decode which stimulus (Fig. 1) a participant was attending to at a given moment in time. In each trial, the end-effector moved either up, down, left, right or forward. During the trial, the participant was tasked with attending the stimulus that corresponded to the direction in which the robot was moving. Each trial comprised a 2-3 s prompt, a 3.6 s go and 2 s rest period. During the prompt period, the stimulus corresponding to the direction for that trial was visible but not flashing, while all other stimuli were turned off. All five stimuli were flashing during the go period and were turned off during the rest period. During the trial, the end-effector travelled from -3 cm to 6 cm in the trial direction relative
to the nominal position (Fig. 3), where the starting position was set during the rest period. The BCI output was computed at each time step but not used to control the movement of the robot and the SC system was disabled in these trials. The observation block was made up of 25 (five per direction) trials presented in random order.

B. Reaching Task

In the reaching task, the participant controlled the robot to touch a designated one out of four cylindrical (4.5 cm diameter, 6 cm height) objects with the robot end-effector [25]. The four objects could take any of nine pre-set positions in a three-by-three grid [28] (11 cm center-to-center spacing) on a three-tiered shelf (Fig. 1). The participant sat 1.5 m away from the shelf, while the nominal starting position of the end-effector was 18 cm directly in front of the central object position (Fig. 3). To test the system in different environments, for each participant, four out of nine object positions were randomly selected and the end-effector starting position was randomly offset from nominal by 4 cm. This object configuration and starting position was used for all reaching trials for that participant. In comparison, we had previously used a different test rig with a single object configuration [25].

One of the four grey objects was designated as the goal ($G^*$) in each trial and replaced with an orange cylinder. Reaching $G^*$ meant a trial was a success, while reaching any other object, colliding with anything in the workspace, exceeding the robot workspace limits or exceeding 38.5 s without reaching any object meant the trial was a failure. Participants completed 12 (three per object) trials in each reaching block in random order. At the end of each trial, the experimenter changed the position of $G^*$ and reset the robotic arm. The next trial began once the robot reached its starting position.

Participants completed each block using either DC, where the BCI command controlled the robot directly ($\alpha = 0$), or SC, where they were assisted by the shared control system (Fig. 2). In SC trials, participants were told that ‘the system would try to predict which object they were trying to reach and provide assistance’. Reaching blocks in which participants were using a control mode for the first time included an additional four practice (one per object) trials at the start that were not used to calculate the reaching performance metrics.

C. Participants

Ten male and eight female healthy participants (randomly labelled P1-P18), with no history of neurological disorders and mean age 29 years (range 23-37 years) took part in the study. Participants had normal or corrected-to-normal vision, where two wore glasses during the session. Eleven participants had never used a BCI, six had 0-4 h and one had over 10 h of BCI experience. Twelve and six participants reported low and medium levels of fatigue at the start of the session, respectively. This study was approved by the University of Melbourne Human Research Ethics Committee (ID: 20853). Written informed consent was obtained from each participant before the start of the experiment. Participants were given a AUD$20 gift card for taking part in this study.

D. Augmented Reality Stimuli

The five SSVEP stimuli were presented using a HoloLens 2 (Microsoft Inc., USA) OST-AR headset at a 60 Hz refresh rate (Fig. 2). The polyhedral stimuli [18] had a diameter of 5 cm and flashed with a sinusoidal waveform at a frequency of $f_j \in \{7, 8, 9, 11, 13\}$ Hz. We did not use 10 Hz to reduce the impact of interference from alpha-wave activity [29], and avoided 12 Hz since it is 1.5 times 8 Hz. The stimuli dynamically

Fig. 2. AR-BCI system comprising the AR stimulus (red), BCI (blue), shared control system (orange) and robot (green). The user interfaces with the system through attending to the AR stimuli, observing the movement of the robot and EEG electrodes placed above the parietal and occipital lobes. The symbols used are $k$: current time step, $P$: end-effector coordinates, $X$: raw EEG, $Z$: filtered and windowed EEG, $F$: stimuli frequencies, $G$: object coordinates, $P$: predicted object, $u_b$: BCI command, $u_a$: assistance command, $\alpha$: assistance level, and $u$: combined command. In direct control, $\alpha = 0$ and $u = u_b$.

Fig. 3. Top view of the experiment layout and equipment: robot (1), objects (2), shelf (3), nominal end-effector position (4), QR code for coordinate alignment (5), EEG equipment (6), AR headset (7), participant position (8). All dimensions in cm.
followed the movement of the robot end-effector, where the middle stimulus was centered on the tip of the ‘finger’. The other four stimuli were 15 cm (center-to-center) to the left, right, above and below the central stimulus in a cross pattern (Fig. 1). The stimulus size and separation distances were maintained in the real-world coordinate system so that the user could accurately perceive that the end-effector was moving towards or away from them. At a distance of 1.5 m, the stimulus size and separation corresponded to visual angles of 1.9° and 5.7°, respectively. Stimulus presentation software was developed using Unity 2022.3 (Unity Technologies, USA).

We mapped the end-effector coordinates from the robot to the HoloLens coordinate frame by calculating a transform between the two coordinate systems using an intermediate frame defined by a quick-response (QR) code placed in the workspace (Fig. 3). To compute the full transform, we first measured the pose of the QR code relative to the robot and then automatically extracted its pose in the HoloLens frame using the QR code tracking module in Unity.

To continuously control the motion of the robot, the participant had to attend to the stimulus that corresponded to the direction they wanted the robot to move, where the central stimulus encoded the forward command. We did not include a back command as a person generally reaches objects in front of them. To avoid a consistent bias for any direction, frequencies assigned to stimuli at random for each participant and kept consistent for all trials. Similarly, we hung a black sheet behind the shelf to maintain similar background contrast for all of stimuli.

E. Brain-Computer Interface

EEG (Fig. 2) was recorded using a g.USBamp amplifier and 16 active wet g.Scarabeo electrodes (g.tec medical engineering GmbH, Austria). Only the nine electrodes that were placed above the parietal and occipital lobes were used for decoding: O1, Oz, O2, PO7, PO8, PO3, POz, PO4, Pz. The ground and reference electrodes were placed at Fz and the left ear lobe, respectively. The impedance of each electrode was confirmed to be below 5 kΩ using the g.NEEDAccess software, also supplied by g.tec.

EEG was recorded at 256 Hz (Fs) and streamed via the lab streaming layer using g.NEEDAccess. The data stream was processed in 0.2 s time steps by custom Python 3.10 software. At each time step, the data was filtered between 1-40 Hz with a fourth-order Butterworth filter (Fig. 2) and added to a buffer. The BCI decoder (Fig. 2) then generated a prediction of which stimulus the participant was attending to based on the previous 1 s of filtered data (Z_k ∈ R^{9×256}).

We used canonical correlation analysis (CCA) to decode which stimulus the participant was attending to by calculating the maximal correlation (ρ_j) between a linear combination of Z_k and a linear combination of a template Y_j ∈ R^{4×256} for each target frequency f_j ∈ {7, 8, 9, 11, 13}, j = 1, 2, ..., 5 [8], [13].

\[
\rho_j = \max_{W_Z, W_Y} \frac{E[W_Z^T Z_k Y_j^T Y_j W_Y]}{\sqrt{E[W_Z^T Z_k Z_k^T W_Z] E[W_Y^T Y_j Y_j^T Y_j W_Y]}},
\]  

(1)

where Y_j included the fundamental and the second harmonic of f_j,

\[
Y_j = \begin{bmatrix}
\sin(2\pi f_j n) \\
\cos(2\pi f_j n) \\
\sin(4\pi f_j n) \\
\cos(4\pi f_j n)
\end{bmatrix}, \quad n = \frac{1}{F_s}, \frac{2}{F_s}, \ldots, \frac{F_s}{F_s}.
\]  

(2)

The decoder output was the direction (d̂) corresponding to the stimulus with the highest ρ_j, which was then converted to a unit vector in that direction (u_d).

F. Shared Control

Similar to other continuous control BCIs [20]–[22] and our previous study [25], our SC system was an example of humanoid robot input mixing at the operational level (Fig. 2) [15], where end-effector velocity (u) was a linear combination of the BCI output (u_b) and an autonomous assistance command (u_a),

\[
u = \alpha u_b + (1-\alpha) u_a.
\]  

(3)

The amount of user vs. autonomous control was dynamically modulated using the assistance level parameter α ∈ [0, 0.7] [23]. This architecture represented a cascaded control framework, where the user and robot inputs were first fused and then regulated based on the internal context of the user (BCI output) and the external context of the task (end-effector and object coordinates) [15], [23]. This implementation significantly differed from typical traded control (TC) systems, where the user provides a goal at the tactical level that the system would then execute autonomously [7]–[9], [11], [12].

1) Prediction: Predicting the goal of the user (Ĝ) requires selecting G_i that maximises posterior probability given the trajectory of user inputs from the initial to the current position (ξ_{S→U}) and any additional information available to the system (Y), such as object or end-effector coordinates [19],

\[
Ĝ = \arg \max_{G_i \in \mathcal{G}} P(G_i | ξ_{S→U}, Y).
\]  

(4)

Using Bayes’ theorem with a uniform prior across the goals,

\[
Ĝ = \arg \max_{G_i \in \mathcal{G}} P(ξ_{S→U}, Y|G_i).
\]  

(5)

Assuming that the user optimises a goal-dependent cost function (C_i), we can use the principle of maximum entropy to induce a probability distribution over all possible trajectories given a goal as

\[
P(ξ|G_i) \propto \exp \left( -C_i(ξ, Y) \right).
\]  

(6)

Given this distribution and if the cost is additive along a trajectory,

\[
P(ξ_{S→U}, Y|G_i) = \exp \left( -C_i(ξ_{S→U}, Y) \right) \int_{ξ_{S→U}} \exp \left( -C_i(ξ_{S→G_i}, Y) \right) \times \int_{U→G_i} \exp \left( -C_i(ξ_{U→G_i}, Y) \right),
\]  

(7)

where ξ_{U→G_i} and ξ_{S→G_i} are the trajectories to G_i from the current and initial end-effector positions, respectively.
Fig. 4. Angles ($\gamma_1$, $\gamma_2$) between the user input ($u_b$) and the vectors to two objects ($G_1, G_2$) in a hypothetical environment, with the end-effector at $P$.

The integrals in (7) can be approximated using Laplace’s method [19],

$$P(\xi_{S\rightarrow U}, Y|G_i) \approx \frac{\exp \left( -C_i(\xi_{S\rightarrow U}, Y) - C_i(\xi_{G_i\rightarrow G_i}, Y) \right)}{\exp \left( -C_i(\xi_{S\rightarrow G_i}, Y) \right)},$$  \hspace{1cm} (8)

where * indicates optimal trajectories. Therefore, prediction (5) can be done by computing the costs associated with the three trajectories in (8).

2) **Angular Policy**: For the reaching task, we modelled the control policy of the user as wanting to move the end-effector directly towards the object that they wanted to reach. Hence, we based our cost function on the angle ($\gamma_i$) between the user input ($u_b$) and the unit vector ($\vec{r}_{PG_i}$) from the current end-effector position to each object $i$ (Fig. 4) [19], [25],

$$\gamma_i = \arccos (\vec{r}_{PG_i} \cdot u_b),$$  \hspace{1cm} (9)

summed across the entire trajectory of user inputs from the start of the trial to the current time step ($K$),

$$C_i = \sum_{k=1}^{K} \gamma_{i,k}.$$  \hspace{1cm} (10)

This control policy assumes that the user wants to minimise the angle between $u_b$ and the vector to the object they want to reach, with optimal trajectories having zero cost. Therefore, combining (5), (8) and (10), and simplifying gives,

$$\hat{G} = \arg \min_{G_i \in \mathcal{G}} C_i(\xi_{S\rightarrow U}, P_{S\rightarrow U}, G_i),$$  \hspace{1cm} (11)

where the Predictor (Fig. 2) used the trajectory of user inputs ($\xi_{S\rightarrow U}$) and the end-effector ($P_{S\rightarrow U}$), as well as the coordinates of all the objects ($G_i$) to predict which object the user wanted to reach. In [25], our decision policy was formulated in terms of the difference between $\gamma_i$ and the minimum possible angle given the commands available to the user. However, taking the difference led to unreliable predictions across objects.

3) **Assistance**: Based on a conical artificial potential field, the Assistance Signal $u_a$ (Fig. 2) pulled the end-effector towards the predicted object, where $u_a$ was the unit vector from $P$ to $G$ [21], [22], [25].

4) **Arbitration**: The level of user vs. autonomous control was arbitrated using a sigmoidal relationship [20], [21], [25],

$$\alpha = L(1 + e^{a(\gamma_0 - c)})^{-1},$$  \hspace{1cm} (12)

where $c$ was an estimate of how confident the system was that $\hat{G}$ matched the goal of the user, $L$ was the maximum level of autonomous control, $a$ was the aggressiveness [19] (i.e., how quickly the robot took control as a function of $c$) and $c_0$ was the inflection point. To always maintain a noticeable level of user control, we set $L = 0.7$. Since $0 \leq c \leq 1$, we set $c_0 = 0.5$, the midpoint of the range. We set $a = 10$, so that $dL/dc$ was approximately constant for $c \in (0.3, 0.7)$ and zero otherwise.

We estimated $c$ as a function of the Euclidean distance from the end-effector to the predicted object ($r_{PG}$) [20], [21], scaled by the initial distance to that object ($r_i$) [25],

$$c = \max \left( 0, 1 - \frac{r_{PG}}{r_i} \right).$$  \hspace{1cm} (13)

This was based on the assumption that, to get close to an object the user would have supplied a trajectory of commands long enough for the system to generate a reliable prediction. The Arbitrator (Fig. 2) used (12) and (13) to dynamically generate $\alpha$, and therefore, modulate the level of assistance. Compared to [25], we modified the arbitration parameters to give more control to the user, and used $r_i$ rather than a single scaling distance for all objects.

G. **Robot Control**

The robot (Reachy, Pollen Robotics, France) was an anthropomorphic right arm with seven DoFs. We replaced the standard gripper end-effector with the 3D-printed ‘finger’ (Fig. 3). End-effector translation was controlled in the task space by supplying the velocity control command ($u$) every 0.2 s, while the orientation was constrained such that the end-effector remained aligned with the forearm, and was not controlled by the user directly.

H. **Workload Assessment**

The NASA-TLX questionnaire generates a workload score based on a weighted average of ratings across six factors: mental demand, physical demand, temporal demand, performance, effort and frustration level [5], [25]–[27]. After block four, participants were asked to select the largest contributor to workload for the reaching task, from each pair of factors (15 comparisons). The number of times each factor was chosen indicated the relative importance the participant gave to that factor. The participants then rated their workload for mode B (either DC or SC) on a 100-point scale. Participants rated their workload for mode A after completing block five. For each participant, the overall workload associated with DC or SC was the sum of the workload ratings for that mode weighted by the importance ratings of each factor. We used a two-tailed paired $t$-test to test if there was a significant difference between the mean workload of DC and SC.

I. **Reaching Performance**

We used the reaching trials to calculate the success rate ($S_{p,m}$) associated with the control modes ($m = \text{DC}, \text{SC}$) for each participant ($p = 1, 2, \ldots, 18$). Using data from successful reaching trials, we calculated the average trajectory length ($L_{p,m,i}$) for each combination of participant, mode and object position ($i = 1, 2, \ldots, 9$). To compute the mean trajectory length associated with DC and SC for each participant ($L_{p,m}$),
we averaged $L_{p,m,i}$ across objects, where objects for which a participant had no successful trials in either mode were excluded from the analysis. We divided $L_{p,m}$ by the Manhattan distance from the starting end-effector position of each participant to each object to calculate the normalised mean trajectory length ($\bar{L}_{p,m}$). We used a paired two-tailed $t$-test to test if there was a significant difference between the mean $S$ and $\bar{L}$ of DC and SC. We applied the Holm correction to account for comparison between DC and SC in terms of workload, success rate and trajectory length, and maintain the significance level of the entire study at 0.05.

We used the failed and successful SC trials across all participants to examine how well the system could predict which object the participant was trying to reach. For each trial, we calculated the percentage of time steps in the trial where the system correctly predicted the goal object. We also examined the success rate and trajectory length using DC for each object to examine baseline task difficulty.

### J. Decoding Performance

We used the online decoder outputs from the observation blocks to analyse the decoding performance of each participant. Directional outputs for each time step were used to construct a confusion matrix, with the trial direction/frequency assumed to be the true label for each time step in that trial. Using this set of labels and predictions, we calculated the overall balanced accuracy for each participant ($A_p$) and the macro-average of class recall (proportion of correctly classified time steps for each class). To explore the relationship between interface accuracy and success rate, we constructed a linear model between $A_p$ and $S_{p,DC}$, as well as $A_p$ and $S_{p,SC} - S_{p,DC}$. $A_p$ was also used to calculate the ITR in bits/min for each participant [4],

$$B_p = \frac{1}{60} \left( \log_2 J + A_p \log_2 A_p + (1 - A_p) \log_2 \frac{1 - A_p}{J - 1} \right),$$

where $J = 5$ was the number of directions/frequencies and $t = 1$ s was the online decoding window length.

We used the data from observation trials to perform an offline assessment of the impact of decoding window length on class recall for participants that had no successful DC trials. Each trial was split into chunks, again using a 0.2 s step size, with window lengths from 1 to 3 s. We used the same filter and decoder as the online sessions but varied the size of the template to match the length of each window. We calculated the proportion of correctly classified chunks for each window length and direction/frequency. As we only used data from the go period (0-3.6 s), longer windows generated less chunks per trial. We also calculated the power spectral density across electrodes for different frequency stimuli using the entire 3.6 s.

### III. RESULTS

#### A. Comparison of Shared and Direct Control

All 18 participants completed 24 trials of shared control (SC) and direct control (DC), where the object and frequency layout was randomised for each participant. Fig. 5a and 5b show the success rate and trajectory length across participants using DC for each object. Four out of nine object positions were randomly assigned to each participant, with each position included in a layout by 6-10 participants. The object position affected the task difficulty, where the median (interquartile range (IQR)) success rate and trajectory length ranged over 8.3%-58.3% (0%-87.5%) and 36.1 cm-51.1 cm (3.3 cm-27.1 cm), respectively. Fig. 5c shows the percentage of correct object predictions produced by the SC system during reaching trials. In total, there were 432 trials with 42-174 predictions per trial. The median (IQR) percentage of correct predictions ranged over 52.4%-96.1% (12.6%-55.7%).

Fig. 6a and 6b show the difference in success rate between the two modes, where SC led to a significantly higher mean success rate (paired two-tailed $t$-test, $p = 0.001$, $\mu = 36.1\%$, $95\%$ confidence interval (CI) [25.3%, 46.9%]). Participants P7 and P9 had no successful trials using DC but had 16 and 10 successful trials with SC, respectively. Participants collided with the workspace or exceeded the robot workspace limits in 125 and 37 trials using DC and SC, respectively (Fig. 7c). The 38.5 s trial limit was exceeded in 128 DC trials and 26 SC trials. There were more SC trials where the participant reached the wrong object (38 vs. 4), representing 9% of all SC trials.

There were less collisions and reaching trajectories were typically more consistent and smoother when using SC (Fig. 8). Fig. 6c and 6d show the mean reaching trajectory lengths for DC and SC. For each participant, the lengths are normalised by the Manhattan distance from the starting end-effector position to the centroid of each object. The mean trajectory length for SC was significantly shorter (paired two-tailed $t$-test, $p < 0.0001$, $\mu = -26.8\%$, $95\%$ CI [-36.0%, -17.7%]). Diagonal end-effector movement due to SC and collisions with the front of an object led to normalised trajectories below 100%. P7 and P9 were excluded from the trajectory length calculation since they had no successful DC trajectories. P14 had the highest mean trajectory lengths of 321.9% and 305.6% corresponding to one and eight successful trials for DC and SC, respectively.

![Fig. 5.](image-url)
There was a significant reduction in mean workload when using SC (paired two-tailed t-test, \( p < 0.02, \mu = -11.6, 95\% \) CI [-21.1, -2.0], Fig. 6f). Seventeen out of 18 and 16 out of 16 participants experienced an increased success rate (Fig. 6a) and reduced mean trajectory length (Fig. 6c) due to SC, respectively. However, five out of 18 participants experienced a higher workload with SC (Fig. 6e).

B. Decoding Performance

Each participant completed five observation trials per direction/stimulation frequency, corresponding to 55-61 time steps due to chunk timing variability. The mean (standard error) class recall across time steps was similar between the five directions, with a range of 62.0%-71.8% (5.3%-6.7%) (Fig. 9a). Instead grouping the predictions by stimulation frequency showed that 13 Hz had the lowest recall of 42.4% (5.6%), compared to 71.7% (5.0%), 74.6% (5.5%), 73.9% (5.0%) and 67.9% (4.8%) for 7 Hz, 8 Hz, 9 Hz and 11 Hz, respectively (Fig. 9b). The mean power spectral density (PSD), in µV²/Hz, for the first (second) harmonic in electrode Oz was 7 Hz: 7.89 (3.87), 8 Hz: 7.00 (4.00), 9 Hz: 6.6 (1.7), 10 Hz: 64.2 (16.9) and 11 Hz: 11.9 (2.5) (Fig. 10).
Fig. 11. Linear regression between decoder balanced accuracy and (a) direct control (DC) success rate and (b) the change in success rate due to shared control. Points show results for each participant, with participants who had no successful DC trials shown as crosses. Shaded regions show 95% confidence interval.

Fig. 12. Effect of increasing decoding window size on recall for each frequency, for participants (a) P7 and (b) P9, who had no successful direct control trials. Online results from the observation trials are shown at 1 s. The remaining results were calculated offline using the observation trials. Dashed line shows chance level.

transfer rate across participants were 66.1% [56.2%, 75.0%] (Fig. 7a) and 49.5 bits/min [32.8 bits/min, 66.2 bits/min] (Fig. 7b), respectively. There was a moderate positive correlation ($\rho = 0.62, p = 0.006$) between decoding accuracy and DC success rate (Fig. 11a) across participants and a weak negative correlation ($\rho = -0.28, p = 0.26$) between decoding accuracy and the change in success rate due to SC (Fig. 11b).

P14 had the lowest overall decoding accuracy of 35.5% (Fig. 7a). P7 and P9 had accuracies of 46.0% and 55.7%, respectively, but were the only participants to have no successful trials using DC. However, the online recall for 13 Hz for P7 and P9 was 20.3% (Fig. 12a) and 7.1% (Fig. 12b), respectively. For them, 13 Hz corresponded to the forward command, which made the task very difficult, since all the objects were in front of the end-effector starting position. Offline analysis (20-70 chunks per direction/stimulation frequency) showed that increasing the window size up to 3 s increased the balanced accuracy from 46.0% to 76% and 56% to 80% for P7 and P9, respectively. Using a 3 s window, the recall for 13 Hz increased to 75.0% for P7 but only to 25.0% for P9.

IV. DISCUSSION

A. Shared Control Framework

The new angular policy that we used in this study produced robust predictions across objects, where most predictions in a trial were correct across all objects (Fig. 5c). This contrasts with less than 4% for some objects in our previous work [25], where compared to direct control (DC), the shared control (SC) system was likely to reduce reaching trajectory length but also reduce success rate due to unreliable predictive performance and overly aggressive assistance. By making the relationship between assistance and robot confidence less aggressive [19], participants were able to maintain control and direct the robot away to avoid a failure, when very close to an incorrect object. Lastly, the current confidence calculation incorporated the distance to each object, allowing it to better adapt to each environment. Therefore, our new SC system was significantly better than DC in terms of success rate, trajectory length and participant workload (Fig. 6). Additionally, the weak correlation between improvement in success rate and decoder accuracy (Fig. 11b) suggests participants with a less accurate decoder benefited more from SC.

Our SC system provided robust improvements in performance in different environments created by randomising object layouts and end-effector starting positions across participants. Success rates (Fig. 5a) and trajectory lengths (Fig. 5b) obtained with DC showed that task difficulty varied by object. However, the variability in success rates by object was also likely due to how well each direction could be decoded for a participant (e.g., the left direction for objects on the left) as well as their initial end-effector position.

Even though we showed SC performed better than DC, the relatively low ITR of noninvasive BCIs means that a fully autonomous traded control (TC) system would still be more effective at performing complex tasks (e.g. reaching and grasping) that require a high number of DoFs (Tab. I). Previous results [17] have been interpreted to mean that users prefer more control [20], [21] and that more user control is helpful in increasing their agency [22]. However, it is likely that their preferred level of automation depends on each user and the task they are performing [19]. As BCI-controlled robots become commercial products, users should be provided with a suite of functionality that allows them to choose the most appropriate level of automation for their internal context (e.g., fatigue) and external context (e.g., task difficulty) [23].

B. Augmented Reality Brain-Computer Interface

As is common to most BCIs [30], our system violated the idealised assumptions of (14), since accuracy was not constant across frequencies and the error was not equally distributed across all non-target frequencies (Fig. 9b). Additionally, continuous decoding differs from a typical selection BCI since the same segment of brain activity could be used in multiple consecutive prediction windows. In contrast, [14] use a modified ITR for asynchronous continuous control based on [31]. Since this definition is a form of a reaching efficiency metric that incorporates the BCI, automation system and robot (i.e., DC and SC would produce different ITRs), we used the original simplified metric for an approximate comparison of our BCI to other AR-SSVEP systems (Tab. I). Our ITR of 49.5 bits/min (95% CI [32.8 bits/min, 66.2 bits/min], Fig. 7b) was comparable to the median (IQR) ITR of 48.0 bits/min (42.8 bits/min) across the eight studies. Chen et al. [8] also suggested that AR-BCIs have lower ITRs than screen-based SSVEP systems. However, they only found a small difference in the mean (standard deviation) ITR across ten participants, with 43.2 bits/min (6.6 bits/min) using a screen vs. 41.2 bits/min (8.7 bits/min) using AR.

Our 1.0 s decoding window was shorter than the mean (IQR) time per selection of 2.0 s (1.1 s) of other systems
For P9, the recall for 13 Hz remained low, even using a 3 s window (Fig. 12b), and the mean online decoding recall for 13 Hz was lower than the other four frequencies (Fig. 9b). The power spectral density (PSD) in electrode Oz in 13 Hz trials was highest at 13 Hz, showing that the HoloLens was not systematically displaying the 13 Hz stimulus at some other frequency. However, the PSD at the target frequency was lowest in 13 Hz trials, and these trials had no noticeable peak at the second harmonic. Our results align with screen-based studies that have shown decoding accuracy [29] and SSVEP power [33] to reduce at higher frequencies (over 11 Hz). To make the decoding performance robust across directions, future work should explore more granular frequencies within 7-11 Hz, where the specific frequency set and layout can be optimised for each participant using calibration data. Similarly, the system can be further tuned to each participant by training a classifier on the calibration data (e.g., using the CCA correlation coefficients as features).

The fatigue associated with attending to visual stimuli acts as a large barrier to the practical use of SSVEP BCIs [1], especially by people with amyotrophic lateral sclerosis (ALS) [34]. The reduced workload due to SC means that this control paradigm may alleviate some of the overall fatigue experienced by the user of the system. Since our study was conducted with participants without neurological disorders, the workload and fatigue associated with using our system should be further assessed by people with ALS and spinal cord injury, as well as other potential BCI users. Additionally, the robustness to decoder errors provided by SC can help to mitigate the lower signal-to-noise ratio of higher frequency stimuli [29], [35], which can reduce fatigue [36].

### C. Alternative Interfaces and Applications

Our SC system was able to assist the user (Fig. 6) despite the relatively low ITR of the interface (Fig. 7b) and poor recall for the 13 Hz direction (Fig. 9b). Therefore, people with disabilities who have residual motor function should be able to also use our system in combination with higher-ITR interfaces (e.g., trackball, accessibility switches etc.) to continuously control a robot. In future work, we also plan to combine our BCI with the head and eye-tracking capabilities of the HoloLens to either continuously redefine the FoV or fuse the directional commands coming from each modality [37]. A dynamic FoV means not all stimuli need to be continuously flashing, simplifying the classification task and reducing visual fatigue. Additionally, we plan to introduce an object detection module [38] in future versions of the system, since object positions are required for the SC algorithm.

Conceptually, our SC paradigm can be translated to any continuous control task in an environment with objectives, such as control of a wheelchair [13] or a cursor on a screen with icons. Wheelchair control is only 2D but safety considerations require the use of a path planning system for obstacle avoidance [39]. In this context, the control policy of the user will be to move along the shortest obstacle-free path towards their destination. For this task, our SC system can be combined with a path planner by creating a path of intermediate locations (goals) to each potential destination, and calculating the angular deviation to each nearest location at each time step.

### D. Scene Visibility

A limitation of our system was that participants found it difficult to see the exact position of the end-effector through the central stimulus. The nature of the OST headset meant that the stimuli appeared bright while the background was relatively dull. Reducing the brightness of the stimuli could make it easier to see the environment but may lead to reduced contrast, which in turn reduces SSVEP decoding accuracy [40]. However, contrast can be improved by using red stimuli, which provide a high contrast relative to the typically white/grey home, office or hospital environments [10], [40]. Alternatively, although VST-AR systems have not been used much in SSVEP-BCIs, it would be interesting to evaluate the ability of the latest VST-AR systems to clearly display stimuli and the environment background (e.g., by dynamically maintaining contrast). Another solution would be to remove the middle stimulus and decode whether the user is not attending to any stimuli as forward [6].

### Table I

<table>
<thead>
<tr>
<th>Study</th>
<th>Robot</th>
<th>Input</th>
<th>Mode</th>
<th>J^4</th>
<th>T^5</th>
<th>DoFs</th>
<th>Acc</th>
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<td>6.8</td>
<td>7(1)</td>
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<td>[9]</td>
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<td>7(1)</td>
<td>90</td>
<td>159.4</td>
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<tr>
<td>[10]</td>
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<td>4(1)</td>
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<td>65.0</td>
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<td>84</td>
<td>15.2</td>
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2 Input paradigm. CC: continuous control, GS: goal selection.
3 Control mode. DC: direct control, SC: shared control, TC: traded control.
4 Number of SSVEP targets.
5 Mean time per selection (s).
6 Total number of DoFs with end-effector DoFs shown in brackets.
7 Mean decoding accuracy (%) across participants.
8 Mean information transfer rate (bits/min) across participants.
9 Length of decoding window (s).
10 Calculated using the values in this table and Eq. (14).
V. CONCLUSION

Our semi-autonomous (shared) control framework allowed users to continuously control a robotic arm with an AR-BCI more effectively than manual (direct) control. This framework also reduced workload, which is critical for technologies designed for people with disabilities. Using this framework, users of noninvasive BCIs can experience increased agency over their assistive robot despite the inherently low information transfer rates of these interfaces. With much focus on neural decoders that adapt to each user, more attention should be given to how the entire system can adapt to the external context of each task and the internal context of the user. Our framework can also be adapted to other user interfaces and applications across the assistive technology ecosystem.

VI. ACKNOWLEDGMENTS

P. Yoo is employed by Synchron Inc. and holds stock options in the company.

REFERENCES