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Dynamic Brain-Machine Interface: a novel paradigm for bidirectional interaction between brains and dynamical systems

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Abstract—**Brain-Machine Interfaces (BMIs) are systems which mediate communication between brains and artificial devices. Their long term goal is to restore motor functions, and this ultimately demands the development of a new generation of bidirectional brain-machine interfaces establishing a two-way brain-world communication channel, by both decoding motor commands from neural activity and providing feedback to the brain by electrical stimulation. Taking inspiration from how the spinal cord of vertebrates mediates communication between the brain and the limbs, here we present a model of a bidirectional brain-machine interface that interacts with a dynamical system by generating a control policy in the form of a force field. In our model, bidirectional communication takes place via two elements: (a) a motor interface decoding activities recorded from a motor cortical area, and (b) a sensory interface encoding the state of the controlled device into electrical stimuli delivered to a somatosensory area. We propose a specific mathematical model of the sensory and motor interfaces guiding a point mass moving in a viscous medium, and we demonstrate its performance by testing it on realistically simulated neural responses.**

I. Introduction

ONE of the most challenging goals of neural engineering is the development of Brain-Machine Interfaces (BMIs) which aim to restore motor functions to paralyzed people by providing these patients with new communication channels with the external world [1, 2]. In the last decade most research on BMIs has focused on decoding the motor intent from neural activity and translating it into commands for an external device. However, a disadvantage of BMIs based purely on decoding is that they lack feedback information, such as the one given by proprioception or touch. This feedback is fundamental for planning and executing many real-life tasks. The drawbacks of BMIs based purely on decoding have led researchers to begin developing bidirectional BMIs [3, 4] which, in addition to decoding the commands expressed by neural activity, also provide the brain with feedback information about the interaction with the external world. Our own research has proposed a model for these bidirectional BMIs based on the emulation of the spinal cord [5]. Spinal interneurons organize muscles in synergy groups whose mechanical outputs are force fields (FFs) acting upon the limbs [6-8]. Taking inspiration from this evidence, we propose a BMI that can interact with an external device, such as a point mass or a multi articulated arm, by generating control policies in the form of FFs. We propose to implement this behavior through a *motor interface* which translates the recorded neural activity into a force vector, and a *sensory interface* which maps the state of the device into a pattern of electrical stimuli to be delivered directly to the brain.

However, the above conceptual setup leaves open many questions regarding the practical implementation of these concepts. First, we need to understand which algorithms should be used to set the sensory maps and the motor decoding interface. Second, we need to test if the interface can work effectively with the amount of information that can be extracted from neural recordings, and if so what is the parameter range of the FF by which the interface works. In the following, we begin addressing these issues by proposing a specific mathematical model for sensory and motor maps (which we term *dynamic brain-machine interface*, dBMI) and by testing its effectiveness on realistically simulated neural responses.

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II. Methods

A. General scheme

The general scheme is as follows (Fig. 1). The brain interacts with the dynamics of an object, which in this paper we choose to be a point mass moving within a planar spatial domain. The interface controls the dynamics of the point mass by generating a FF which establishes a correspondence between the position of the controlled object and a resulting force.

The procedure begins by specifying a particular desired FF (in this paper chosen to be a radial field converging to the origin of the plane) corresponding to the control policy of the dynamical system that we wish to implement. Then, during a calibration phase run on a "calibration set" of neural responses, the dBMI creates an approximation to the desired FF in two steps. A motor interface transforms recorded neural activities into forces on the plane over which the point mass moves. A sensory interface identifies an electrical stimulus that encodes the current position of the controlled object. The calibration procedure is designed to enforce that the sensory mapping is consistent with both the desired FF and with the force vectors produced by the motor interface.

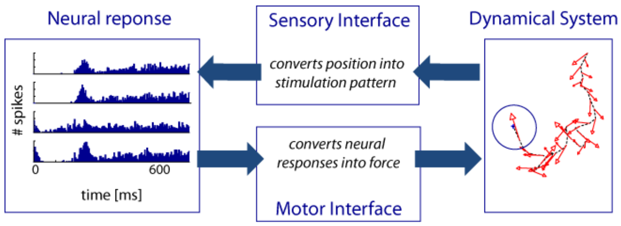

Fig. 1. Schematic of the dynamic BMI system. The interface between the brain and a dynamical system is established by a motor interface that converts neural responses into a force and a sensory interface that maps the instantaneous position of the controlled object onto one of the stimulation patterns in the calibration vocabulary**.**

It is important to note that, because of the variability of neural responses (see below) each time a stimulus is applied a different force may be produced. Therefore, the actual field generated by the interface is the superposition of a noiseless component (corresponding to the desired field) and of a variable component induced by neural response variability. For this reason, we also refer to the FF generated by the interface as "*neural force field*".

B. Simulated data set

To test the dBMI, we constructed a simulated neural response dataset. Its first order statistics matched those observed from real motor neural responses recorded in conditions mimicking artificial injection of information into a sensory area. In brief, we obtained these data by first implanting an array of 16 micro-electrodes (50 µm wire diameter, Tucker-Davis Technologies) in the vibrissal representation of primary somatosensory cortex (S1) and a similar array of recording electrodes in vibrissal motor cortex (M1) of a rat anaesthetized with Zoletil using procedures compliant with NIH and EU guidelines about animal experiments, and fully approved by the local Government and the IIT ethical committee. We then selected a set of electrical stimulation patterns delivered on S1 which were empirically found to reliably modulate responses in M1 [9].

In this particular study we used R=200-250 repetitions of each of the S=4 electrical stimulation patterns. For each stimulation we simultaneously recorded the evoked spiking responses of n=13 single neurons. From these data we computed the time dependent firing rate of each unit ($r_s(t)$, s=1,...,S) to each stimulus, binned in the 0-600 ms post-stimulus window with a 10 ms temporal resolution. We then generated simulated responses of the M1 neurons to the electrical stimulation patterns by using a time dependent Poisson process with a time dependent firing rate equal to that measured experimentally. The time dependent Poisson process is a simple model, widely used to generate neural responses with a variability close to that observed from real cortical responses [10]. The simulated neural responses take the form of the list of spikes numbers emitted by each neuron in each 10 ms time bin.

To evaluate how robust is the dBMI to degradation of the quality of responses of the motor neurons, we also generated neural responses with progressively reduced amounts of information about the electrical stimuli. This was done by "blurring" the firing rate in response to each stimulus $r_s(t)$ with the average firing rate in response to all stimuli r(t) as follows:

$$r_{s,\gamma}(t) = r_s(t) + \gamma \cdot (r(t) - r_s(t)) \qquad (1)$$

This parametric modification increases the stimulus specific firing rates which are below average, and decreases rates above average. The parameter γ regulates the amount of information and was varied from 0 to 1. For γ=0 the firing rates equal the original ones and all original stimulus information is available, while for γ=1, each stimulus triggers the same firing rate and information is zero.

The same simulated process generated both the "calibration" neuronal responses (50 per stimulus) used to set up the motor and sensory interface, and the "test" trials (again 50 per stimulus) used to evaluate the dBMI performance.

C. Motor interface

The motor interface is the algorithm translating neural activity into force vectors applied to the dynamical system and was set up on calibration responses as follows. First the neural population response was rewritten as a weighted sum of the average response to each stimulus. The resulting S-dimensional vectors were then subjected to PCA and projected on the first two principal components (PCs) which explained 69% of the variance on average. The projection matrix and the mean calibration responses to stimuli generated a map from the responses to two-dimensional force vectors. The motor interface calibration was finalized by rescaling the PCs to match the range of variation of the *x-y* components of the desired FF vectors (specified below) over the field's spatial domain.

D. Sensory Interface

The sensory interface maps the instantaneous position of the controlled object onto one of the electrical stimulation patterns. The first step in setting up the sensory interface consisted of computing the average force vector triggered by each stimulus across the calibration trials (represented by the colored vectors in Fig. 2.B). We then associated the corresponding stimulus with the position at which each average force can be found in the desired FF (white dots in Fig. 2.A). Any given point in the sensory space is subsequently encoded by the stimulus associated with the closest of these points, thereby defining a look up table between 4 regions in the field domain and the electrical stimuli (colored areas in Fig. 2.A). The sensory map established in this way is well defined under the assumption that the desired FF is invertible (i.e. there is a one-to-one mapping between force vectors and positions).

E. Simulations of the dynamical system interacting with neural activity

To test the above concepts, we made neural activity interact with a simulated point mass in a viscous medium which moves on a plane. Our desired FF was a linear FF defined by the equation $F = K \cdot x$, whose magnitude depends only on the radial distance *x* from the origin of the plane. This resulted in the following linear differential equation:

$$M \cdot \ddot{x} + B \cdot \dot{x} + K \cdot x = 0 \quad (2)$$

The critical parameter determining the dynamics of this system is the damping ratio, defined as follows:

$$\zeta = B \, / \, (2 \cdot \sqrt{K \cdot M}\,) \quad (3)$$

We explored different behaviors: we varied the damping ratio from 1.03 (system almost critically damped) to 2.93 (system overdamped). This was achieved by fixing the stiffness K and the mass M to 4 N/m and 10 kg, respectively while varying the viscosity B from 13 to 37 $N{\cdot}s{\cdot}m^{-1}$.

The force decoded by the motor interface from the simulated neural activity was supplied as an input to the dynamical simulation which was integrated for 1 s. The position of the simulated point mass was then retrieved and fed to the sensory interface to determine the next stimulus to be applied.

III. Results

A. Procedure for testing the operation of the dBMI

After setting the sensory and motor interfaces during calibration, the operation of the dBMI was tested as follows:

1) The point mass was placed at a randomly selected starting position inside the FF spatial domain.

2) The sensory interface determined the stimulus to be delivered at that position, based on the nearest calibration site. The algorithm selected at random a simulated neural response from the pool of responses that were obtained from repeated application of that stimulus.

3) The motor interface decoded the simulated neural signal and derived the force vector to be applied to the point mass. An example of 100 forces derived from 100 random realizations of the simulated neural responses to each electrical stimulus is shown in Fig. 2.B.

4) The next position was computed by integrating the equation of the dynamical system for 1 s.

5) The process was repeated from step 2 until the mass reached an *end zone* surrounding the equilibrium point. If convergence to the equilibrium point was not achieved within 200 steps, we classified it as a converge failure.

B. Performance of the dBMI for different values of neural information and field viscosity

We first investigated the performance of the system as we varied the amount of neural information from the one matching that available in real neural firing rates (γ=0) down to smaller and smaller information values (obtained by increasing γ up to 1). The forces derived from these responses are represented by the black arrows in Fig. 2.B for γ=0. Note that these forces reliably point in the same direction as the average force obtained during calibration (i.e. colored arrows), indicating that calibrating and running the interfaces with realistic neural information values yields well behaved neural fields.

The reliability of the neural field as a function of the information in neural responses can be quantified by the Circular Variance defined as 1 - | <exp(iθ)> |, with θ being the angle of a force vector [11]. We observed a raise in the Circular Variance when we deteriorated the neural information by increasing γ (Fig. 2.C). Thus, as γ increases, the distribution of forces spreads more and more until there is no more neural information (γ=1) and they spread in all possible directions.

We then further evaluated the behavior of the dBMI by computing both the fraction of simulations in which the system successfully converged and the average number of steps needed to reach convergence. Figure 3.A shows that with the most stimulus informative data sets ($\gamma \leq 0.5$) the

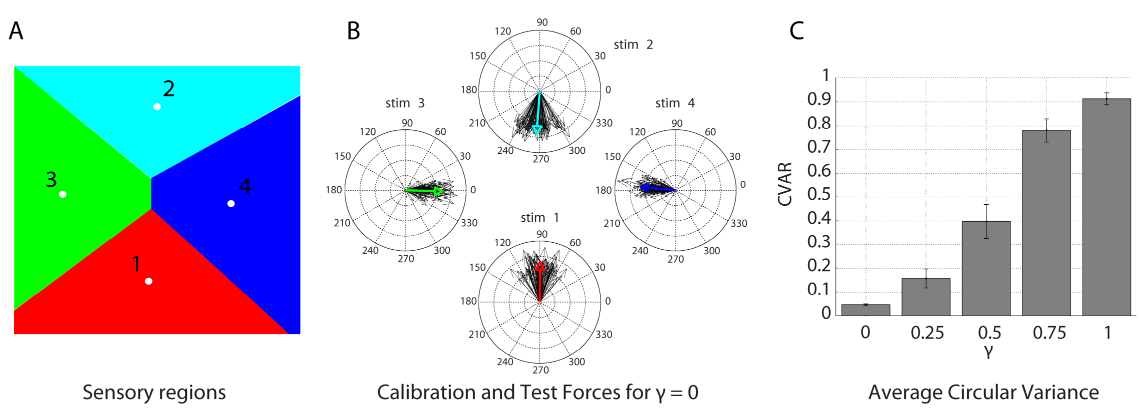

Fig. 2. Operation of the dBMI. **(A)** A graphical representation of four sensory regions generated by the sensory interface mapping each position of the point mass to a stimulation pattern. The regions are defined with a nearest neighbor criterion relative to the position associated with the mean force produced by each stimulus (white dots). **(B)** The motor interface output represented by one hundred test force vectors (black arrows) collected during the testing phase grouped for each stimulus. Colored arrows represent the mean calibration force produced by each stimulus. **(C)** Circular Variance of test forces averaged across stimuli as a function of γ. The spread of test force vectors increases with less stimulus-informative datasets.

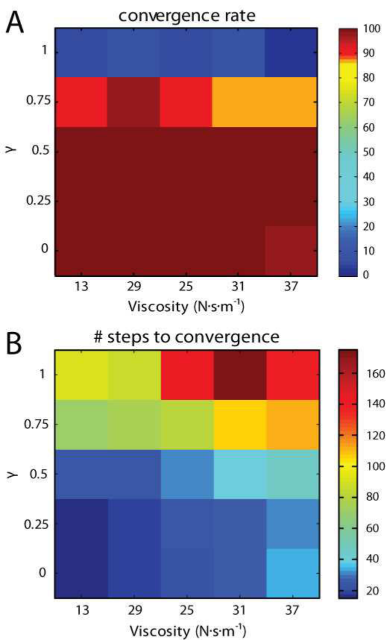

Fig.3. Performance of the dBMI averaged over 100 simulations. **(A)** Rate of convergence of the point mass as a function of γ and of viscosity. **(B)** Number of steps it takes the point mass to reach the center of the sensory area as a function of γ and viscosity.

point mass converged 100% of the time and on average in less than 25 steps. The performance was still high (90% of convergences) even with the least informative data set that still contained information (γ=0.75), although the point mass would take longer to converge. Only when neural information was totally erased (γ=1), did the point mass generally fail to reach the center (it did so by chance 5% of the time).

We finally studied how the dBMI performed when varying the viscosity (and thus the damping ratio) of the dynamical system. We found (Fig. 3) that increasing viscosity increased the average number of steps needed to converge, consistent with the intuition that high viscosity slows down the dynamics. The dependence of convergence speed upon viscosity was much more pronounced at low neural information values (γ>=0.5) than for high neural information values (γ<0.5). This suggests that at low neural information values the effect of the mechanics of the dynamical system on the point mass become relatively more important than the neural component, as the brain exerts a less tight control on the mass in such conditions.

IV. CONCLUSION

Here we proposed and implemented an explicit mathematical model for a bidirectional BMI which can communicate bidirectionally with the brain and control movement of objects by generating FFs, of the type proposed as a concept in [5].

Using simulated neural responses and a simple dynamical system, we explored the efficiency of our proposed dBMI after it had been calibrated to implement an elastic convergent radial FF. We found that the system was robust and convergent even when run with neural information values much lower than the ones obtained experimentally by implanting microelectrodes arrays into cortical areas. The system produced a convergent behavior of the point mass for a wide range of damping ratios, showing robustness to parameter changes. The algorithm proposed and its validation provide a proof of concept of the feasibility of the dBMI design and lay down the algorithmic bases for implementing the dBMI in real-time *in vivo* experiments.

An important algorithmic challenge for our future research is how to modulate in awake animals the automatic behavior implemented by the current system according to a volitional command expressed for instance by another neural population. The research presented here, together with these successive developments, lays down solid mathematical foundations for a new family of BMIs with the potential to provide patients suffering from a wide range of sensory or motor disabilities with the capability to perform goal-related actions requiring accurate non-visual feedback.

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