Adapting to progressive paralysis: A tongue-brain hybrid robot interface for individuals with amyotrophic lateral sclerosis

Rasmus L. Kæseler , Dario Farina, Bo Bentsen, Izabella Obál, Lotte Vinge, Kim Dremstrup, Mads Jochumsen, and Lotte N. S. Andreasen Struijk

***Abstract*—Individuals suffering from progressive neuromuscular diseases gradually lose all muscle control and therefore are forced to repeatedly adapt to new control interface technologies to maintain some level of independence. Accordingly, the ideal interface technology should adapt to the progression of paralysis. We propose an adaptive tongue-brain hybrid interface framework for the three-dimensional control of a robotic arm. The interface was tested with able-bodied individuals and individuals with amyotrophic lateral sclerosis. The experiments demonstrated the importance of flexible frameworks for cooperation between control modalities as this allows a critical optimization of the control performance relative to the disease stage. The hybrid framework allowed a 4-34% stepwise decrease in performance rather than a 200% decrease when moving directly from a tongue to a brain control interface. This hybrid framework is the first step towards a new concept of assistive robotic control with a higher focus on adapting to the functionality of disabled individuals.**

***Index Terms*—Human-robot interaction, Neurodegenerative diseases, Multimodal control, Brain Control, Tongue Control.**

I. Introduction

AMYOTROPHIC LATERAL SCLEROSIS (ALS) is a motor neuron disease that causes progressive degeneration and death of both the upper and lower motor neurons [1]. It is a fatal disease, with the most common cause of death being respiratory failure. 10-20% of individuals with ALS survive longer than five years after being diagnosed and only 5-10% survive more than ten years [1]–[3]. With the knowledge of an inevitable fatality and while their body progressively declines to a completely paralyzed state (called the locked-in stage), individuals with ALS feel an increasing degree of hopelessness [4]. Similarly, the quality of life (QoL) for individuals with ALS and their caregivers has also been shown to decrease, mainly because of the limited time available for oneself [5], [6].

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Case studies on long-term use of an assistive robotic arm have shown general user satisfaction and an increase in independence [7]. Thus, assistive robotic devices may improve the QoL for both individuals with ALS and possibly family caregivers. Moreover, questionnaires have shown that individuals with ALS have a high interest in the availability of brain-computer interfaces (BCIs), specifically for the control of robotic arms and motorized wheelchairs [8].

While the robotic technology is mature for assistive applications, it is still very challenging to achieve sufficient information transfer in the interfacing technologies for users with severe motor impairments [9]. To allow full control of the translation and rotation of objects in the three-dimensional (3D) space, a robot arm will require at least six-degrees of freedom (DoF) and one functional end-effector, such as an open/close functional gripper. We will define such a robot as a general purpose assistive robotic manipulator (ARM). Furthermore, we will aim to provide full manual control of an ARM with a 1DoF end-effector which we define as *time-continuous access to all translational and rotational manipulations of an object in the 3D space*. This will require an interface with at least 14 time-continuous control actions, which can be difficult with limited moveability.

A. Single-Modality Control Interfaces

Different interface solutions have been developed and used for assistive technologies [39]. In the early stages of ALS in which the patients may still control some movements of hand or finger muscles, the control may be achieved through a hand-controlled joystick or physiological signals generated through muscle contraction and/or activation (such as electromyography). However, the motor capacity declines with the progress of the disease until the patient reaches a tetraplegic condition. This limits the individual to alernative technologies. Lobo-Prat et al. highlights speech, eye-, head-, and tongue movements as alternative sources of interfacing [39]. Lip-movements [40] or sip-and-puff control [41] have been also considered for interfacing. Table I provides an overview of recently developed interfaces that allow for some degree of control (though rarely full control) of an ARM while using only modalities available to an individual with tetraplegia (i.e. with no motor functionality below the neck). It should be noted that most interfaces have only been evaluated with healthy participants (see ”evaluation” column in Table I), despite

TABLE I
INTERFACES USED FOR ARM CONTROL

Ref	Control Modality					Usability				Full control				Evaluation		
	Tongue	Eye	Evoked Brain	Spontaneous Brain	Other	Modality adaptable	≤30min calibration	Eyes free operation	≤1 day of training	Manual	Continuous	Asynchronous	≥14 commands	ALS	SCI	Healthy
[10]	✗					÷	✓	✓	✓	✓	✓	✓	✓	0	1	1
[11]	✗					÷	✓	✓	✓	✓	✓	✓	✓	0	0	12
[12]	✗					÷	✓	✓	✓	✓	✓	✓	÷	0	0	1
[13]	✗					÷	✓	✓	✓	✓	✓	✓	✓	0	0	10
[14]		✗				÷	✓	÷	✓	÷	✓	?	÷	0	0	1
[15]		✗				÷	✓	÷	✓	✓	✓	✓	÷	0	0	30
[16]		✗				÷	✓	÷	✓	✓	✓	✓	✓	0	0	10
[17]*			✗			÷	✓	÷	✓	✓	÷	÷	÷	4	0	4
[18]			✗			÷	✓	÷	✓	✓	÷	÷	✓	0	0	12
[19]			✗			÷	✓	÷	✓	÷	✓	✓	÷	0	0	16
[20]			✗			÷	✓	÷	✓	÷	÷	÷	÷	0	0	10
[21]			✗			÷	✓	÷	✓	✓	÷	✓	÷	0	0	5
[22]			✗			÷	✓	÷	✓	÷	÷	✓	÷	0	0	7
[23]				✗		÷	?	✓	÷	✓	✓	✓	÷	0	0	11
[24]				✗		÷	?	✓	÷	✓	✓	✓	÷	0	0	13
[25]				✗		÷	✓	✓	✓	✓	÷	÷	÷	0	0	4
[26]				✗		÷	✓	✓	✓	÷	÷	✓	÷	0	0	11
[27]				✗		÷	✓	✓	✓	✓	✓	✓	÷	0	0	5
[28]				✗		÷	÷	✓	✓	✓	✓	✓	÷	0	0	15
[29]				✗		÷	?	✓	÷	✓	✓	✓	÷	0	0	6
[30]			✗	✗		÷	✓	✓	÷	✓	÷	✓	÷	0	0	5
[31]			✗	✗		÷	✓	✓	÷	✓	÷	✓	÷	0	0	12
[32]			✗	✗		÷	?	✓	?	✓	÷	✓	÷	0	0	10
[33]		✗	✗		✗^{J,H}	✓	✓	✓	✓	✓	✓	✓	÷	0	0	2
[34]			✗	✗	✗^{J}	÷	✓	✓	✓	✓	÷	✓	÷	0	0	3
[35]		✗		✗		÷	✓	÷	✓	✓	✓	✓	÷	0	0	8
[36]		✗	✗			÷	✓	✓	✓	✓	÷	✓	÷	0	0	15
[37]		✗		✗		÷	✓	÷	✓	✓	✓	✓	÷	0	0	10
[38]		✗			✗^{H}	÷	✓	✓	÷	✓	✓	✓	÷	0	0	3
This work	✗					✓	✓	✓	✓	✓	✓	✓	✓			
	✗		✗			✓	✓	✓	✓	✓	✓	✓	✓	3	0	10
			✗			✓	✓	÷	✓	✓	✓	✓	✓			

Existing literature of robot arm interfaces using modalities available to individuals with tetraplegia. ✗ : uses modality, ✓: meets requirement, ÷: does not meet requirement, ?: not reported. *: This study did not use a robot arm but a humanoid robot, but was kept in this table as it is evaluating a robot with ALS users. ^{J}: Using jaw movements. ^{H}: Using head movements.

being designed for users with tetraplegia (such as individuals with ALS or a spinal chord injury, SCI). Furthermore, very few current interfacing systems provide at least 14 control commands, that are necessary for controlling 7DoFs. When all motor functions are eventually lost, a BCI is the only viable option. These systems could utilize spontaneous brain-signals generated through detection of movement imagery (MI) or cognitive tasks, or externally evoked brain potentials [42], [43].

Though not included in Table I, invasive BCI technologies have been used to provide continuous control of high DoF ARMs or exoskeletons [44]–[48]. However, these technologies require surgery and months of training for the user. Thus, end users are more likely to adopt non-invasive wireless electroencephalogram (EEG) systems [49]. For this reason, the present study only evaluated non-invasive BCI technologies.

A non-invasive BCI is very limited in performance with respect to peripheral interfacing or invasive BCIs. It has not yet been possible to achieve full ARM-control using a non-invasive BCI. State-of-the-art approaches to achieve this goal depend on semi-automation of the robot and/or provide control of fewer DoFs [18], [20]–[29], [39], [50].

BCIs can be designed to use either spontaneous signals (self-generated by the user), evoked signals (generated by external stimulation), or a combination of signals to construct hybrid BCI systems. Hybrid BCI systems have been used for positional control of quadcopters [51] and for control of three joints of a robot arm [30]–[32]. Systems using only one type of brain signal have also achieved some control of a robot arm.

While spontaneous signals may be desirable as they do not require an external stimulation, evoked potentials can usually be decoded with shorter training and higher accuracy from brain signals. Using a BCI based on evoked signals (steady state visually evoked potentials (SSVEP)), Chen et al. almost achieved full ARM-control [18]. However, the control was built on a discrete-time method in which the selection of a control action (such as forward) would make the robot move forward for a fixed time interval (4s in the study). With this approach, it was not possible to grasp objects placed outside specific stop locations (for example, placed 3s of movement away). Han et al., who created a similar discrete control interface, further highlight this issue as time-consuming and exhausting for the user [21]. Indeed, state-of-the-art manual BCI control using a discrete-time method requires a relatively long time to achieve grasping. On average the control by Chen et al. required on 10 minutes to grasp an object placed 29 cm away from the initial position. While excellent performing classifiers for evoked signals exists (e.g. above 40 control actions classified at above 95% accuracy within 1s of stimulation) [52]–[54], very few are designed for online asynchronous and continuous control.

Full ARM control has also been achieved with eye-tracking systems [16]. Several autonomous and semi-autonomous eye-tracking control schemes have been proposed [14], [15], [55]. However, the accuracy of eye-tracking may decreaser for certain eye-types and/or because of disturbances caused glasses or contact lenses [56]. Furthermore, while eye-tracking can provide the system with a directional pointer, it lacks the possibility of providing a go command (similar to a computer-mouse without any buttons). It also requires the user's visual focus which may cause issues while controlling a robot arm.

Possibly, tongue control provides the best performance of full control of an ARM [10], [11], [13] as it has provided control much faster than other tetraplegia accessible modalities. In a prior tongue control study, healthy individuals performed pick-up tasks of an object placed more than 40 cm away from the initial position within 40s [11]. Similarly, an individual with tetraplegia managed to pick up objects within just 70s [10]. Tongue has also been used to control upper-limb exoskeletons [57] or wheelchairs [58], [59].

B. Multimodal Control Interfaces

Using a combination of eye-tracking and spontaneous BCI, the semi-autonomous control of a 5-DoF arm, which included

2 DoF direct controls, has been previously achieved [35]–[37]. Similarly, eye movements have been combined with shoulder and/head movements to improve control [33], [38]. Tongue control has also been used in multimodal interfaces, but not for controlling an ARM. Johansen et al. combined tongue control with myoelectric signal for improved prothesis control [60]. Nam et al. controlled a humanoid robot using combined tongue, eye, and jaw movement (measured using EEG, electrooculography, and electromyography) [61].

Minati et al. reached limited control of a robot arm using a combination of head movements, jaw clenching, eye movements, and spontaneous brain signals. Uniquely, they developed four different interfaces by coupling different modalities. While not being the focus of their study, this could potentially be beneficial for users with ALS at it may allow a multimodal framework where the user can select a preferred modality combination based on their disease progression.

Similar multimodal control frameworks have previously been suggested, but have not been used for continuous control of a robot arm [62]–[64]. These frameworks do not directly combine different modalities to improve control, they instead make multiple modality control options available to the user. This gives the individual user the possibility of selecting a preferred control modality for a given task and/or time. This concept of a user-tailored interface is especially beneficial for users with ALS or other progressive diseases. However, we believe that these systems should be further improved. Instead of only allowing the users to select their preferred control modality, we intend to let the user combine their preferred number of control options from each modality in a true multimodal control framework. We believe that this will provide an improved user-tailored control system which can also ease the transition between control modalities experienced by the ALS user during disease progression.

C. Transition between Control Modalities

Each interface requires a training period, during which it will not operate to its full capability. This is a significant issue as ALS often progresses rapidly. Thus, the individuals with ALS may never get fully comfortable with an interface before it must be changed. Additional challenges are related to economic and bureaucratic barriers associated with advanced assistive technologies [65], [66]. All these reasons (worsening performance, adaption to technology, and bureaucratic complications) have been reported as common causes for users to abandon self-help devices [67]. We propose a new concept within multimodal control interfaces for users with ALS or similar progressively paralyzing diseases, or diseases with different stages, and thus with different needs for the users. Instead of replacing the entire control modality when the user no longer possesses the full motor functionality required for its use, the interfacing system adapts to the user by complementing the lost modality with a new one.

This approach prolongs the use of the original modality while also training and preparing the user for the new modality, which will eventually replace the original one. In this work, we present a novel control framework with a focus on patients

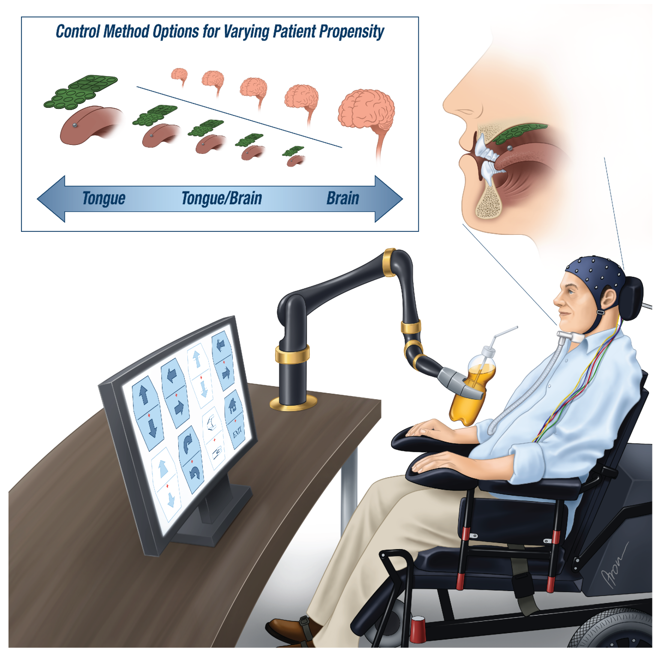

Fig. 1. Control of a robotic arm using the proposed framework: Using combination of the TCI and BCI, the user has direct access to all 7DoF in the robotic arm.

in the later stages of spinal-onset ALS, as they may benefit from an assistive robotic arm due to the limited movability of their limbs. If the bulbar muscles (such as the tongue) are still fully or partly functional, the high performing tongue interface is attractive for control. As ALS will gradually impact the patients' bulbar function, which includes the tongue motor functionality, the user must eventually turn towards either eye-tracking or BCI. In this study we propose a novel continuous BCI rather than eye-tracking, as it can also allow some control if the eye movement is impaired. Thus, the developed adaptive multimodal control framework will focus on the optimal transition from controlling a robotic arm using tongue movement towards using brain signals in order to maintain a high degree of control effectiveness.

II. Proposed Framework

We have designed and tested a hybrid tongue-brain interface framework for full ARM-control which adapts to the users reduced tongue functionality by complementing the tongue computer interface (TCI) with a BCI as illustrated in Fig. 1.

The framework incorporated six sub-systems to allow for adaptation to a decreasing tongue functionality (Fig 2) by decreasing the number of TCI commands and increasing the BCI commands in the sub-systems. For instance hybrid B used eight tongue-based control-outputs, while hybrid E used only one.

To allow for full ARM control, the control layouts should all be designed to have at least 14 control actions. However, we included two additional control actions to achieve a total of 16 control actions in all layouts. The additional actions were a go home and an exit system control command, which we considered essential for the end-users. However, in these

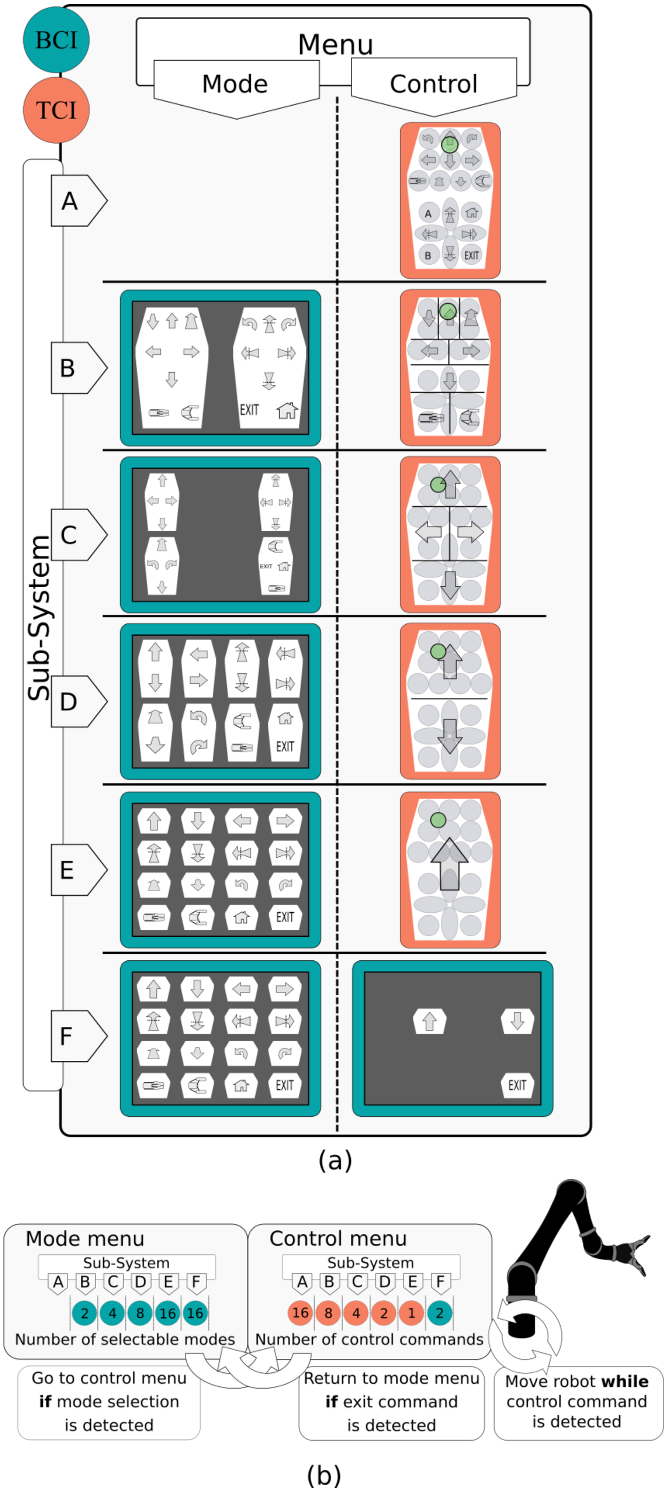

Fig. 2. Control of a robotic arm using the proposed framework. (a) Using combination of the TCI and BCI, the user has direct access to 16 control command, that can manually control all 7DoFs in the robotic arm. Six sub-systems (A-F) were designed in which A uses only tongue signals, B-E uses a combination of tongue and brain, and F uses only brain signals. (b) The user could switch to to the control menu by selecting a mode and could then move the robot by continuously activating a control command. They returned to the mode-menu by executing an exit command.

experiments, the exit system command did nothing when activated. Fig. 2 shows an overview of the framework consisting of six different sub-systems (A to F) and video S1 shows an able-bodied participant using each of the six sub-systems.

A. Framework Design

The tongue control system was based on an adapted version of the iTongue from the company TKS A/S (Nibe, Denmark) [68], which is an intraoral wireless mouthpiece mounted at the palate [69]–[71]. It contained 18 inductive coils (outlined with white in Fig. 3(a)), which were each activated as a small intraoral keyboard using an activation unit glued or medically pierced to the tongue. The full TCI was designed by allocating 16 of the 18 coils of the mouthpiece to directly control the actions of the robotic arm. Thus, users a sufficient tongue functionality to utilize the full TCI could control all DoFs of the robotic arm directly without any mode switching. Algorithm S1 presents the pseudo-code of the main-node handling the full TCI ARM control.

However, without proper tongue functionality, the user will experience difficulties in reaching and hitting the relatively small keys on the intraoral keyboard. Therefore, the interface was progressively adjusted by increasing the area of each key and consequently decreasing the number of keys available on the keyboard. This was conducted through the software, thus not requiring new hardware. To accommodate the reduced number of keys, we introduced a mode control in which the control-modes were selected through a BCI. Algorithm S2 presents the pseudo-code of the main-node handling the hybrid tongue-brain computer interface for ARM control.

We used SSVEP, which is a reliable and well-performing control signal used in several existing BCI systems [72]. When a user focused on a light blinking at a specified frequency, the brain signals showed a higher power at the blinking frequency in the visual cortex. By presenting several control modes blinking with unique frequencies, the user could select the desired action by attending the respective blinking light (henceforward referred to as BCI target), which could be classified through an EEG template matching. The user could activate the visual stimuli by hitting anywhere on the TCI. Then, after having classified the desired control mode using the BCI, the user could activate the available control actions within the control mode using the TCI.

Four tongue-brain hybrid sub-systems (hybrid B-E) were designed with 2, 4, 8, or 16 modes selected using the BCI in

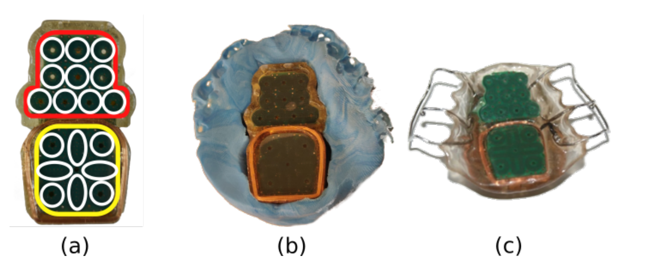

Fig. 3. Images of the TCI used in this study. (a) Surface area of the TCI with the 18 inductive coils outlined by white lines, the front panel outlined by red line and the back panel outlined by yellow line. (b-c) The TCI in braces made of (b) dental two-component A-silicone soft putty used in these experiments and (c) in the commercial custom-made metallic brace.

the ”mode selection” menu, coupled with a respective 8, 4, 2, or 1 control actions selected through the TCI in the ”control” menu. Thereby, providing the user access to all 16 control commands.

To control the robot using a hybrid system the user would start in mode selection and issue the following sequential steps: (1) By activating an arbitrary coil on the mouthpiece, the user could activate the visual stimuli and select the control mode through the BCI by focusing on the respective stimuli. (2) The interface would then present the TCI layout represented by the selected control mode in which the user could send the control commands by continuously activating the allocated areas of the mouthpiece. (3) Lastly, the user could return to the control mode selection by issuing an exit command (double-clicking anywhere on the mouthpiece with the tongue mounted activation unit). The layout would then return to showing the possible control modes as idle visual stimuli which the user could re-activate and then select the following step (1).

Similarly, the full BCI system was designed with a ”mode selection” and a ”control” menu. However, both were controlled through a BCI scheme. Algorithm S3 presents the pseudo-code of the main-node handling the hybrid tongue-brain computer interface for ARM control. In this case, the mode-selection presented the 16 modes, in which each control mode represented only one control action (similar to hybrid E). However, in the full BCI all control modes blinked constantly (whereas they were idle until activation by the TCI in hybrid E). When the BCI detected the users mode selection the interface shifted to the control menu. Here, the interface showed the selected control action as a stimulus at the center of the screen, a stimulus representing the opposing direction (i.e. ’backward’ if ’forward’ was chosen) to the right of the selected control action, and an exit stimulus at the lower right corner which would bring the user back to control mode selection. To activate a control action in the full BCI the user was required to focus on the desired control action, as the robot would only move accordingly while the frequency power analysis for the corresponding control action was above a threshold (and bellow for all other control actions).

B. System Setup

A Lenovo ThinkPad T480 running Ubuntu 18.04 was used as the central unit for the asynchronous proceedings of online data processing of both TCI and BCI data, control of the robotic arm, presentation of visual feedback to the user, and data sampling, which was all conducted using Robotic Operating System (ROS) [73]. Individual ROS-nodes were programmed using either Python3 or C++. The assistive robotic arm used in this study was the Jaco®gen2 from Kinova® [74] and it was controlled using a ROS package provided by Kinova®.

C. Tongue-Computer Interface

The iTongue system was adapted to the application in this study by changing the standard software processing the sensor outputs to develop new sensor layouts, as shown in Fig. 2, and to allow for a ROS-based tongue control of the robot. For this study, we replaced the standard mounting braces with dental two-component A-silicone soft putty (TopDent ImpressA) by embedding the iTongue mouth-piece unit (MPU) in the putty and forming it against the palate of the participant until it solidified (after approximately 2 minutes). In addition, the tongue piercing, used as an activation unit in the commercial version, was replaced with a non-invasive activation unit glued to the tongue as has been done in previous studies [11], [13]. The raw signals (the electrical potential measured over the individual coils and filtered by an LC bandpass filter [71]) recorded from the MPU were wirelessly sent to a central unit from which the signal was transmitted to a laptop via a COM-port for processing. The weighted average of the nearest neighbor algorithm was used to estimate the position of the activation unit on the MPU surface as conducted by Mohammadi et al. [75].

D. Brain-Computer Interface

The brain signals were recorded using eight ring electrodes connected to an OpenBCI Cyton board [76] sampled at 1000Hz and wirelessly transmitted to a laptop using a WiFi board. The OpenBCI board was chosen due to its low cost, which we deemed important for an end-product which individuals with ALS may eventually wish to buy. Similarly, the choice of only eight electrodes compared to the typical 64- or 128-electrode systems would reduce the necessary setup-time, which is also an important factor for potential end-users [8].

Ground and reference electrodes were placed on the left and right mastoid bone respectively. The eight electrodes were placed on O1, Oz, O2, Po3, Poz, Po4, P5, and P6 according to the International 10-20 System with impedances kept below 5k. The raw data were notch filtered at 50Hz to reduce the powerline noise using a 2nd order Butterworth filter. Further, the data was bandpass filtered between 7 and 17Hz, using a 2nd order Butterworth filter. A spatiotemporal beamformer (STBF) based algorithm was used to classify the attention to any of the predefined visual stimuli [77], [78]. The STBF utilized the periodic nature of SSVEP by splitting the EEG into expected periods (i.e. segments of 0.1s for a 10Hz SSVEP signal), averaging the newest segments to reduce noise, and applying calibrated spatial beamformer weights over the channels to achieve an activation value for each BCI target [77].

The recursive STBF (R-STBF) is a computationally improved version of the STBF, and was chosen for this work due to its relatively high performance at a low computational cost [79]. It averages the segments recursively by applying an exponentially weighted moving average [79] rather than an equally-weighted average as used in earlier research [77], [80]. This reduced the computational cost and weighted the more recent data higher to allow a faster response [79].

The STBF was calibrated to the individual user, day, and sub-system. The calibration was conducted through a quick training data-collection before the first run with a new sub-system. In each of the sub-systems control modes were cued to the user five times and then stimulated for 5s in a controlled

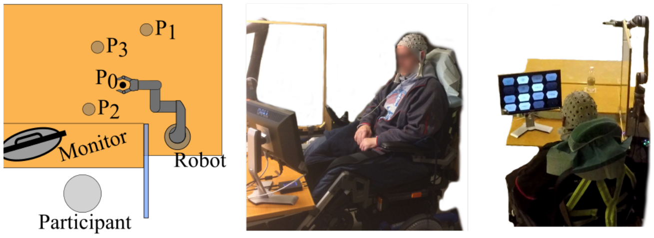

Fig. 4. Experimental setup. (a) Graphical illustration of the important robot positions during experiments. Robot end-effector starts in home position P0 ([21, 26, 51]cm). Able-bodied participants grabbed the bottle placed in position P1 ([8, 60, 0]cm) and poured water in the cup placed in position P2 ([35, 31, 0]cm). Participants diagnosed with ALS grabbed the bottle placed in P3 ([37, 46, 0]cm). (b-c) One of the participants with ALS during the experiment.

randomized order. The participants controlled the pacing of the cues and were allowed short breaks between cues. Depending on the sub-system and the user the data collection time was between a few minutes and 15 minutes.

The visual stimuli were programmed using the Pyglet python library and displayed on a 24" monitor with a refresh rate of 60Hz. The stimuli were programmed with a unique frequency between 8-15.5 Hz and a unique phase. A photoresistor was placed on the corner of the monitor to synchronize the EEG with a reference phase of the stimuli.

E. Experiments and Case Studies

Two evaluations of the framework were conducted within this study: experiments with participants without disability and case studies with participants diagnosed with ALS. The setup illustrated in Fig. 4 was used for both evaluations. The experiments with able-bodied participants provided performance measures of the sub-systems while acting as pilot testing for the case studies with participants with ALS. The research procedures and protocols for both the experiments and case studies were exempt from review board approval by the local ethical committee of Region North Jutland.

1) Experiments with Participants without an ALS Diagnosis: These experiments were designed to provide performance measures of the sub-systems while acting as pilot testing for the case studies with participants with ALS. The experiments were performed over three consecutive days. On each test day, the participants tried the six sub-systems four times in a controlled randomized order. The task was to control the ARM from a home position, grasp a bottle, move it, and pour water into a glass. The positioning of the equipment is illustrated in Fig. 4(a).

2) Case Studies with Participants with an ALS Diagnosis: These case studies were designed to provide proof-of-concept of the framework with potential end users and to consider and evaluate their potential feedback. The participants participated in two days of trials. Test day 1 was used to introduce the sub-systems to the participant in addition to identifying the hybrid sub-system most suited for the participant. Test day 2 was used to evaluate the full TCI, the full BCI, and the best suited hybrid sub-system. To reduce the cognitive load, the participants with ALS performed a simpler task than the able-bodied individuals: reaching and grasping a bottle (in position P3 in Fig. 4(a)) followed by placing the robot in the home position using the allocated "home" button. They performed this task three times with each of the evaluated sub-systems.

F. Statistics

IBM SPSS Statistics 27 was used as statistics software to evaluate potential statistical significant differences in the median task completion times between the sub-systems and trial days for the experiments with participants without ALS. The median task completion time was calculated as the median over four successful trials conducted over a day of trials. A 2-way repeated-measures analysis of variance (rmANOVA) was used with the sub-system (six levels) and trial day (three levels) as factors. A Greenhouse-Geisser correction was applied if the assumption of sphericity was violated. Significant tests were assumed when $p<0.05$ and were followed up with post hoc analysis using Bonferroni correction.

III. RESULTS

A. Benchmarking with Participants without an ALS Diagnosis

Ten participants without an ALS diagnosis (five males, five females, 27 ± 5 years old) were recruited for this experiment. The BCI classification performance is evaluated from the training data and presented in Tab. S.I. The time between the first and the last command issued was recorded and is shown in Fig. 5(a). Data file S1 provides a full overview of all task completion times. Task completion time significantly decreased over the three test days for all sub-systems ($F(2, 18) = 16.4$, $p < 0.001$), indicating learning when using the interfaces and robotic arm. The post-hoc analysis indicated that day 3 achieved significantly faster task completion times compared with day 2 ($p=0.023$) and day 1 ($p=0.003$). The participants also achieved a significantly faster task completion time on day 2 compared with day 1 ($p=0.029$). Further, a significant difference was found across the sub-systems ($F(5,45) = 38.5$, $p<0.001$). The full BCI had a significantly higher task completion time compared with the opposing sub-systems, while the full TCI had a significantly lower task completion time compared with the opposing sub-systems (258 ± 74s in the last day for the BCI, 147 ± 37, 141 ± 34, 121 ± 22, 113 ± 42, and 86 ± 16s for hybrid E, D, C, B, and the full TCI respectively). This shows a stepwise increment in the average task completion time of 32% when moving from the full TCI to hybrid B. Further progression between sub-systems led to an increase of 4-16% per step. Moving from hybrid E to the full BCI caused an increase of 76%. If the individuals would transition from the TCI to the BCI without the hybrid sub-systems, the task completion time would increase by 200%. A closer investigation into the average time spent on each task was conducted by separating the time into three intervals: time associated with the control mode selection menu, with the control selection menu, and with moving the robot (Fig. 5(b)). Data file S2 provides the associated times for all tasks. The participants spent more idle time within a control mode when using the full BCI (130 ± 59s) compared with the

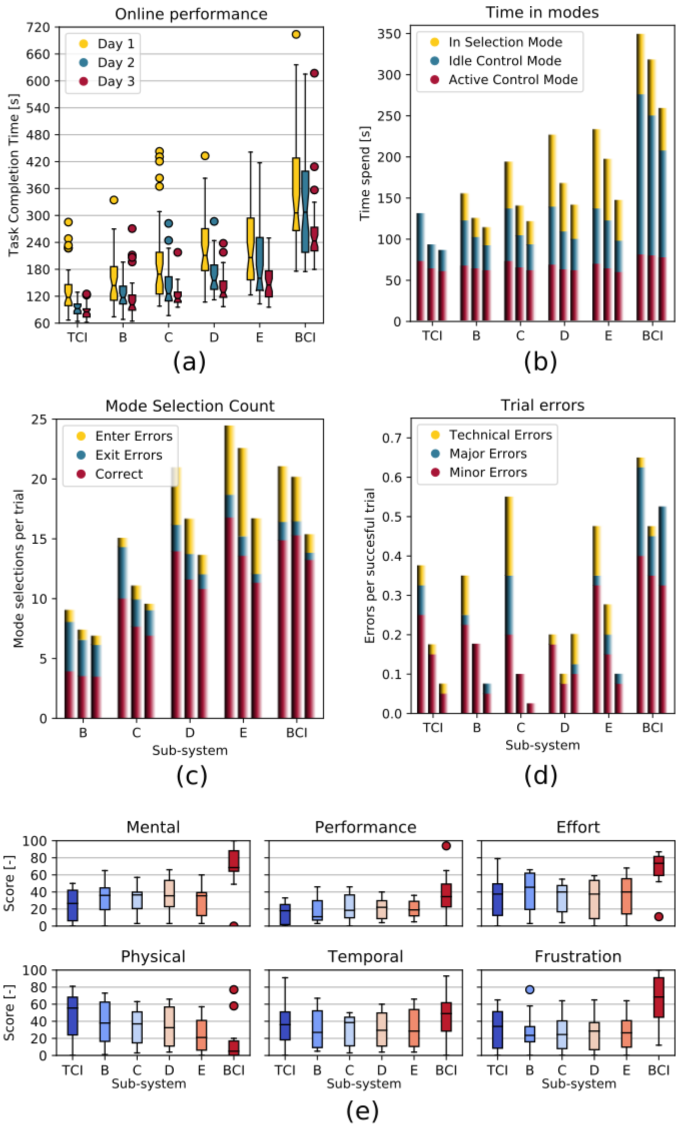

Fig. 5. Results from the tests with able-bodied participants. (a) Task completion time for the successful trials using each of the six sub-systems, on three consecutive days. (b) Mean time spent either selecting a control mode, or being idle or active within a control mode for each for the successful trials. (c) Average selection and error count per trial for the successful trials. (d) Average number of minor, major, and technical errors per successful trial. (e) NASA-TLX scores for the TCI, BCI, and four hybrid sub-systems reported by the participants (scores between 0 and 100, where a lower number indicate a better system).

other sub-systems (31±19, 31±10, 38±17, and 37±13s for hybrid B to E, respectively). This time difference was caused by the difficulty of activating the robot to move through the BCI compared with the TCI. Similarly, the uncertainty using the BCI signal occasionally caused the robot to overshoot, thus requiring the user to spend additional time correcting this issue. Therefore, the time spent moving the robot with the full BCI was also longer than for the opposing sub-systems (77±11s with the full BCI, while the robot only moved for 59-61s with any of the hybrid sub-systems or the full TCI). As measures of real-time system accuracy, we introduced enter and exit errors. The enter errors estimated the number of incorrect control mode selections (when the user exited a control mode without performing control within it to then later perform control in another control mode). The exit errors estimated the number of incorrect exit mode commands (when the users would exit a control mode that would later be the control mode in which they performed the next control). The number of correct control mode selections compared with the two error types is shown in Fig. 5(c). Data file S3 presents the error counts for each trial. The full TCI is not represented in this analysis as it had only one control mode. The hybrid sub-systems had a decreasing quantity of exit errors as the quantity of TCI control inputs decreased: hybrid B led to 2.65±3.13 errors/trial on the third day and hybrid E to 0.73±1.18 errors/trial. The increasing error rate suggests that the higher complexity of TCI usage with the early hybrid sub-systems led to a higher false-positive detection rate of double-clicks within the TCI. Furthermore, the full BCI (which used a visual stimulus as an exit command) had even fewer exit errors (0.60±0.94 errors/trial on the third day), which indicates that the exit stimulus detection used within the full BCI carried a lower false-positive rate compared to the TCI double-clicks.

When the number of control modes increased, so did the number of enter errors, with hybrid B having 0.78±0.99 errors/trial and hybrid E 4.60±6.37 errors/trial on the third day. The full BCI had fewer enter errors (1.53±2.24 errors/trial on the third day) compared with hybrid E, while it had a similar rate as hybrid (1.63±2.12 errors/trial on the third day). This may be caused by the design of the control modes within each of these sub-systems as hybrid E only provided control of one command within the control mode, while the full BCI provided control of two commands, similar to hybrid D.

Control errors also occurred throughout the trials. These were categorized as minor, major, or technical errors. Minor errors were errors that caused an imperfect trial, without resulting in an unsuccessful trial (such as spilling water and accidentally hitting home which moved the robot to the initial position). Major and technical errors were errors that would terminate the current trial, which would then be retried immediately. Major errors were errors caused by the participants (such as tipping the bottle or the glass). Technical errors were software glitches or the glued-on tongue piercing unit falling off. The frequency of the control errors (errors per successful trial) is shown in Fig. 5(d). Data file S4 presents the control errors for each participant. The rate of user-caused control errors (major- and minor errors) decreased over the three test days. These errors occurred at a much higher rate for the BCI (0.325 minor and 0.2 major errors per successful trial on day 3), compared with the TCI (0.05 minor and 0.0 major errors per successful trial on day 3) and the hybrid sub-systems (with hybrid D having the highest error rate of 0.1 minor and 0.025 major errors per successful trial on day 3). This was presumably caused by the accurate time-continuous signal provided by the TCI, which allowed the participant to both focus on the robot while moving it and stopping it with a short delay. The BCI required that the participant had visual focus on the stimuli for the robot to move, thus removing some attention and feedback from the robot's moving position and surroundings. Furthermore, a delay between the intention

TABLE II
PARTICIPANT INFORMATION

ID	Sex[b]	Age	MSS[c]	MSD[d]	ALSFR-R[a] B.	ALSFR-R[a] S.	ALSFR-R[a] R.
C1	M	57	20	3	12/12	7/24	12/12
C2	M	74	40	27	12/12	12/24	12/12
C3	F	73	58	42	0/12	1/24	2/12

[a] ALS-Functional Rating Revised scores separated into Bulbar (B), Spinal (S), and Respiratory (R) scores. A maximum score (i.e. 12/12 or 24/24) indicate no symptoms. [b] M = male, F = female. [c] MSS = month since first symptoms. [d] MSD = month since diagnosis.

TABLE III
EXPERIMENTAL DATA FOR CASE STUDIES

ID	sub-system	Task Completion Time [s] Trial #1	Trial #2	Trial #3	Average	Control Errors [-] Minor	Major	Technical	NASA-TLX Scores[a] [-] Mental	Physical	Temporal	Performance	Effort	Frustration
C1	A	34	60	37	44	0	1	0	**2**	**1**	**5**	**1**	**4**	**5**
	B	55	36	30	40	0	0	0	**2**	**1**	5.5	2.5	5	**5**
	C	186	262	112	187	0	0	0	3.5	6.5	**5**	2	5.5	5.5
	F	275	353	318	315	0	0	0	8	10	6	5	6	6
C2	A	87	128	84	100	1	0	1	**3.5**	**1**	**1**	5	5	**1**
	B	115	204	88	136	0	0	0	7	7.5	**1**	**1**	5	**1**
	F	183	218	225	208	0	1	0	4	5	**1**	6	**4**	2
C3	F	-	-	-	-	-	-	-	**2**	**2**	**5**	**5**	**2**	**9**

[a] NASA Task Load Index Scores reported on scale from 1 to 10, with a lower score indicating a better system and where the best score in each category is highlighted with bold.

of stopping the robot and measuring this from the BCI was also observed causing the robot to occasionally overshoot. On the third test day, the participants were asked to answer a NASA Task Load Index (NASA-TLX) questionnaire [62] after completing the final trial with each sub-system. The scores were rated using a visual analog scale score from 0-100, with 100 indicating a very high and 0 indicating very low for all scores except performance, where 0 indicate "very good" and 100 indicate "very poor". Fig. 5(e) shows the reported scores which can also be found in Data file S5. The TCI and hybrid sub-systems achieved very similar scores, while the scores for the BCI indicated that it required a higher effort to control while achieving worse performance. The BCI was also the sub-system with the highest temporal and mental workload. However, it achieved the lowest score for the physical load.

B. Case Studies with ALS Diagnosed Participants

Following the tests with able-bodied participants, case studies were conducted with potential end users as a proof-of-concept. The hybrid sub-systems were slightly modified to overcome the challenges observed in the tests with able-bodied participants. The biggest changes in the systems were: (1) The double click used in the hybrid sub-systems was replaced with an exit stimulus similar to the one used in the BCI. (2) The hybrid sub-systems utilized only the front area of the TCI (red area in Fig. 3(a)) as some able-bodied participants reported difficulties in reaching the back area (yellow area in Fig. 3(a)). The system was tested over two days by three individuals diagnosed with ALS. Table II reports the scores on the ALS Functional Rating Revised (ALS-FR-R) questionnaire (reported on test day 1) by a caregiver to the individual. The scores have been separated into bulbar, spinal, and respiratory scores, as proposed by Rooney et al. [81]. The NASA-TLX questionnaire was reported on test day 2 after completing the last trial for each of the tested sub-systems. The scores were given verbally by the participant as a value between 1 and 10. Table III reports the NASA-TLX scores, control errors, and task completion times for the trials on day 2.

The first participant, C1, was a 57-year old male who had been diagnosed with spinal-onset ALS three months before the experiment. He was severely paralyzed with limited motor function in his right hand and forearm but had no noticeable speaking difficulty. He was capable of holding a cup and drinking using a straw as well as feeding himself with some difficulties. On test day 1, he experienced issues reaching the lower buttons of the TCI (outlined with a yellow line in Fig. 3(a)). His preferred sub- system on day 1 was hybrid B as it utilized only the top part of the TCI without having too many visual stimuli. Hybrid B, along with hybrid C, the full TCI and full BCI were tested on day 2. Video S2 shows C1 using these sub-systems during the trials on day 1. From these tests, C1 reported the full TCI as his favorite sub-system followed by hybrid B with which he achieved a slightly lower task completion time (40.2±10.2s against 43.8±11.4s for the full TCI) but made one major error (tipping the bottle). Using the full BCI, he achieved the slowest task completion time of 315±32s. Indeed, he also reported the full BCI as his least favorite sub-system since the continuous visual stimuli caused fatigue and a high cognitive load. Surprisingly, he also reported the full BCI as the sub-system with the highest physical requirements in the NASA-TLX questionnaire. Further questioning revealed that this was due to his use of bifocal glasses that required him to move the head to utilize the different lenses. Similar to the able- bodied participants, he further negatively noted the lack of feedback on the robot position when controlling it using the full BCI.

The second participant, C2, was a 74-year-old male diagnosed with progressive muscular atrophy two years before the experiment. Similar to C1, he had no noticeable speaking difficulty. He had full motor functionality of both arms and hands, but with some difficulties, and he experienced fatigue during prolonged use. He also had some functionality in his legs but was not capable of walking or standing unsupported. On both test days, C2 reported discomfort when the mouthpiece unit for the TCI (Fig. 4(a)) as well as some slight discomfort while using it (as the TCI was used with the bigger putty based retainer in our study than the standard dental retainer shown in Fig. 4(a)). For this reason, he selected the full BCI as his favorite sub-system despite having a higher task completion time of 208±19s (against 136±50s and 100±20s for the hybrid and full TCI, respectively). Moreover, he also made a major error (tipping the bottle) using the full BCI. C2 reported having an issue with visual depth sensing, which could also explain the higher task completion times compared with C1.

The third participant, C3, was a 73-year-old female diagnosed with ALS 3.5 years before the experiment. C3 had no remaining bulbar functionality, communicating only through gaze-tracking, and was fed through a percutaneous endoscopic gastrostomy. As evaluations showed no tongue functionality only experiments using the full BCI were performed. On the first test day, she successfully performed a trial with full BCI control in 414s, showing the ability of the interface to adapt to a severely-impaired individual by switching to complete brain control. However, on the second test day, C3 could not fully complete the task. She managed to move the robot-gripper close to the bottle (12cm Euclidian distance, P=[30; 50; 8.5]cm) in 534s, but she did not manage the grasp and the trial was terminated to avoid fatigue. During the interview following the experiments, C3 expressed her frustration that she was unable to succeed with the task on the second test day and noted that the constant visual stimuli caused fatigue. Further investigations using a 5-fold cross-validation of the BCI training data showed that she achieved the best offline classification performance out of the three ALS participants as can be seen in Tab. S.II. Her unsuccessful online performance may have been caused by fatigue or a lack of training with the robot. Despite the failure in completing a full task on the second day, it is remarkable that the interface allowed full control of the robot and a successful task on the first day, with almost no training. This proves the feasibility of the interface also for individuals in the late stage of ALS. However, it is evident that longer training is needed for individuals with severe motor impairments.

IV. Discussion

This study presents a novel control interface framework that utilizes a combination of a TCI and BCI to allow direct control of a robot for individuals with late-stage ALS. While we tested the framework with a robotic arm, it could also be interfaced with other robotic devices, such as a wheelchair or an exoskeleton. Similarly, the framework can easily be coupled with both autonomous and semi-autonomous systems which can improve the task completion time significantly [82]. However, we recommend including a direct-control option for situations in which the autonomy may fail. As a direct control system requires a time-continuous asynchronous control signal, the TCI was shown as an excellent asset. A single TCI signal (as used in hybrid E) can provide the control interface with a fast and precise detection of when the robot should move or stop, while also allowing the user to have visual attention to the robot and potential obstacles rather than a visual stimulus. This resulted in significantly better performance than the full BCI. The BCI presented in this study is a state-of-the-art full ARM control with relatively high performance. In previous studies, 12 able-bodied participants used an average of 10.65 $\pm$ 2.45 minutes to reach and grab an object located 29 cm from the initial position [18]. In this study the ten able-bodied participants grabbed an object located 60 cm from the initial position, moved it to a secondary location 41cm away, and then proceeded with pouring water with an average of 5.82 $\pm$ 2.06 minutes on the first day and 4.30 $\pm$ 1.23 minutes on the third day. Nevertheless, improvements could be made.

To the reduce the need for a high-end computer to handle the online processing nodes, the BCI classifier was chosen for its relatively good performance at low computational costs [79]. However, other classifiers may achieve an even better performance but will likely also require longer training sessions and more electrodes. Similarly, alternative visually evoked potentials could be considered; such as the less fatiguing P300 or the higher performing code modulated visually evoked potential. This would be relatively simple to implement, as the chosen classifier has previously been shown sufficiently versatile to classify these signal types [78].

The most commonly reported issue with the BCI was the requirement of attending a visual stimulus to make the robot move, thus not allowing the user to observe the robot while it moved. To solve this, visual feedback could be included on the screen along with the stimulus. This would allow the user to observe both the stimulus and robot concurrently. Other BCI signals, such as movement-related potentials could be implemented to act as the movement-pedal when a TCI can no longer provide this. Movement-related potentials are also generated when imagining or performing tongue movements, and could provide the users with an intuitive replacement for the TCI [83], [84]. These signals could also be used if the individuals reach a complete locked-in stage, in which the loss of gaze functionality could prove to be impactful on the SSVEP based BCI performance (as a gaze-independent SSVEP or P300 BCI has significantly lower performance [85]–[87]).

It might be beneficial to progressively replace the SSVEP based signal with the new type, similar to how this work progressively replaced the TCI signals with SSVEP based signals. This allows the users to achieve training for future signal types while utilizing the remaining signals with higher performance [88]. We observed a big impact of training over just three days of usage for both the TCI, hybrids, and BCI, and expect this to improve further with long-term usage. Long-term usage would also offer a large potential for further improvement by co-adaptation of the user and machine learning algorithms. This study utilized a relatively simple SSVEP classification algorithm to optimize computational power and to reduce the need for collection of training data. However, long-term data-collection may allow better performing algorithms without requiring longer calibration times.

We utilized a TCI based on iTongue as this system has previously proved capable of directly and continuously controlling a robotic arm using this system [10], [11], [13]. In this study, the adapted iTongue generally outperformed the BCI and the hybrids, as expected. The adapted version of the TCI (Fig. 4(b)) had a considerably larger size than the commercial iTongue (Fig. 4(c)) and used a worse performing activation unit to avoid an invasive medical procedure. Further, a software-defined double-click-based control mode switch of the TCI was used with the healthy individuals, which resulted in some errors. These changes may have had a negative impact on the tongue mobility and contribute to the satisfaction in the TLX score of some of the participants.

In trials with both able-bodied participants and participants with ALS, the full BCI had both the poorest performance while also being reported as the most mentally demanding sub-system. The able-bodied participants reported the full BCI as the least physically demanding, while two participants with ALS reported it as the most physically demanding. We believe this was due to impaired vision and limited training of the participants. The two participants (C1 and C2) suffered from vision impairment, which required frequent head movements for navigating between the 16 stimuli. C3 had corrected to normal vision and reported the full BCI as a low physically demanding system. Moreover, the able-bodied participants received more training with the full BCI before reporting the NASA-TLX scores. This ensured familiarization with the system and thus the able-bodied participants had an easier time searching for their control command, which is among the most physically demanding tasks in this sub-system. One of the participants with ALS (C2) preferred the full BCI, despite performing better with the full TCI, while C1 preferred a hybrid system on test day 1 but the full TCI on test day 2. Consequently, the optimal sub-system should also be selected based on the individual user preferences on a task-to-task and day-to-day basis. C3 was unable to utilize a tongue control interface at her stage of the disease and could not use the hybrid version of the interface and thus experienced less training with the robotic arm, possibly giving her a steeper learning curve. Yet, she managed to move the robot in both sessions, and on the first day, she completed the reaching and grasping task proving the feasibility of the full BCI system.

For both the able-bodied and the ALS participants, the experiments underlined the importance of hybrid sub-systems and of including high performing signals (such as TCI signals) when the user has the motor functionality capable of using them. The results showed an increase in the average task completion times between the full TCI and the full BCI in the range of 200%. This indicates a major loss of robot usage efficiency if no hybrid sub-system is available to allow a gradual change from the TCI to the BCI when the full TCI can no longer be efficiently used. The hybrid sub-systems presented in this study allowed for a step wise increase between 4-32% in the average task completion time from the full TCI system until the last hybrid sub-system, allowing the user to sustain a higher degree of functionality through the robot for a longer time.

V. Conclusion

As the requirements for motor functionality depend both on the users disease, stage, and preference, the control modalities should be flexible and allow a personally tailored maximization of the performance. Our framework is the first step towards a new control interface methodology in which the technology evolves and adapts to the users progressive disease rather than requiring the user to progress with entirely new technologies. It allowed for a 4-32% stepwise decrease in task completion time instead of a nearly 200% decrease when no adaptation was provided. Thus, the proposed new framework will both reduce the workload, sustain performance, and thereby likely improve the quality of life for severely paralyzed individuals.

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SUPPLEMENTARY MATERIALS

Algorithm S1 Control using the tongue interfaces

```
Present control selection on GUI
while Run do
    Check TCI
    if TCI is active then
        Send TCI command to robot
    else if Robot is moving then
        Stop robot
    end if
end while
```

Algorithm S2 Control using the hybrid tongue-brain interfaces

```
Present mode-selection on GUI
while Run do
    Check TCI for any activity
    if TCI is active then
        Start visual stimuli on GUI
        repeat
            Check BCI for control mode selection
        until Control mode classified
        Present control mode on GUI
        repeat
            Check TCI for control command
            if Control command is found then
                Send command to robot
            else if Robot is moving then
                Stop robot
            end if
        until exit command
        Present mode-selection on GUI
    end if
end while
```

Algorithm S3 Control using the brain interface

```
Present mode-selection on GUI, start visual stimuli
while Run do
    repeat
        Check BCI for control mode selection
    until Control mode classified
    Present control mode on GUI, start visual stimuli
    repeat
        Check BCI for control command
        if Control command is classified then
            Send control command to robot
        else if Robot is moving then
            Stop robot
        end if
    until Exit command detected
    Present mode-selection on GUI, start visual stimuli
end while
```

TABLE S.I
OFFLINE BCI PERFORMANCE FOR HEALTHY PARTICIPANTS

ID	Day	AT [s]	TPR [%]	FPR [%]	FNR [%]	ID	Day	AT [s]	TPR [%]	FPR [%]	FNR [%]
1	1	0.86	95.0	0.3	4.7	6	1	1.63	86.3	0.8	12.9
	2	0.87	97.4	0.3	2.4		2	1.60	86.4	1.1	12.5
	3	0.82	98.3	0.0	1.7		3	1.50	91.8	1.5	6.8
2	1	0.85	96.7	0.4	2.9	7	1	1.58	89.4	0.2	10.3
	2	0.84	95.9	0.2	4.9		2	1.27	94.8	0.3	4.9
	3	0.88	94.3	0.0	5.6		3	1.14	96.7	0.3	3.0
3	1	0.89	96.3	0.0	3.7	8	1	1.41	75.7	2.6	21.7
	2	0.80	96.7	0.0	3.3		2	1.08	95.8	0.1	4.1
	3	0.77	93.3	0.0	6.7		3	1.09	97.9	0.0	2.1
4	1	0.95	89.9	0.1	10.0	9	1	0.97	97.3	0.0	2.7
	2	1.02	91.1	0.8	8.0		2	0.87	96.0	0.1	3.9
	3	1.01	89.0	0.6	10.4		3	1.33	96.9	0.1	3.0
5	1	1.08	89.3	0.5	10.2	10	1	1.05	95.1	0.0	4.9
	2	1.13	71.8	1.6	26.6		2	0.87	98.9	0.0	1.1
	3	1.08	84.0	0.4	15.6		3	1.05	96.9	0.0	3.1

The offline evaluated BCI performance based on training data for the full 16-class BCI. The the average activation time (AT) show the time before an activation is detected. The average true positive rate (TPR), the average false positive rate (FPR), and the average false negative rate (FNR) show the rate of activation after the AT.

TABLE S.II
OFFLINE BCI PERFORMANCE FOR PARTICIPANTS WITH ALS

ID	Day	AT [s]	TPR [%]	FPR [%]	FNR [%]
C1	1	1.34	93.9	0.6	5.5
	2	1.80	68.5	3.5	28.0
C2	1	1.49	62.6	9.6	27.8
	2	1.43	72.7	3.3	24.0
C3	1	1.47	94.4	0.5	5.2
	2	1.14	94.7	0.1	5.2

The offline evaluated BCI performance based on training data for the full 16-class BCI. The the average activation time (AT) show the time before an activation is detected. The average true positive rate (TPR), the average false positive rate (FPR), and the average false negative rate (FNR) show the rate of activation after the AT.