

Volitional neural control with the CorTec Brain Interchange by an individual with chronic stroke

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ABSTRACT: We report the first demonstration of volitional control of a Brain-Computer Interface (BCI) using the CorTec Brain Interchange by an individual with chronic hemiparetic stroke and no prior BCI experience. Subdural electrocorticographic (ECoG) recordings were acquired from sensorimotor cortex to facilitate voluntary control over a velocity-defined Pong paddle. Linear-discriminant and autoregressive ridge-regression decoders trained on mu and beta band-power features were trained on data collected during monthly study visits prior to the BCI testing. Across three short Pong sessions (96 min; 400 rallies) the participant attained 0.53–0.61 mean paddle hits per rally, above the static-paddle physics baseline (0.28; permutation $p \leq 0.013$ for all three sessions) and a stricter pipeline-replay shuffled baseline (~ 0.36 ; $p \leq 0.011$). Participant self-report demonstrated strategy-level insight into their control of motor-imagery and related game performance.

INTRODUCTION

Control of external devices by thought alone has been demonstrated across several recording modalities. These include non-invasive electroencephalography (EEG), intracortical electrode arrays with externalized percutaneous leads to body-external amplifiers [1], wireless implanted intracortical electronics [2], and implanted ECoG arrays with wireless electronics used for long-term communication in a patient with amyotrophic lateral sclerosis (ALS) [3]. Each modality varies in signal quality, coverage, invasiveness, and longevity. It remains to be determined which modality best supports durable deployment and maximally enhances functional status. Sensorimotor ECoG carries spatially specific mu, beta, and broadband high-gamma signals that track motor intent at millisecond resolution and have been used in

human BCIs since the first demonstrations in 2004 [4]. Since then, ECoG has driven neuroprosthetic skill acquisition [5], chronic cursor control in tetraplegia [6], simultaneous BCI and residual motor control [7, 8, 9], and has been used to read out error-related potentials during continuous BCI play [10]. Most of this work relied on research-grade acquisition hardware not amenable to long-term or free-living deployment.

The Brain Interchange (CorTec GmbH, Freiburg, Germany) is an implanted system intended for long-term, research deployment [11, 12]. Using its programming interfaces, our group at the University of Washington developed an open-source real-time stimulation and streaming platform (OMNI-BIC) to support rapid prototyping through modular system integration [11, 13]. The recording performance of the various components of the integrated system have been positively evaluated in a clinical benchmark study with epilepsy patients [12, 13], while separately, the implanted Brain Interchange has been used successfully for >500 days of longitudinal wireless ECoG recording in non-human primates [14]. To our knowledge, no BCI-type demonstration of closed-loop volitional control of a virtual effector with the Brain Interchange has previously been reported in humans.

Stroke is the second leading cause of long-term adult disability worldwide [15], and individuals with chronic upper-limb impairment after stroke are a priority population for restoration of motor capabilities through BCI. Nonetheless, most chronically implanted neural interfaces have been tested by people with tetraplegia or ALS populations, where cortical motor representations are largely intact. Cortical motor representations are context-dependent even in healthy micro-ECoG recordings [16], and potential post-stroke reorganization adds further variability, challenging decoder reliability and cross-session feature stability. We present a case

Table 1: Brain Interchange Specifications - Stroke BCI

Feature	Value
Channels	32 (sense, sense reference, stim, or ground)
ECoG arrays	2 arrays, 2×8 contacts, 10 mm contact spacing
Electrode contacts	2.4 mm Ø, PtIr
Recording sampling rate	32× 1 kS/s @ 16 bit
Bandpass filtering	~5 Hz to 320 Hz
Amplification options	750×, 380×, 190×, 95×
Max. stim. amplitude	5.4 mA
Sense latency: brain to PC	10 ms
Wireless power supply	130 kHz inductive link
Wireless RF data link	2.54 GHz, 5Mbit/s, AES-128 encrypted, ½ -duplex

report of a participant with chronic hemiparetic stroke, no prior BCI exposure and no recent video-game experience, implanted with the Brain Interchange over peri-lesional sensorimotor cortex. He played a velocity-controlled Pong-style game driven by band-power decoders trained from monthly study visits collected prior to the BCI-testing period. We hypothesized that volitional paddle control would be feasible from band-power features over a small responsive-channel set despite chronic post-stroke reorganization.

MATERIALS AND METHODS

Participant

The participant was enrolled and implanted with the Brain Interchange as part of an ongoing NIH-funded clinical study on the use of neural stimulation to enhance stroke rehabilitation (NIH UH3NS121565; clinical-trials.gov ID NCT06506279). The protocol for the primary study, which received an investigational device exemption (IDE) from the US Food and Drug Administration and approval from the University of Washington Institutional Review Board prior to any study activities, includes a dedicated period at the end of the implanted study window for next-generation therapy development. The right-handed male participant, 52 years old at study enrollment with his most recent stroke 4 years prior, had moderate-to-severe upper-limb impairment (Upper-Extremity Fugl-Meyer 37 at baseline, 47 at the time of BCI experiments following study-provided intensive rehabilitation therapy). BCI activities described here began after the parent study's therapy and monitoring program, approximately nine months after implantation.

The Brain Interchange System

The Brain Interchange System (Fig.1a) is a 32-channel neural interface platform that provides sensing and stimulation access to the brain. In the configuration used in this study, two ECoG electrode arrays were used. The implant (Fig. 1b) is wirelessly powered via an inductive link provided by an external head piece, which aligns to the implant using magnets. The head piece is powered and controlled by the communication unit (com-unit), which also provides a wireless radio frequency (RF) data

link to the implant. A personal computer (PC) running Microsoft Windows communicates with the com-unit and powers it via USB 2.0. The electronics are seated in a recess in the internal table of the skull. The specifications of the system used in this study are listed in Tab. 1. The peri-lesional electrode reconstruction for this participant is shown in Fig. 1c, and a representative gameplay frame in Fig. 1d.

Offline preparation

Monthly study visits prior to the BCI testing period combined a digitized hand grasp task, a standard arm task, and a resting-state recording. Adaptive linear discriminant analysis (LDA) decoders trained on Hilbert-envelope log-band-power features at cued movement vs inter-trial rest (80/20 within-session train/test split) reached 72.8 % binary decoding accuracy on hand-task data and 89.2 % on a separately collected physical-to-imagined transfer block — in which the participant first executed cued physical movements then attempted them as motor imagery within the same session — confirming that decoded motor intent generalized to imagined movement.

The deployed online decoder was a per-channel autoregressive ridge regression (AR; history length 5, $\lambda = 1 \times 10^{-3}$) on mu (8–13 Hz) and beta (13–30 Hz) Hilbert-envelope log-band-power features. High-gamma (70–150 Hz) was extracted by the real-time pipeline but excluded from deployed AR decoders given inconsistent cross-session modulation in this participant. The deployed three-channel set (CH9, CH26, CH28; Fig. 1c) was selected as the most consistent move-vs-rest band-power responders across the prior parent-study visits, accommodating substantial visit-to-visit variance and a feature-shift observed at the monitoring visit immediately preceding the BCI testing period. Smoothed AR variants applied a Gaussian $\sigma \approx 500$ ms to the velocity target. AR outputs were not drift-corrected; sub-

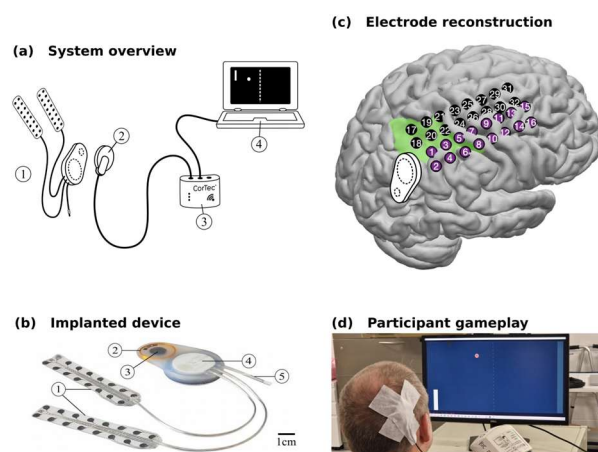


Figure 1: (a) Brain Interchange System, consisting of Implant ①, head piece ②, com-unit ③, and PC ④. (b) Implant with ECoG arrays ①, inductive coil ②, alignment magnet ③, electronics ④, and ground lead ⑤. (c) MRI reconstruction of cortex with electrode contact locations and outlined electronics; green area: stroke-affected region. (d) Gameplay with head piece taped over the implant for additional fixation.

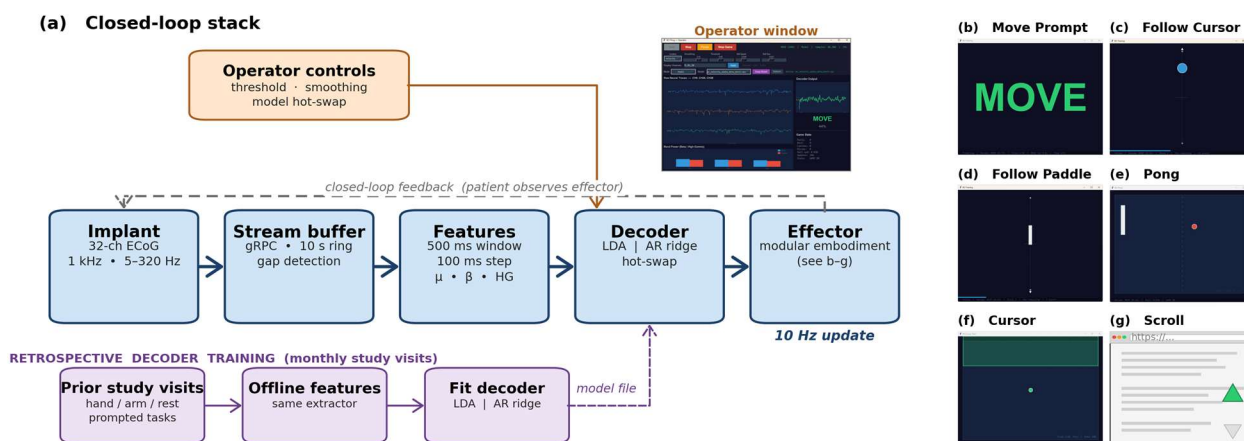


Figure 2: Closed-loop stack and participant interface. (a) Offline training arm feeds saved model into hot-swappable decoder in online arm (100 ms tick, 10 Hz update); operator controls expose threshold, smoothing, and model selection; dashed arc marks closed-loop feedback; inset shows the Operator window. (b–g) Participant interface: Prompt cues MOVE/REST for training-data, tasks of ‘Follow Cursor’ and ‘Follow Paddle’ trajectory tracking with effectors, velocity-controlled Pong, center-out Cursor, and OS-level browser Scroll.

threshold decay toward zero (see §Pong task) provided implicit zero-restoration. LDA decoders were less usable online than AR variants in this participant and were not deployed during Pong play.

Real-time BCI system

The closed-loop BCI system (Fig. 2a) was organized in four stages. A gRPC client connected to OMNI-BIC [11] maintained a 10-second rolling buffer of the 32-channel ECoG stream of macroscale cortical potentials. Every 100 ms (10 Hz update), the most recent 500 ms was passed through a feature extractor (Welch or Hilbert-envelope spectral power in μ 8–13 Hz, β 13–30 Hz, high-gamma 70–150 Hz). The decoder produced a label and confidence value that drove a velocity-controlled Pong paddle on the patient display; an operator-facing window driven from the same tick showed raw neural traces, per-band power bars, and a 30-second rolling history of decoder output (Fig. 2a). All ticks were logged to HDF5 with derived features and decoder outputs.

Analysis pipeline, tick scheduling, and latency

The pipeline ran as a self-paced cycle: after each iteration completed, the next was scheduled to run 100 ms later. Each cycle read the latest neural data, computed features over a 500 ms analysis window, ran the decoder, and updated the paddle. The operator window (Fig. 2a, inset) allowed for three types of adjustments: a decoder-model selector; an exponential-smoothing slider on the decoder output; and a confidence-threshold slider to change a minimum threshold of confidence before modulating the output, with speed proportional to the over-threshold margin. All three were set during initialization from brief participant feedback and left static throughout the retained use-trials; they are reported for transparency and not treated as an experimental variable.

Session protocol

Each in-person session followed the same short protocol. First, a cueing block (≈ 3 minutes) presented MOVE/REST prompts on the patient display, with cue transitions timestamped as ground-truth labels (Fig. 2b). Second, a trajectory-tracking block (≈ 3 –5 minutes)

displayed either a circular cursor (Fig. 2c) or vertical pong-style paddle (Fig. 2d) moving along a fixed trajectory (sinusoidal sweep or step-and-hold) irrespective of decoder output, while the relative decoder state was available in the operator window for tuning. Dynamically following targets was intended as a guide to executing faster motor behaviors than the slow, controlled rehabilitation movements the participant had been performing, more closely mirroring real-time game control. Motor imagery was explained verbally prior to the first BCI session; the participant reported strong familiarity from his youth as a wrestler, where motor-imagery rehearsal had been a routine athletic-training tool. Because arm movements yielded more consistent offline response features than hand movements in this participant, cued retraining used an attempt-to-topple push gesture against the clinician’s monitor for overt rehearsal, with the corresponding motor-imagery instruction being to imagine moving against this resistance for upward paddle motion and disengagement for downward motion. After these trainings, the participant engaged with the Pong game (Fig. 2e); a 2-D cursor task (Fig. 2f) and a browser-scroll controller (Fig. 2g) were also developed but, with limited time available, the participant requested focusing on Pong.

Pong task

The patient display showed a unit-square arena where all positions and velocities are given in arena units (AU) and the arena spans 0–1 AU on each axis. A ball was launched from the right edge at a random angle ($\pm 36^\circ$) and bounced off the top, bottom, and right walls. The paddle was velocity-controlled: the decoder confidence above the positive threshold set a positive target paddle velocity (proportional to confidence – threshold, capped); below the negative threshold the target velocity was negative; sub-threshold output decayed the target velocity toward zero. Position was integrated from velocity per tick. The ball’s speed increased by 0.002 AU/tick on each successful catch up to a cap of 0.08 AU/tick (≈ 0.8 AU/s at the 10 Hz update rate). A ball that

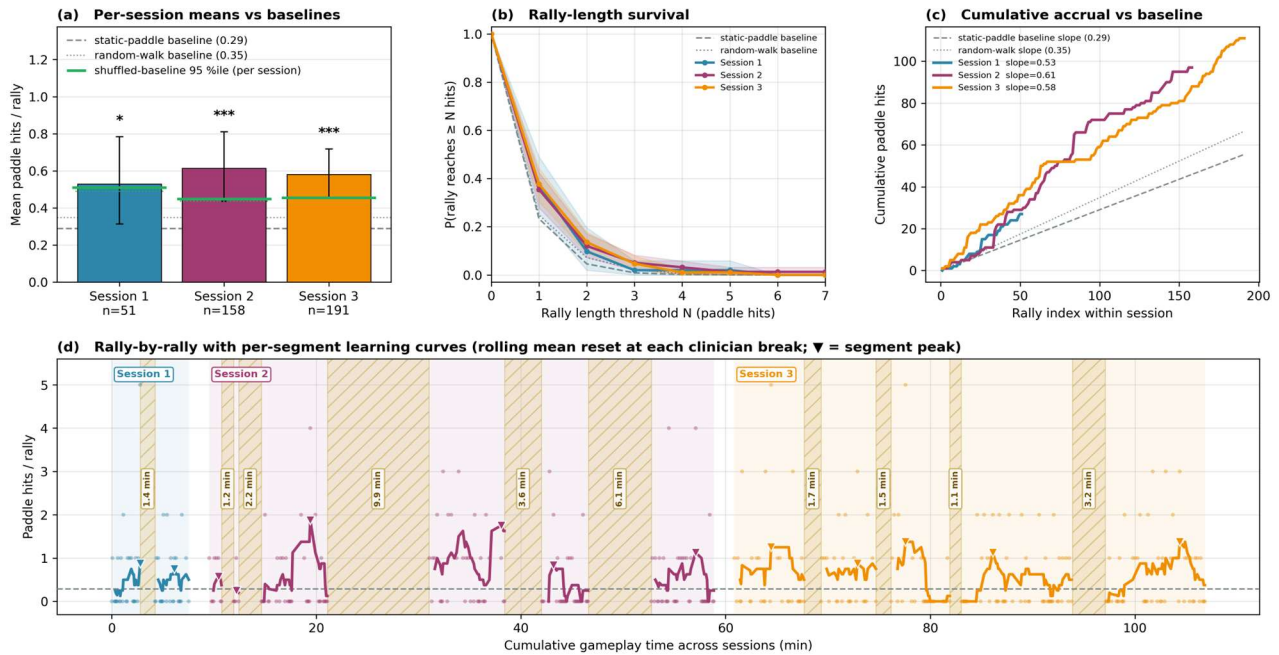


Figure 3: BCI results across sessions. (a) Per-session mean hits/rally with 95 % bootstrap CIs; static-paddle (0.28) and random-walk physics baselines (dashed); asterisks denote permutation $p < 0.05/0.01/0.001$ vs static. (b) Rally-length survival per session against baseline curves. (c) Cumulative hits with baseline slopes (dashed). (d) Rally-by-rally timeline with clinician-initiated breaks (≥ 60 s) shaded; per-segment rolling mean resets at each break, ▼ marks segment peaks.

passed the paddle ended the rally; the next rally launched immediately on the following tick (no explicit inter-trial interval). We define a rally as the span from one ball-launch event to the next miss (or to a game stop), and count paddle hits as the successful events within a rally.

Data analysis

For each session multiple decoders were evaluated. Trial (rally) segments per-decoder containing fewer than 10 rallies were excluded as truncated. Per-session means are reported with 95 % bootstrap confidence intervals after rallies are resampled with replacement 2,000 times. Permutation p-values are the fraction of resampled means that fell at or below the static-paddle baseline. For each decoder $\times$ session cell with at least 10 rallies, 10,000-resample bootstrap confidence intervals are reported alongside the mean hit rate, and inclusion-threshold sensitivity was assessed under minimum rally-count thresholds of 5, 10, 15 and 20. For each inbound rally leg we additionally computed the peak paddle-versus-ball y-position cross-correlation (± 1.5 s lag window) and the terminal positional error at ball arrival.

We observed hit rates against two reference distributions. (i) A physics-matched baseline: 2,000 re-simulations with the paddle held at arena center give 0.28 hits/rally as the geometry-only chance level. (ii) A stricter pipeline-replay baseline: for each retained rally we circularly shift the recorded decoder trace by a random lag (5 s to $T - 5$ s) and re-integrate the paddle through the recorded per-tick smoothing, threshold and control-mode values; unshuffled replay reproduces the recorded paddle at $r = 0.91$, confirming a faithful loop. 1,000 shuffles per trials pooled within session give the pipeline-replay distribution (mean ~ 0.36 hits/rally); observed hit rates exceeding its 95th percentile cannot be attributed to

chance alignment of the actual decoder dynamics with the ball, because temporally shifted versions of the same trace fail to produce comparable rates [17].

RESULTS

Analysis pipeline tick performance

Across all retained rallies, the control loop performed stably. Median tick interval was 124 ms (95th percentile 132 ms), with fewer than 1% of ticks delayed beyond 150 ms. This reflects a 100 ms scheduled delay between iterations plus roughly 24 ms of per-iteration processing (gRPC stream poll, feature extraction, decoder evaluation, paddle command update, and log write). This update rate is comparable to those used in prior ECoG BCI control studies [4, 6, 10].

Pong performance above chance

The participant completed 3 sessions (1/day) totaling 96.1 minutes of gameplay and 400 rallies, achieving 235 paddle hits. Mean hit rates were 0.53 per rally on Session 1 (95 % CI 0.31–0.78, $n = 51$), 0.61 on Session 2 (CI 0.44–0.81, $n = 158$), and 0.58 on Session 3 (CI 0.46–0.72, $n = 191$). All three sessions exceeded the 0.28 physics-imposed static-paddle baseline at permutation ($p = 0.013$, 0.0001 and < 0.0001 , respectively; Fig. 3a). Rally-length survival (Fig. 3b) was above both the static-paddle and random-walk physics baselines in every session, with a peak of nine consecutive hits in Session 2. Cumulative-hit slopes of 0.53, 0.61, 0.58 per rally (Fig. 3c) were each roughly twice the 0.28 static baseline. Mean hit rate did not differ significantly between sessions (all pairwise $p > 0.65$; differences ≤ 0.08 hits/rally), indicating sustained performance across the testing period.

The stricter pipeline-replay baseline (Fig. 4) produced

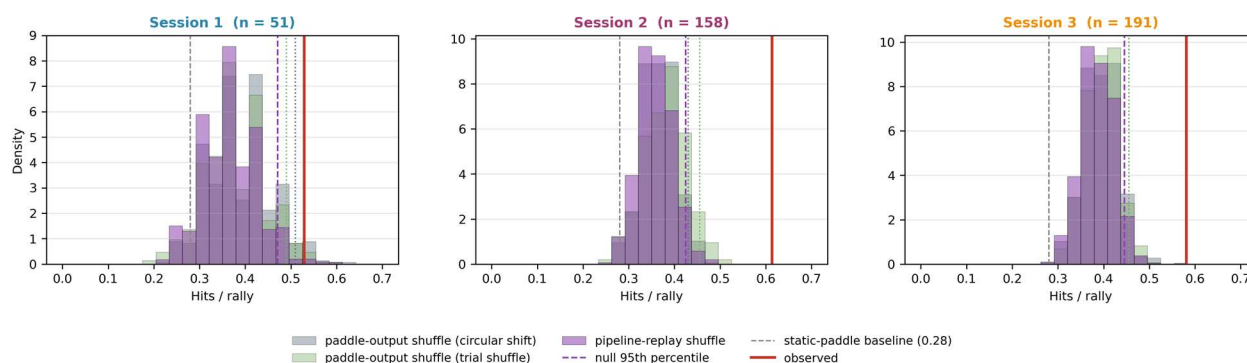


Figure 4: Per-session chance comparisons (Sessions 1–3, $n = 51, 158, 191$ rallies). Density histograms overlay paddle-output shuffle nulls (circular shift in grey, trial shuffle in green) and the stricter pipeline-replay shuffle null (purple), which preserves decoder output and paddle dynamics but destroys their alignment with the ball. Vertical lines mark observed catch rate (red; 0.53/0.61/0.58), 95th percentiles, and the static-paddle physics baseline (0.28). Pipeline-replay $p = 0.011 / <0.001 / <0.001$.

per-session 95th-percentile values of 0.47, 0.42 and 0.45 (pooled mean ~ 0.36 per rally, comparable to the random-walk paddle baseline). Observed hit rates exceeded the pipeline-replay 95th percentile at $p = 0.011$ in Session 1 and $p < 0.001$ in Sessions 2 and 3. A weaker paddle-output shuffle gave consistent 95th percentiles (0.44–0.51 across sessions) and was exceeded at comparable levels. Partitioning rallies by the clinician-initiated breaks (≥ 60 s) reveals a consistent within-segment learning shape in each session (Fig. 3d): performance rises from a low initial level, peaks within the epoch ($\blacktriangledown$ marker), then declines before the next break. In each between-break segment with enough rallies on either side of the peak (9 of 13), pre-peak hit rate exceeded post-peak by 0.43 hits/rally (signed-rank $p = 0.008$), supporting a within-segment post-peak decline.

Decoder choice dominated variability

Of the eight decoder $\times$ session cells with at least 10 rallies, three had lower 95 % bootstrap CI bounds above the 0.28 static baseline. The strongest configuration was the smoothed AR variant on the three best-responding channels used for most of Session 2 (0.78 hits per rally; CI 0.53–1.09; $n = 95$ rallies). Two further AR variants on Session 3 (best-3 and CH9/26/28 triads) tied at 0.64 hits per rally. Across inclusion-threshold sensitivities ($n \geq \{5, 10, 15, 20\}$) the headline per-session means shifted by no more than 0.03, and every session $\times$ threshold combination remained above the static baseline at permutation $p \leq 0.017$.

Paddle tracked position, not direction

Across 628 inbound ball-legs the peak paddle-versus-ball y-position cross-correlation averaged $r = 0.39$ to 0.48, peaking at zero lag. The instantaneous velocity correlation was not distinguishable from zero on any session. Median terminal positional error at ball arrival was 0.22–0.30 arena units, roughly twice the paddle half-height (0.12), consistent with the observed miss rate. The control signal supported coarse positional control but not fine-grained trajectory matching.

Participant-reported experience

The participant had no prior BCI experience and reported “not having touched a video game in years”. He reported during Session 3 that the paddle felt “very responsive

compared to what I’m thinking”. Self-insight followed: noting that the paddle tended to drift up in the final moments before ball arrival, the participant remarked “I think I’m celebrating hitting the ball before it gets there”, and generalized that control was “more the whole brain... it doesn’t really seem to be connected to the movement of my arms,” analogous to focusing on the position of a wrench in space rather than arm movement to achieve a desired position. The participant attributed fluctuating performance to internal state (“a bit of brain fog”) rather than to the system, ultimately finding the design “very achievable... very exciting.”

DISCUSSION

These data establish feasibility of closed-loop ECoG BCI task control with the CorTec Brain Interchange, providing the first such demonstration with a chronic ECoG array fully implanted in a stroke patient. Hit rates exceeded the physics-imposed static-paddle baseline on every session ($p \leq 0.02$) and the more stringent pipeline-replay shuffled baseline (~ 0.36 mean per rally), which preserved the participant’s own decoder and paddle-motion statistics but shuffled their temporal alignment to the ball [17]. Survival curves and cumulative-hit slopes confirm that above-baseline accrual was sustained over dozens of minutes of gameplay rather than concentrated in isolated hits.

Although the paddle mechanism was velocity-defined, the participant’s achieved control was position-dominated rather than fine instantaneous velocity tracking: the paddle tended to hover as the ball arrived, suggesting some coarse control and the ability to track target trajectory. The within-segment rise–peak–decline learning shape visible in Fig. 3d suggests adaptation on a minutes-timescale, with internal-state fluctuation possibly contributing to the within-segment decline; self-report placed the limiting factor on ‘brain fog’ rather than on the system. Longer breaks were initiated by the attending occupational therapist on observation of participant fatigue or strain, not by participant request. In fact, the participant consistently expressed a desire to continue, so breaks are best interpreted as clinician-

determined breaks to prevent fatigue.

Per-decoder rally counts remain small for fine-grained inference, addressed here by 10,000-resample bootstrap confidence intervals per decoder $\times$ session cell and by inclusion-threshold sensitivity checks. Decoder selection prioritized the most consistent neural dynamics available in this individual with chronic stroke. A continuous-velocity decoder tuned to multi-band features, longitudinal stability, and cross-session decoder transfer are the natural next directions for chronic BCI deployment in this population [6, 18].

CONCLUSION

We present the feasibility of closed-loop volitional neural-control using the Brain Interchange for an individual living with chronic stroke. Our preliminary results highlight the rapid development of rudimentary control and motivate further experiments with future participants. We anticipate expanding BCI technology for people with neurological disease and sensorimotor dysfunction will enable a range of neuroprosthetic therapies and interventions to improve recovery.

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