

# Goal-Directed BCI Feedback Using Cortical Microstimulation



Yohannes Ghenbot, Xilin Liu, Han Hao, Cole Rinehart, Sam DeLuccia, Solymar Torres Maldonado, Gregory Boyek, Milin Zhang, Firooz Aflatouni, Jan Van der Spiegel, Timothy H. Lucas, and Andrew G. Richardson

**Abstract** Paralyzed individuals would benefit from brain-computer interface (BCI) systems that restore not just motor function but also tactile and proprioceptive feedback. Such feedback has been shown to be critical to motor performance. Intracortical microstimulation (ICMS) has often been employed to provide artificial sensory feedback. However, it remains a question of how best to encode the multidimensional nature of this information (e.g. location, intensity, frequency of tactile signals). This project explored encoding goal-directed error signals as a way to simplify the feedback. We used a behavioral paradigm with rats in which ICMS was used as a tunable error signal to direct the subjects to unseen goal locations. We found that with relatively little training, the rats performance in the task with ICMS feedback was statistically as good as with natural sensory feedback. The results provide a demonstration that multidimensional sensory feedback can be mapped to single goal-related encoded signal in certain behavioral contexts to decrease the cognitive burden associated with interpreting multiple ICMS-evoked percepts.

**Keywords** Brain-computer interface (BCI) · Intracortical microstimulation (ICMS) · Sensory feedback

---

Y. Ghenbot · C. Rinehart · S. DeLuccia · S. T. Maldonado · G. Boyek · T. H. Lucas · A. G. Richardson (✉)

Department of Neurosurgery and Center for Neuroengineering and Therapeutics, University of Pennsylvania, Philadelphia, PA, USA

e-mail: [andrew.richardson@pennterapeutics.upenn.edu](mailto:andrew.richardson@pennterapeutics.upenn.edu)

X. Liu · H. Hao · M. Zhang · F. Aflatouni · J. Van der Spiegel

Department of Electrical and Systems Engineering, University of Pennsylvania, Philadelphia, PA, USA

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2020

65

C. Guger et al. (eds.), *Brain–Computer Interface Research*,  
SpringerBriefs in Electrical and Computer Engineering,  
[https://doi.org/10.1007/978-3-030-49583-1\\_7](https://doi.org/10.1007/978-3-030-49583-1_7)

# 1 Introduction

## 1.1 *Paralysis and Motor BCI*

An estimated 5.4 million United States citizens (approximately 2%) live with some degree of paralysis as a result of CNS insult—primarily stroke and spinal cord injury [1]. Several emerging therapeutics are under investigation to restore mobility to paralyzed patients. Motor brain computer interface (BCI) technology has been extensively investigated as a strategy to replace lost movement abilities [2]. Motor BCIs bypass damaged neural tracks, allowing action intention signals recorded from intact cortical motor areas to command external actuators (e.g. cursor or myoelectric prosthesis) or the paralyzed limb directly through functional electrical stimulation [3].

Motor BCI technology is currently limited by a lack of tactile and proprioceptive sensory feedback, which is also disrupted in paralysis. Indeed, even in sensory deafferented states where volitional movement is preserved, skilled motor performance has been shown to degrade and not improve with time and training [4]. Thus, researchers are quantifying the sensory percepts elicited by intracortical microstimulation (ICMS) and developing strategies to incorporate this artificial feedback into closed-loop BCI paradigms [5].

## 1.2 *Closed-Loop Sensory Feedback Strategies*

Somatosensory information is complex and multidimensional, originating from distributed skin, muscle, and joint mechanoreceptors with a wide range of sensitivities. Artificial replication of this information for BCI applications is a challenging problem. Most studies have taken a straightforward biomimetic approach, replacing a missing sense (e.g. fingertip force) with microstimulation of the brain area normally encoding that sense (e.g. primary somatosensory cortex, S1) [6]. However, given the complexity of the feedback and potential cognitive burden of interpreting multiple artificially-derived sensory percepts, the biomimetic strategy is not necessarily scalable. Investigations into alternative encoding strategies are warranted.

As an alternative approach, we posit: (a) some BCI-controlled actions or sub-actions have a known goal that is dependent on some measurable aspect of the environment and (b) that a scalar function of the actions and measurements can be derived whose value represents the deviation from the goal. In these cases, goal-directed BCI actions can be guided simply by a one-dimensional map from the deviation value to cortical stimulation. Although the feedback may not correspond with any natural sense, we hypothesize that it would be intuitive for a user to adjust actions to minimize the deviation and reach the goal. The closed-loop BCI system thus would operate akin to a simple servo-controlled mechanism (e.g. thermostat). Our rationale for this approach is that it places the burden of interpreting multiple

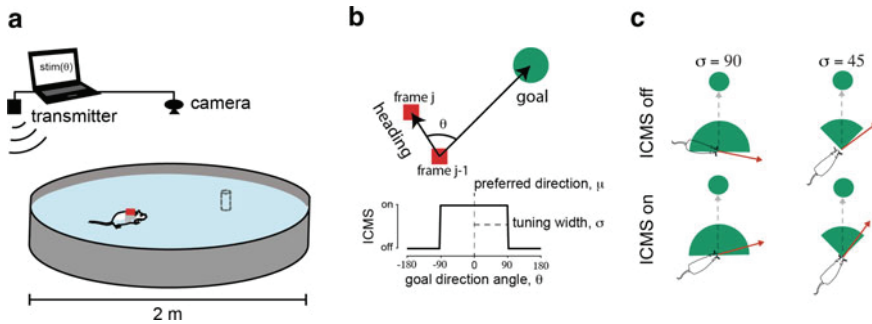
sensory signals on the BCI hardware rather than on the brain, in contrast to the biomimetic approach.

To test this hypothesis, we designed a novel searching task for rats [7]. Instead of conveying overly detailed information about goal locations, we informed the rats of their heading relative to the straight path to the goal using ICMS. While in our prior study we focused on task learning with this error-related feedback, here we reanalyzed the data to quantify the plateau performance (i.e. shortest path to goal) achieved in natural and artificial sensory feedback conditions.

## 2 Methods

### 2.1 Paradigm

Our experiment used adult male Sprague-Dawley rats ( $N = 6$ ) and was approved by the Institutional Animal Care and Use Committee of the University of Pennsylvania. Five rats (Sa, Sn, Ro, Ge, Fr) were implanted unilaterally with a concentric bipolar stimulating electrode in S1. One rat (Mk) was implanted in A1 to investigate encoding outside of S1. During testing, the electrode was connected to a custom wireless neural stimulator [8]. On each trial, the rat was placed at the center of a 2-m diameter pool and had to swim to an invisible, submerged platform (Fig. 1a). Unlike the classic Morris water maze task [9], in our experiment, the platform was moved to a random location on each trial so that a visually-cued memory of platform location could



**Fig. 1** Experimental paradigm. **a** Rats implanted with a stimulating electrode in sensory cortex and wearing a wireless neural stimulator (red box) were placed in a water maze with a hidden, submerged platform. An overhead camera tracked the swim path and updated stimulation parameters in real time. **b** ICMS was delivered as a function of the rat's instantaneous goal direction angle ( $\theta$ ). The step encoding function was defined by a preferred direction ( $\mu$ ) and tuning width ( $\sigma$ ). **c** Illustration of conditions in which ICMS was on or off for two different tuning width values. A rat received ICMS when its heading (red arrow) was within a range (green sector) whose width was defined by  $\sigma$  and whose orientation relative to the platform (green circle) was defined by  $\mu$ . Figure adapted with permission from [7]

**Table 1** ICMS encoding function parameters for each rat

$\sigma$ (deg)	$\mu$ (deg)	rat
5	0	Ge, Fr
15	0	Ge, Fr
45	0	Ge, Fr, Mk
90	0	Ge, Sa
90	180	Sn, Ro, Sa

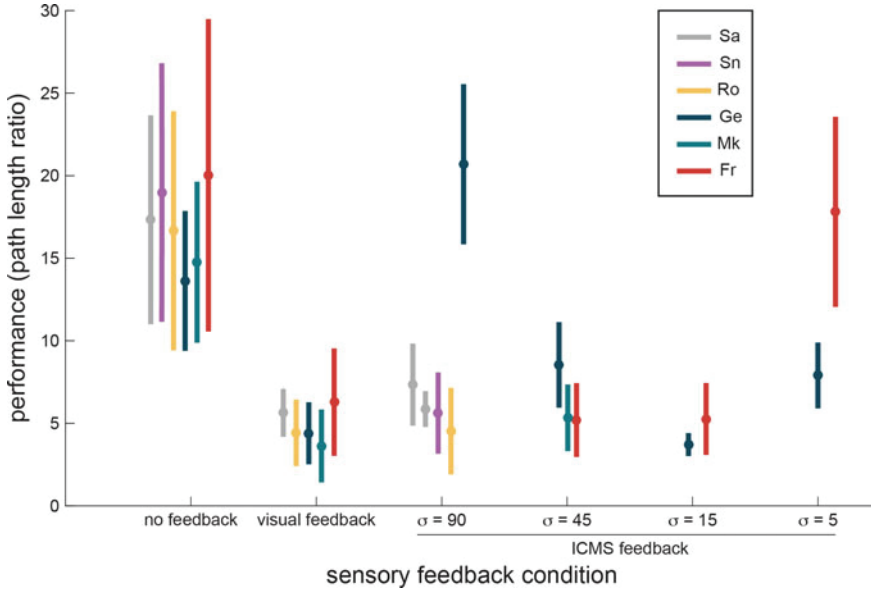
not be formed. Indeed, prior work has shown that rats are not able to improve their performance on this random-location task using their natural senses [10]. First, the rats were trained on the task using a visual cue attached to the platform that rose above the surface of the water for baseline performance. In subsequent trials, the rats were given platform directional information through ICMS of sensory cortex. Catch trials were intermittently incorporated, in which the ICMS was turned off. For two rats, obstacles were added to the behavioral arena after achieving plateau performance to increase task complexity and to investigate the dependency on continuous sensory feedback.

## 2.2 ICMS Parameters

The rat's swim path was monitored by a video camera at 12 frames/s. On each frame, custom software computed the goal direction angle,  $\theta$ , on the basis of the rat's current heading relative to the direction of the platform and wirelessly updated ICMS parameters as a function of this angle (Fig. 1b). The goal encoding function was defined by a preferred direction ( $\mu$ ) and tuning width ( $\sigma$ ). When  $\theta - \mu \leq \sigma$ , we delivered 100-Hz trains of charge-balanced, 0.2- $\mu$ s duration current pulses at suprathreshold intensity (15–75  $\mu$ A, measured by evoked behavioral response prior to water maze experiments). When  $\theta - \mu > \sigma$ , we provided no stimulation. The binary, rather than continuous, function output ensured that the stimulus was felt by the rat throughout the entire tuning width. The tuning width parameter provided control over the acuity of the encoded goal direction information (Fig. 1c). The sensory encoding conditions tested are listed in Table 1.

## 3 Results

Each rat performed a series of trial blocks ( $127 \pm 49$  trials per block on average), where each block was defined by a specific sensory feedback condition. Performance on each trial was quantified by the path length ratio, which was the ratio of the swim path length to the straight-line path between the start and platform locations. Within each block, the rats typically exhibited learning (i.e. decreasing path length ratio



**Fig. 2** Plateau performance of rats under each tested sensory condition: no feedback, visual feedback, and ICMS feedback. Shown are the mean and 95% confidence interval of the path length ratio after learning

values) until they reached a plateau level of performance [7]. Plateau performance was calculated as the average path length ratio in the final 10–30 trials of each block. Results are summarized in Fig. 2.

Rat Ge was tested over a wide range of encoding parameters (Table 1). Ge was unable to learn the task using the low acuity encoding parameter of  $\sigma = 90^\circ$  after 85 trials, as performance was actually worse than that of catch (i.e. no feedback) trials (Table 2). When directional feedback was less ambiguous ( $\sigma \leq 45^\circ$ ), Ge was able to utilize the goal-direction signals for significantly enhanced task performance (Fig. 2). Performance was best at a tuning width of  $\sigma = 15^\circ$ . Further decreases in acuity of ICMS feedback ( $\sigma = 5^\circ$ ) resulted in worse performance (Fig. 2).

Rat Fr learned to perform the task with ICMS feedback ( $\sigma = 45^\circ$  and  $15^\circ$ ) at a proficiency equal to that with visual feedback. However, similar to rat Ge, Fr's performance worsened under the  $5^\circ$  tuning width. Thus, there was an optimal encoding function for conveying goal direction information with ICMS. Furthermore, performance was dependent on the acuity of the goal-direction information, but not upon the site of stimulation. The encoded information remained useful in other primary sensory areas, as rat Mk learned to use the artificial directional information when encoded into A1.

In order to further test the rats' proficiency in using ICMS feedback, we incorporated obstacles into the water maze. The platform was located behind the obstacles during only half of these trials to ensure that rats did not use the barrier as a visual cue

**Table 2** Statistical analysis of behavioral performance

$\sigma$ (deg)	$\mu$ (deg)	Rat	ICMS versus no feedback	ICMS versus visual feedback
5	0	Ge	$t(48) = -3.18, p = 0.0026$	
		Fr	$t(44) = -0.438, p = 0.664$	
15	0	Ge	$t(47) = -5.95, p = 3.26 \times 10^{-7}$	$t(58) = 0.914, p = 0.365$
		Fr	$t(44) = -4.16, p = 1.44 \times 10^{-4}$	$t(43) = -0.0788, p = 0.938$
45	0	Ge	$t(47) = -1.41, p = 0.165$	
		Fr	$t(44) = -4.48, p = 5.22 \times 10^{-5}$	
		Mk	$t(34) = -3.89, p = 4.39 \times 10^{-4}$	$t(38) = -0.0833, 0.934$
90	0	Ge	$t(48) = 2.25, p = 0.0292$	
		Sa	$t(45) = -2.97, p = 0.0048$	
90	180	Sn	$t(27) = -2.53, p = 0.0175$	
		Ro	$t(23) = -2.59, p = 0.0162$	
		Sa	$t(50) = -3.97, p = 2.33 \times 10^{-4}$	
			$t(45) = -2.97, p = 0.0048$	

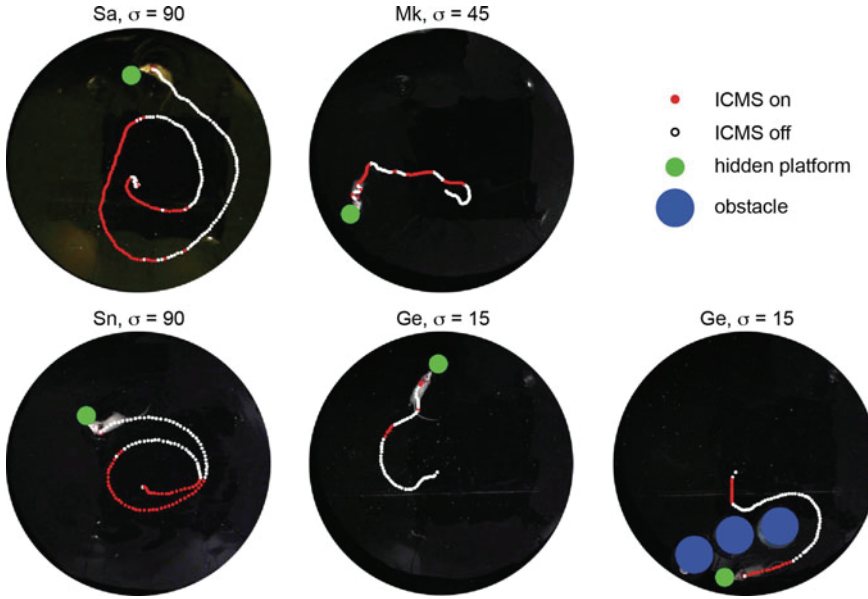
of platform location. Rats Ge and Fr were still able to complete the task efficiently despite absence of continuous ICMS feedback guiding them to the platform (Fig. 3). This result highlights the skill that rats attained with ample training.

Next, we explored whether rats could utilize low acuity sensory signals that were ineffective in rat Ge ( $\sigma = 90^\circ$ ). This is relevant to BCI technology as sensors may be limited in the quality of information that could be delivered to a BCI user. In particular, there may be delays in task relevant event detection and conversion to the appropriate stimulus as well as sensory noise. In the remaining rats (Sn, Ro, and Sa) we explored  $\sigma = 90^\circ$ , with  $\mu = 0^\circ$  or  $180^\circ$ . At plateau performance, all three rats demonstrated superior performance during ICMS trials when compared to catch trials. We further challenged rat Sa by reversing the preferred direction  $\mu$ . He was able to learn the new remapping by the end of the trial block (Table 2).

Overall, five rats reached a plateau performance with ICMS feedback that was not statistically different than with visual feedback (Table 2). The impressive performance despite changes in acuity of information was achieved by adopting behavioral strategies that were customized to the high and low acuity sensory conditions. Rats using low acuity feedback adopted a looping strategy to find the platform, while rats that used higher acuity signals performed zigzagging behaviors (Fig. 3).

## 4 Discussion

We investigated goal encoding as a unique approach to avoid biomimetic scalability issues. Our results show that rats were able to use continuous, non-native, egocentric information concerning the direction of a hidden goal at a proficiency identical to



**Fig. 3** Example trials showing search strategies tailored to different sensory encoding functions. Plots show final frame of each trial with superimposed graphics indicating swim path, platform, and obstacle locations. With low acuity goal direction encoding ( $\sigma = 90^\circ$ ), rats adopted looping strategies (left column). With high acuity encoding ( $\sigma \leq 45^\circ$ ), rats adopted zigzagging strategies (middle column). Rats were able to circumvent obstacles to find the platform using only minimal initial ICMS feedback (right)

natural vision. Interestingly, despite being placed under different sensory conditions, rats attained similar plateau performances by adopting search strategies tailored to sensory constraints [7].

Similar goal-directed error signals have been demonstrated in a primate reaching task [11] and a human hand aperture task [12]. In the human task, percepts were generated by stimulation of somatosensory cortex using electrocorticographic electrodes. The subject wore a glove that sensed hand aperture, equipped with the ability to measure whether hand aperture was wide, appropriate, or tight. Deviation from the goal aperture was communicated to the user via three stimulus functions—two perceptually discernable stimuli for wide and tight apertures and no stimulation for the appropriate aperture. This information allowed the subject to maintain the appropriate aperture.

In addition to hand aperture, we suggest that goal-encoding feedback could be useful in another critical aspect of grasping: grip force. Grasping tasks require appropriate grip force to lift and transport an object without the object slipping (too little grip force) or getting crushed (too much grip force). Performance on this task degrades in the absence of somatosensation [13]. Sensors on the hand could detect all the appropriate variables: shear forces at each contact point due to object mass and acceleration and change in joint angles after contact due to object compliance. In