A Nonhuman Primate Brain–Computer Typing Interface

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ABSTRACT | Brain–computer interfaces (BCIs) record brain activity and translate the information into useful control signals. They can be used to restore function to people with paralysis by controlling end effectors such as computer cursors and robotic limbs. Communication neural prostheses are BCIs that control user interfaces on computers or mobile devices. Here we demonstrate a communication prosthesis by simulating a typing task with two rhesus macaques implanted with electrode arrays. The monkeys used two of the highest known performing BCI decoders to type out words and sentences when prompted one symbol/letter at a time. On average, monkeys J and L achieved typing rates of 10.0 and 7.2 words per minute (wpm), respectively, copying text from a newspaper article using a velocity-only 2-D BCI decoder with dwell-based symbol selection. With a BCI decoder that also featured a discrete click for key selection, typing rates increased to 12.0 and 7.8 wpm. These represent the highest known achieved communication rates using a BCI. We then quantified the relationship between bitrate and typing rate and found it approximately linear: typing rate in wpm is nearly three times bitrate in bits per second. We also compared the metrics of achieved bitrate and information transfer rate and discuss their applicability to real-world typing scenarios. Although this study cannot model the impact of cognitive load of word and sentence planning, the findings here demonstrate the feasibility of BCIs as communication interfaces and represent an upper bound on the expected achieved typing rate for a given BCI throughput.

KEYWORDS | Brain–computer interfaces; monkeys; neural prosthesis

I. INTRODUCTION

One potential application of brain–computer interfaces (BCIs) is the restoration of communication for people with movement disabilities. The goal of such systems is to communicate text quickly and efficiently. Healthy individuals type text via a keyboard through near simultaneous discrete selections of keys using multiple fingers. This is a relatively high throughput task, and even the highest performing BCI algorithms are several times too slow to sustain such data rates [1]–[3]. One alternative

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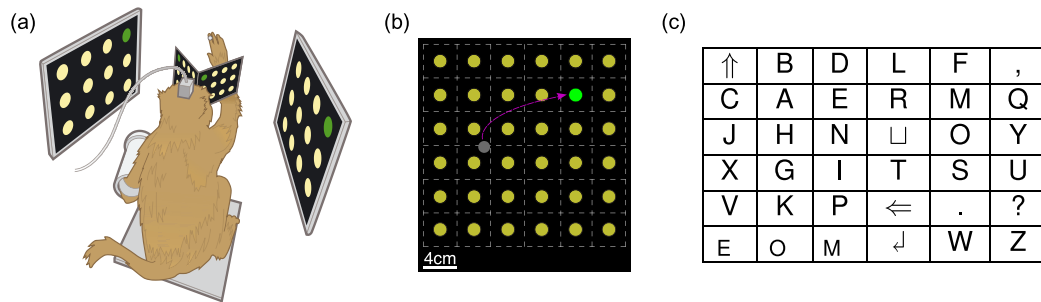Nuyujukian *et al.*: A Nonhuman Primate Brain–Computer Typing Interface

Fig. 1. *Experimental setup. (a) Diagram of monkey performing typing task using experimental neuroelectrophysiology rig. (b) Diagram of virtual typing task. Workspace was divided into a 6 × 6 grid of 4-cm square targets. Gray cursor was under control of monkey. Monkeys were presented with yellow targets and a green prompted target to navigate to. Dashed lines denote the acquisition region boundaries—not shown to the monkey. (c) Layout of the 6 × 6 keyboard. Special keys were: ⇑—shift, ⊔—space, ⇐—delete, ↵—return, EOM (bottom left)—triplet of keys to select in sequence to note "end of message."*

approach is to leverage the use of a neurally driven cursor on a virtual keyboard, akin to using a computer mouse or a finger on a mobile computing device. In this manner, the interface has fewer degrees of freedom (e.g., 2-D movement and optionally a single discrete click), and operates with lower data rates. This approach has demonstrated feasibility in both preclinical [2]–[8] and early clinical [9]–[14] studies. The current highest sustained throughput achieved via a BCI has been with primate studies and achieves around 4–6 bits per second (b/s) [2], [3], [15]. Although bitrate is an important measure of achieved performance, for a communication BCI, a more relevant measure is typing rate. However, the relationship between bitrate and typing rate is not well understood. The aim of this study was to conduct typing task experiments in nonhuman primates using the highest known performing BCIs to then quantify typing rate. Although this experiment is limited because monkeys do not possess a written language, such a study would provide an upper limit to the expected effective typing rate with a given level of BCI throughput.

II. METHODS

Two sets of experiments were conducted in this study. They differed in the neural decoder and the resulting method of selection. The first experiment, termed *dwell typing*, involved only cursor velocity control [7], while the second, called *click typing*, included both cursor velocity control and a discrete click [3]. The aim in both experiments was to communicate prompted text as quickly and accurately as possible.

A. Experimental Setup

1) Monkey Protocol and Behavior: All procedures and experiments were approved by the Stanford University Institutional Animal Care and Use Committee (IACUC). Experiments were conducted with two adult male rhesus macaques (L and J), implanted with 96 channel Utah

electrode arrays (Blackrock Microsystems, Salt Lake City, UT, USA) using standard neurosurgical techniques. Electrode arrays were implanted in arm motor regions of primary motor cortex (M1) and dorsal premotor cortex (PMd), as estimated visually from local anatomical landmarks as previously described [1]. Monkey L was implanted with a single array at the M1/PMd border on January 22, 2008. Monkey J had two arrays implanted on August 24, 2009, one in M1 and the other in PMd. All available channels were used from both monkeys. Monkeys had been previously trained to make point-to-point reaches in a 2-D plane with a virtual cursor controlled by the contralateral arm or by a neurally driven decoder, as diagrammed in Fig. 1(a). They exhibited no learning behavior to the task during these studies. The arm ipsilateral to the implanted hemisphere was gently restrained at all times during these experiments. The contralateral arm was left unbound and typically continued to move even during neurally controlled sessions. This approach was preferred because it minimized any behavioral, and thus neural, differences between the training set (arm control sessions) and the testing set (neural prosthesis sessions). This animal model was selected because we believe it more closely mimicked the neural state a human user would employ when controlling a neural prosthesis in a clinical setting [16]. This model has previously demonstrated comparable performance to the dual arm-restrained animal model, where the contralateral arm is additionally restrained [7].

2) Experimental Hardware: The virtual cursor and grid of targets were presented in a 3-D environment (MSMS, MDDF, USC, Los Angeles, CA, USA) [17] as previously reported [2]. Hand position was measured with an infrared reflective bead tracking system (Polaris, Northern Digital, ON, Canada) polling the acquisition region at 60 Hz. Neural data were processed by the Cerebus recording system (Blackrock Microsystems, Salt Lake City, UT, USA) and made available to the behavioral control

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system within 5 ± 1 ms. Spike counts were collected by applying a single negative threshold, set to $-4.5\times$ root mean square of the voltage of the spike band of each neural channel using the Cerebus software's thresholding algorithm [18]. Behavioral control and neural decode were run on separate PCs using the Simulink Real-Time/xPC platform (Mathworks, Natick, MA, USA) with communication latencies of 3 ms. This system enabled millisecond-timing precision for all computations. Visual presentation was provided via two LCD monitors with refresh rates at 120 Hz, yielding frame updates within 7 ± 4 ms. Two mirrors, setup as a Wheatstone stereograph, visually fused the monitors into a single 3-D percept for the monkey, although all cursor motion was constrained to two dimensions [19]. Data sets are referenced by a monkey and date format where a data set from monkey J would be JYYYYMMDD.

B. Decoder Design

Both of the decoders used in this study have been previously described and demonstrated [3], [7], but are briefly described below.

1) ReFIT Kalman Filter: The cursor movement decoder used in this task was the Recalibrated Feedback Intention-Trained Kalman Filter (ReFIT-KF) [7], [20]. The ReFIT-KF algorithm uses a two-step training protocol that corrects the errors made during an initial block of closed-loop control to arrive at a final high-performing decoder. The ReFIT-KF has demonstrated the highest sustained throughput [2] and longest sustainable performance [15] of any single BCI decoder to date.

To build the decoder used in this study, 500 trials of center-out and back trials were performed under a hand-controlled cursor to targets in eight directions in a 12-cm radius as previously reported [7]. This initial data set was used to build a first pass decoder, which was then tested online to collect another training set for which the kinematics were corrected, yielding the final decoder that was used for the remainder of the experimental day.

2) HMM Click Decoder: A hidden Markov model was used to decode the intention of click during the second set of experiments. Details of this decoder were described in a prior study [3]. A click decoder helps avoid the dwell time necessary in a cursor movement only BCI when selecting targets, yielding performance gains of up to 50%. Running in parallel with the ReFIT-KF, these two decoders achieved the highest throughput of any BCI under any control modality.

In general, the HMM is trained by separating the hand-controlled reaches into two states: move and stop. The stop state is the period of time where the cursor is dwelling over the target. These labeled states are used to build the transition model and the corresponding neural time bins are used to estimate the emissions model.

Together with the ReFIT-KF, these two decoders enable 2-D cursor control and a click signal, akin to using a conventional computer mouse.

C. Typing Task

The typing task was setup in a grid layout. The task was similar to that used in a prior study that optimized keyboard-like tasks [2]. The grid was laid out in a 6×6 grid with 4×4 cm acceptance regions, where letters and symbols were assigned to specific "keys" in the workspace as shown in Fig. 1(b). The arrangement of letters was derived from a Metropolis keyboard layout [21], [22], as shown in Fig. 1(c). The monkeys were not shown this mapping and saw only yellow dots in a grid layout. However, the prompting of these targets was done in a specific sequence as dictated by the text to be copied. The prompted target was lit in green, and the monkey's goal was to navigate the cursor to that green target and select it while avoiding selection of a yellow target. Monkeys were rewarded with a liquid reward for each successful trial. Selection of a yellow target was considered an error and resulted in a failed trial and no liquid reward. Every error was required to be corrected by the selection of the "delete key" before resuming the text sequence, just as done in a conventional keyboard. In this fashion, the task simulated the typing of words and sentences that a human participant would perform.

There were two methods for selecting a letter, depending on which experiment was being conducted. In the dwell typing experiment with only the ReFIT-KF and 2-D cursor control, targets were selected by dwelling on them for the required 450-ms hold time. In the click typing experiment, the HMM click decoder controlled symbol selection by detecting the intention to select the target under the cursor.

The passages for the two experiments were different and selected from articles from the *New York Times* (i.e., dwell [23] and click [24] typing). For the purpose of this study, capitalization and punctuation were ignored. These experiments were repeated on more than one day, but only one representative day from each control modality is shown from each monkey. From the monkeys' points of view, these experiments were effectively identical to prior experiments where only bitrate was measured [2], [3], [15], differing only in that targets were prompted in a nonrandom fashion. For clarity and simplicity of presentation, as these three prior studies contained over a million trials between them and confer significant confidence in the tasks and decoding paradigms, we elected here to show only a single representative day of typing tasks under each decoding modality.

D. Metrics

There are three relevant metrics in this study. Each will be discussed briefly below.

1) Typing Rate: Typing rate is the primary measure used in this study and the most intuitive because of its

familiarity and applicability. Conventional typing rate is measured as the effective characters per minute transmitted when copying text. These approaches have varying ways to account for uncorrected errors (e.g., a misspelled word). However, we did not utilize any of these in this study as we continually prompted the delete key until all errors were corrected before resuming. Thus, the stream of text transmitted was always correct, except for the most recent sequence of errors.

Typing rate can be described via the following equation:

$$T = \frac{S_c - S_i}{5t} \tag{1}$$

where T represents typing rate in words per minute, S_c represents the correct number of symbols/keys transmitted (including spaces and deletes), S_i is the incorrect symbols/keys transmitted (that would then have to be deleted), and t the elapsed time. The division by five is the convention used to convert characters (including spaces) per minute into words per minute [25]. Note that this measure is independent of information-theoretic influences such as dictionary size and channel code. Any coding method can be used so long as the output is meaningful English, though the most common method used is the single-symbol channel coded QWERTY keyboard.

2) Achieved Bitrate: Achieved bitrate represents the effective throughput of the system under a single-symbol channel code, previously described in detail [2]. A single-symbol channel code is the most conventional form of communication channel used by people when they type (i.e., a QWERTY keyboard). Although multisymbol channel codes are more efficient and resistant to errors and considered best practice in electronic communication channels, they are not practical or easy to use by people. In a single-symbol channel coded keyboard, the delete button is used to correct errors one symbol/letter at a time. The equation for achieved bitrate under this coding scheme is as follows:

$$B = \frac{\log_2(N-1)\max(S_c - S_i, 0)}{t} \tag{2}$$

where B is the achieved bitrate in bits per second (b/s) and N is the number of selectable symbols on the interface (including delete key). As with typing rate, the other three parameters are the same: S_c is the correct number of symbols, S_i is the number of incorrect symbols, and t is the elapsed time. The $N-1$ term accounts for the reduction in dictionary size by one because the delete key does not produce a symbol, but instead is a marker which edits the stream of transmitted symbols. The max function is necessary because bitrate cannot be negative, and this demonstrates that a 50% success rate (i.e., where $S_c = S_i$)
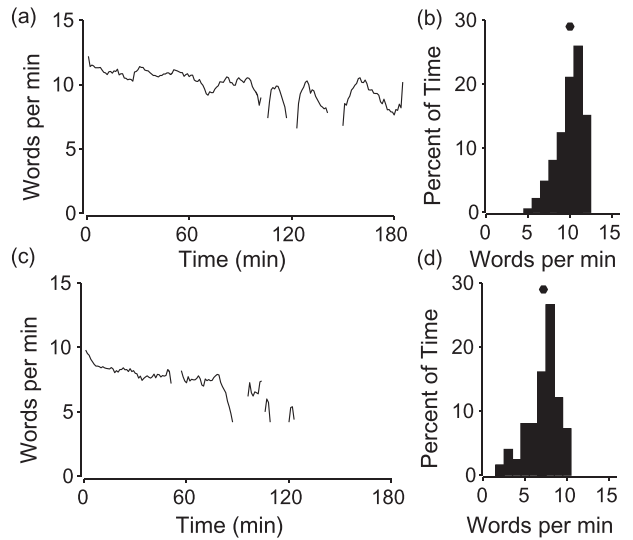

Fig. 2. *Dwell typing performance. (a) Plot of dwell typing experiment of monkey J. Discontinuities seen after 100 min are when the monkey took voluntary pauses. Data from data set J20111021. (b) Histogram of dwell typing performance from the same data set in monkey J. Dot at top notes the average typing rate of 10.0 wpm. (c) Same plot as in (a), but for monkey L, from data set L20111103. (d) Same plot as in (b), but for monkey L, with an average typing rate of 7.2 wpm.*

conveys no net information. This metric was been previously derived in a slightly different, but mathematically equivalent form termed "practical bit rate" in an EEG-based BCI study [26].

3) Information Transfer Rate: The most popular metric in the field of BCIs is information transfer rate and was first introduced nearly 30 years ago [27]. It is a measure of channel capacity and thus always overestimates the throughput of the communication channel. Further, it is not a practical measure because of the many assumptions it makes [28], including infinite length channel codes. The equation for information transfer rate is shown as follows:

$$\text{ITR} = \frac{\log_2 N + P\log_2 P + (1-P)\log_2 \frac{1-P}{N-1}}{t} \tag{3}$$

where ITR is the information transfer rate in bits per second, N is the number of selectable symbols, P is the probability of correctly selecting a symbol (i.e., $S_c/(S_c + S_i)$), and t is the elapsed time. Comparisons between ITR and achieved bitrate appear toward the end of the text.

III. RESULTS

Both the dwell and click typing experiments were successful in simulating typing under the varying control modalities. Performance on the dwell typing experiment with both monkeys is shown in Fig. 2. Monkey J achieved

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Fig. 3. *Example of dwell typing. Still frame from Supplementary Video 1 showing performance of dwell typing task of monkey J. Data are from J20111014. Monkey only saw yellow and green dots; letters were overlaid in postprocessing. The particular decoder used in this video had been held constant for over 30 days from a prior study [15]. The trial shown in this frame is trial 157, where the period key is prompted.*

Fig. 4. *Click typing performance. (a) Plot of click typing experiment of monkey J. Data from data set J20120411. (b) Histogram of click typing performance from the same data set in monkey J. Dot at top notes the average typing rate of 12.0 wpm. (c) Same plot as in (a), but for monkey L, from data set L20120501. (d) Same plot as in (b), but for monkey L, with an average typing rate of 7.8 wpm.*

an average rate of 10.0 words per minute (wpm), completing the prompted article in about three hours. Monkey L achieved an average of 7.2 wpm and completed about two thirds of the article in two hours before voluntarily stopping. Part of the reason for monkey L's lower performance is that he has lower overall behavioral motivation and BCI throughput than monkey J. An example video of monkey J using the BCI to transmit text with the dwell typing experiment is shown in Fig. 3, which is a still frame from Supplementary Video 1.

Performance on the click typing experiment with both monkeys is shown in Fig. 4. Monkey J achieved an average rate of 12.0 wpm, completing all but the last two paragraphs of the article in just over an hour. Monkey L achieved an average rate of 7.8 wpm in just over an hour and half, stopping at the sentence prior to where monkey J stopped. As the click typing experiment is faster paced and more strenuous, the monkeys (monkey J in particular) are less willing to perform the click typing task for as long [3]. Example videos of monkey J using the BCI to transmit text under the click typing experiment appear as Supplementary Videos 2 and 3.

Combining these data sets with data collected from these same monkeys using the same decoding methods from earlier studies [2], [3], [15], we related typing rate to achieved bitrate, shown in Fig. 5(a). This plot shows the average typing rates and bitrates achieved by both
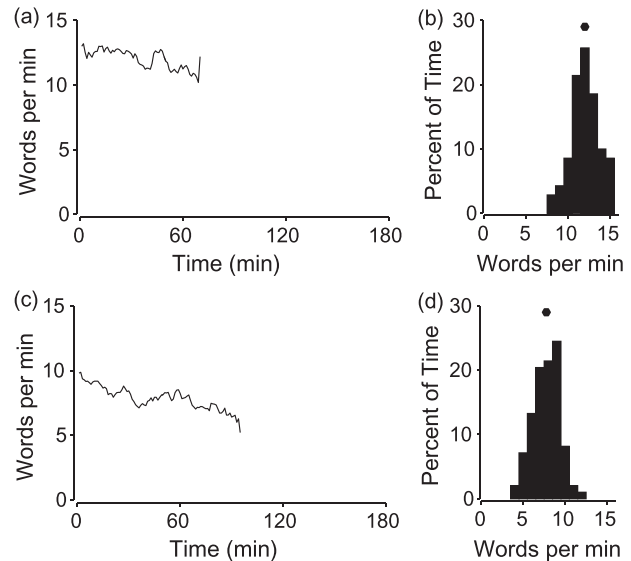
monkeys using both experiments. A regression line fit to these data (with an assumed intercept at the origin), yielded a slope of 2.69 (95% CI: 2.43–2.96). Thus, the
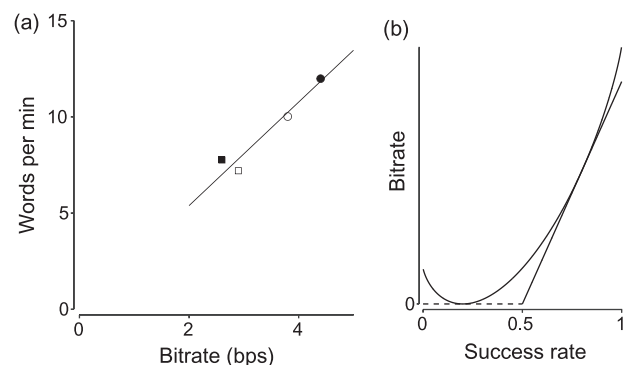

Fig. 5. *Metrics comparison. (a) Plot of typing rate versus achieved bitrate. The achieved bitrate measures are from prior studies [2], [3], [15]. Circles denote monkey J. Squares denote monkey L. Hollow markers denote dwell typing experiment. Filled markers denote click typing experiment. The regressed line is of the form $T = 2.7 \cdot B$. (b) Plot of achieved bitrate and ITR as a function of success rate. The y-axis does not have ticks because only the relationship of the lines is important in this plot and absolute bitrate varies as a function of dictionary size. Achieved bitrate is the linear piecewise line and ITR is the curved line. Note that the ITR curve is always greater than or equal to the achieved bitrate line. This plot is for $N = 5$. Intercept points are at $1/N$ (chance rate) and $(N-1)/N$.*

relationship between typing rate in words per minute and achieved bitrate in bits per second can be approximated by the following equation:

$$T = 2.7 \cdot B \qquad (4)$$

Finally, we mathematically modeled the relationship between achieved bitrate and information transfer rate. For a dictionary size of five, this relationship is plotted in Fig. 5(b). The precise shape of the ITR curve and the slope of the achieved bitrate line vary with dictionary size, but the general features do not change for all tasks with $N > 2$. Consistent with the notion that ITR is a measure of capacity, we see that it is strictly higher than achieved bitrate regardless of the BCI communication accuracy (i.e., success rate). The ITR curve touches zero at the chance level: $1/N$. However, achieved bitrate is zero at all values at or below 50% success rate, reflecting the fact that no symbols are effectively transmitted at these success rates because of the constant need to select the delete key. The other point at which achieved bitrate and ITR are equivalent is when the success rate is $(N-1)/N$. Note that the relationship to ITR is not one-to-one for success rates at or below 50%. This implies that a single measurement of ITR cannot well predict typing rates at low success rates.

IV. DISCUSSION

This study demonstrates the feasibility of BCIs as communication devices for transmitting text. To our knowledge, the typing rates achieved in this study represent the highest of any BCI under any control modality. We also found that text can be communicated uninterrupted for hours via a single BCI decoder without any changes. The click typing experiment was conducted 2.5 (monkey J) and 4 (monkey L) years postsurgical implantation, serving as an additional existence proof that these electrode arrays can facilitate high-performing BCI control for years. We note that this study is limited by the use of monkeys who were only acquiring prompted targets. The results presented here do not account for the cognitive load of word and sentence formation that a person would encounter. However, for a copy typing task as is commonly used for measuring typing performance, this may be a close approximation. At the least, this study provides an upper limit for the expected typing rate for a given achieved bitrate. A more accurate measure of the relationship between achieved bitrate and effective typing rate would best be performed by human participants with comparable high-performing BCIs. Nevertheless, this study builds additional evidence toward the promise of BCI neural prostheses for people with motor disabilities. ∎

AUTHOR CONTRIBUTIONS

P. Nuyujukian was responsible for designing and conducting experiments, data analysis, and manuscript writeup. J. C. Kao assisted in conducting experiments and manuscript review. S. I. Ryu was responsible for surgical implantation and assisted in manuscript review. K. V. Shenoy was involved in all aspects of experimentation, data review, and manuscript writeup.

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