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Prerequesites for Symbiotic Brain-Machine Interfaces

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***Abstract*—Recent advancements in the neuroscience and engineering of Brain-Machine Interfaces are providing a blueprint for how new co-adaptive designs based on reinforcement learning change the nature of a user's ability to accomplish tasks that were not possible using static methodologies. By designing adaptive controls and artificial intelligence into the neural interface, computers can become active assistants in goal-directed behavior and further enhance human performance. This paper presents a set of minimal prerequisites that enable a cooperative symbiosis and dialogue between biological and artificial systems.**

***Keywords*— Brain-machine interface, co-adaptive, symbiotic, perception-action cycle.**

I. INTRODUCTION

In the 1960s, Licklider stated that computers would be eventually expected to form a symbiotic relationship with humans such that complex problems could be cooperatively solved [1]. The idea was that a partnership between the human and computer would be formed to enable cooperative decision making such that complex situations could be controlled without inflexible dependence on predetermined programs. Linklider was quick to point out that this relationship should not simply be a mechanical extension of the human but have an intelligent interaction (or dialogue) and would require substantial artificial intelligence. While Linklider had great prospects for the future, much of the framework for which the symbiosis was built had a heavy emphasis on computing architectures and very little attention to biology. Issues such as memory structure, programming languages, and I/O equipment were viewed as primary bottlenecks.

Since the time of Licklider, many advances in bio-mimetic control have served to expand the notion of man-computer symbiosis to synergize engineering with biology [2-6]. An area of that has benefited from all this work has been robotic research because of the importance of autonomous behavior. In the last 10 years, several subfields in robotics have emerged, from behavior based robotics [7], evolutionary robotics [8], intentional robotics [9], developmental robotics [10] and brain based systems [11], just to name a few. These systems are being designed more and more using neurobiology knowledge. However, we submit that an important factor that is missing in all of these appliacations is the ability to interact with the human brain. The appeal is that these advanced robots already have the computational power, the sensors, and sophisticated architectures for processing and reasoning, but what is missing is a paradigm for co-adaptation with humans. This will be immensely important for neural rehabilitation and will open a new window for symbiotic human machine research. We believe it is possible to establish a direct communication channel between the user's brain and the machine with the goal of sharing the perception-action cycle the user. This paper presents a new framework to enable symbiosis between biological and artificial systems.

The new framework presented here builds on the design of motor Brain-Machine Interfaces (BMI). Within the motor BMIs there are three basic types: the trajectory BMIs, the goal driven BMIs, and the command and control BCIs. Trajectory BMIs as the name indicates learn how to control a robotic arm to follow a trajectory. They are basically signal translators to actuate prosthetics; they collect firing patterns of dozens to hundreds of neurons in the motor cortex and surrounding areas to decode the user's intent expressed in the neural signal time structure. Since the pioneering work of Chapin in 1999 that showed this was possible in real time, trajectory BMIs are probably the most popular [12]. The goal driven BMIs extract the location in space for the intended movement from a set of predetermined targets using electrodes in the parietal cortices and they can be used for high level coarse command for robots to implement the motion to the desired location in space [13]. The command and control brain-computer interfaces (BCIs) utilize multiple electrodes placed on the scalp (or directly over the cortex) to translate signature of cognition related to imagined movement, expectation, or simply an imagined set of brain states that can control cursors on a screen for action selection [14].

While many groups have made great advances in BMI research, the majority of them have taken approaches that have been strongly signal processing based without much concern to incorporate the design principles of the biologic system in the interface. Many of the prospects that Linklider alluded to in his paper have yet to be realized because the BMI implementation path has either taken an unsupervised approach by finding causal relationships in the data [15], a supervised approach using (functional) regression [16], or more sophisticated methods of sequential estimation [17] to minimize the error between predicted and known behavior. These approaches are primarily data-driven techniques that seek out correlation and structure between the spatio-temporal neural activation and behavior. Once the model is trained, the procedure is to *fix the*

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model parameters for use in a test set that assumes stationarity in the functional mapping. Some of the best known linear models that have used this architecture in the BMI literature are the Wiener filter (FIR) [18, 19] and Population Vector [20], generative models [21-23], and nonlinear dynamic neural networks (a time delay neural network or recurrent neural networks [12, 24, 25]) models that assume behavior can be captured by a static input-output model and that the spike train statistics do not change over time. While these models have been shown to work well in specific scenarios, they carry with them these strong assumptions and will likely not be feasible over the long term because they will be need to be reprogrammed.

However, the success of BMI control is due in part to the remarkable ability of the brain to incorporate the artificial interface into its own cognitive space [26] and use it as part of the biologic body [27]. If we analyze in detail the trajectory BMI paradigm it still follows the egocentric approach of privileging the user versus the computer (hereafter referred to as a *computer agent*) controlling the robot. We can argue that from an engineering perspective this is fine, as long as the combined system solves the task. Unfortunately, there have been difficulties in translating the trajectory paradigm to clinical environments because it requires too much information from the setting, namely the existence of a desired trajectory to train the decoding algorithms. Moreover, with continuous neural interface use, the neural representation supporting such behavior will change [28]. It has been shown unequivocally in animals and humans that intelligent users can switch to brain control seamlessly [28, 29]. However, it has also been shown that the time that it takes to achieve a certain level of "mastery" of the prosthetic device can be slow especially when the details of the dynamics of control are unknown to the user. From a behavioral perspective, even simple issues of scale (i.e. dynamic range of reaching) can create problems for input-output models if the full range of values was not encountered during training [30]. Even with the great adaptability of the user's brain, it can take significant time for the performance to recover. To contend with these issues, it has been suggested by a few groups that adaptability of the interface is a critical design principle for engineering the next generation BMIs [31-33]. In these studies, the concept of adaptability typically refers only to very detailed aspects of the signal translation to include automatic selection of features, electrode sites, or training signals [34, 35]. We submit that this concept of adaptability does not go far enough, because it is unable to raise the level of the bidirectional dialogue with the user and still does not provide opportunities to build intelligence into the tool to model the user's goals.

We present here a new computational architecture that is not only adaptable but also intelligent because it can serve as an assistant to the user to facilitate the control and can serve as an equalizer to share the burden of learning the rules of control. An intelligent system is defined here as a system that uses a model of the external world in its interaction with it. Here, the user interacts directly via their neural signals with a prosthetic arm. However, the decoder of the neural signals also shares the same goals as the user. It is precisely in the sharing of bidirectional goal-directional behavior, that the decoder can act as an intelligent assistant that co-evolves with the user to solve tasks. This aspect of sharing goals is very different from the concept that Licklider proposed where the human specified the goals and the computer performs the menial tasks. In that case the roles of the human and computer are still inherently lopsided. This aspect of shared goal-directed behavior has been overlooked in the present BMI computational paradigms, which assign rudimentary roles to the computer that is controlling the robotics, which constrains the type of tasks, the level of attainable performance and the time required for proper training. This framework is a significant departure from other BMI architectures because it implements the interface at a much higher functional level.

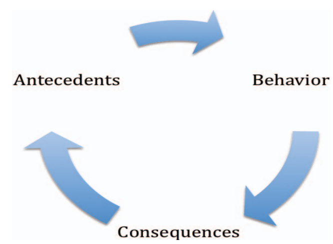

Figure 1. Elements of a Perception Action Cycle (PAC).

II. Minimum Prerequesites

The design of a new framework to transform BMIs begins with the view that intelligent tools emerge from the process where the user and tool cooperatively seek to maximize shared goals while interacting with a complex, dynamical environment. Emergence as is discussed here and in the cognitive sciences depends on a series of events or elemental procedures that promote specific brain or behavioral syntax, feedback, and repetition over time [36]; hence, the sequential evaluative process is always ongoing, adheres to strict timing and cooperative-competitive processes, and is very different from the notion of static computational methods. With these elemental procedures, intelligent motor control and more importantly goal-directed behavior can be built with closed-loop mechanisms which continuously adapt internal and external antecedents of the world, express intent though behavior in the environment, and evaluate the consequences of those behaviors to promote learning. As shown in Fig. 1, Collectively these components contribute to forming a Perception-Acton Cycle (PAC) which plays a critical role in organizing behavior in the nervous system [37]. This form of adaptive behavior relies on continuous processing of sensory information that is used to guide a series of goal-directed actions. Most importantly, the entire process is regulated by external environmental and internal neurofeedback, which is used to guide the adaptation of computation and behavior. The PAC in goal-directed behavior provides several key concepts in the formation of a new framework for BMI. However, unlike the PAC that is central in the animal interaction with the world, the PAC in a co-adaptive BMI will be distributed between the user and the computer agent (CA). Next, we introduce the prerequisites for modifying the PAC to incorporate two intelligent entities.

In order to symbiotically link computer agents with neural systems, a new set of protocols must be derived to enable and empower dialogue between two seemingly different entities. A minimal set of six prerequisites given in Table I describe the essential computation that is required to enact a symbiotic PAC. These prerequisites are based on concepts considered to be key in value-based decision making [38]. Unique to the development of intelligent BMIs is that the user and computer agent each have their own perspective and contribution to each prerequisite as described below.

TABLE I. USER-AGENT PREREQUESITES FOR CO-ADAPTATION

	User	***Computer Agent (CA)***
Representation	Brain States	Environmental States
Valuation	Goal-Directed	Goal-Directed
Action Selection	Neuromodulation	Competition
Outcome Measures	Internal Reward Expectation	Predicted Error
Learning	Reinforcement Based	Reinforcement Based
Co-Adaptation	Dynamic Brain Organization	Optimization of Parameters

Representation: Internal to the user, the spatio-temporal structure of neural activation forms a coding of intent for action in the external world. Understanding the properties of information transmission in the code and determining how this information translates into commands of the motor system as a whole is one of the cornerstones of BMI development. At any given moment, the neural code can be sampled as a brain state defined as the vector of values (from all recording electrodes) that describe the operating point within a space of all possible state values. The syntax or sequence of brain states must be able to support a sufficiently rich computational repertoire and must encode a range of values with sufficient accuracy and discriminability. These brain states could contain either a local or distributed representation depending on where the signals are being collected.

While the representation of brain states are embedded internally in the user, the representation of the neuroprosthetic tool is embodied in the environment [39]. The BMI connection created from the brain state to the environment forms a channel for communication from the internal to external worlds. In the external world, the state representation of the neuroprosthetic includes the sequence of sensory information about the environment that is relevant to goal directed behavior. For example, environmental state could be action oriented and update the position or velocity of the neuroprosthetic tool. It is important to note that the state need not contain all the details about the environment but a sufficiently rich sequence that summarizes the important information that lead to the current state. If the environmental state representation has this property, it could be considered to be Markov.

Valuation: Valuation is the process of how a system assigns value to actions and behavior outcomes. For goal-directed motor behavior, we seek systems that compute with action-outcome sequences and assign high value to outcomes that yield desirable rewards. In the design of intelligent BMIs, it is desirable for both the user to be highly responsive to each other through the immediate update of value as soon as an outcome changes. This approach is very different from habitual valuation which does not participate in continual self-analysis [40]. For intelligent BMI, one of the main computational goals is to develop real-time methods for coupling the valuation between the user and neuroprosthetic tool for a variety of action-outcome associations.

Action Selection: To complete goal-directed behaviors, both the user and neuroprosthetic tool must perform actions in the environment. The method of precisely timing and triggering particular actions that support the task objective is dependent on if there are internal or external representations used. For the user, action selection is performed through the intentional and transient excitation or inhibition (neuromodulation) of neural activity that is capable of supporting a subset of actions. This functional relationship between neuromodulation and the signaling of actions defines the process of action selection. It is expected that under the influence of intelligent BMIs, the primary motor cortex will undergo functional reorganization during motor learning [41-43]. This reorganization in action selection is due in part to how the neuroprosthetic tool synergistically performs action selection in the external environment. Computationally, choosing one action from a set of actions can be implemented through competition, where actions compete with each other to be activated. Using a set of discriminant functions, the action or actions with the highest values can be declared the winner and selected for use in the goal-directed behavior.

Outcome Measures: To determine the success of the goal-directed behavior, both the user and neuroprosthetic tool have different measures of outcome. The prediction error, as its name implies, is the consequence of uncertainty in goal achievement and can be linked either directly to an inherent characteristic of the environment or to internal representations of reward in the user. Reward expectation of the user is expressed in reward centers of the brain [44] and evaluates the states of environment in terms of an increase or decrease in the probability of earning reward. During the cycles of the PAC the reward expectation of the user can be modulated by the novelty and type of environmental conditions encountered. Ideally, the goal of intelligent BMIs is to create synergies in both outcome measures so that the expectations are proportional to the prediction error of the neuroprosthetic tool.

Learning: Because of the rich interactions between the user and the neuroprosthtic, the way that the system learns cannot be a fixed input output mapper (as in conventional BMIs), but it has to be a state dependent system that utilize experience. Throughout this process it develops a model of the world, which in BMIs will include a model of the interaction with the user. Reinforcement Learning (RL) is a computational framework for goal based learning and decision-making. Learning through interaction with environment distinguishes this method from other learning paradigms. There have been many developments in the machine learning RL paradigm [45-49] which originated from the theory of optimal control in Markov Decision Processes [50]. One of its strengths is the ability to learn which control actions will maximize reward given the state of the environment [51]. Traditionally, RL is applied to design optimal controllers because it learns how a computer agent (CA) should provide control actions to its interface with an environment in order to maximize rewards earned over time [50]. The CA represents an intelligent being attempting to achieve a goal that is coded in the environment through a reward "field" (i.e. locations in the environment are assigned different rewards). The environment represents anything the CA cannot directly modify but can interact with. The interaction is defined by actions, which influence the environment and what the CA can sense (states and rewards) from the environment. The CA is initially naïve but learns through interactions, eventually developing an action selection strategy, which achieves goals to earn rewards. However, in intelligent BMIs where computational models are conjoined with neurophysiology in real-time, it may be possible to acquire the knowledge to bring more realism into the mathematical theory of reinforcement learning.

Co-Adaptation: Here we make the distinction between adaptability and cooperative co-adaptation that refers to a much deeper symbiotic relationship between the user and the computational agent who share control to reach common goals, hence, enabling the possibility of continual evolution of the interactive process. This approach must go beyond the simple combination of neurobiological and computational models because this does not elucidate the relationship between the linked, heterogeneous responses of neural systems to behavioral outcomes. A co-adaptive BMI must also consider the interactions that influence the net benefits of behavioral, computational, and physiological strategies. First, adaptive responses in the co-adaptive BMI will likely occur at different spatial and temporal scales. Second, through feedback the expression of neural intent continuously shapes the computational model while the behavior of the neuroprosthetic tool shapes the user. The challenge is to define appropriate BMI architectures to determine the mechanistic links between neurophysiologic levels of abstraction and behavior and understand the evolution of neuroprosthetic usage. The details of how co-adaptive BMIs are engineered through reinforcement learning will be presented next.

III. System Design

With the prerequisites of intelligent BMIs defined, the computational and engineering design challenge becomes one of architectural choices and integrating both the user's and CA's contributions into a cooperative structure. It is obvious that the symbioses will be easier to define and implement if both the user and computer agent share similar learning architectures. From a review of the literature, reinforcement learning (RL) became the natural choice since there is evidence that parts of the limbic system implement a reinforcement learning type of architecture [52]. The conventional way to implement RL in a CA is to let the CA initiate actions, couple its state with the environment, and observe the acquired rewards. This allows the RL algorithm to evaluate actions and choose optimal policies. If the computer agent architecture is based on the same basic design principle, then the issue is how to integrate the two architectures in a synergistic way, i.e. parts of the PAC will reside in the CA and the other parts in the user. Figure 2 presents the relationship between the key elements of a RL framework: actions, states, and goals distributed between the user and the CA [53]. In this new BMI framework, there are two tightly coupled systems: the user and the CA working in synergy. The existence of two co-adaptive intelligent systems is the novel ingredient here since the user's neuromodulation is directly fed as states to the CA that subsequently uses them to select actions for the robot arm. Moreover, the rewards of the CA and the user coincide in the environment thru programming of the agent and operant conditioning of the user. Note that the evaluation subsystem (critic) and the controller (actor) are split between the user and the CA respectively, creating a symbiotic (man-machine) system due to the tight and real-time feedback. We define neuromodulation in this context as the action potential's time structure over channels. The key problem in this co-adaptive BMI is the estimation of a state-action value function (shown mathematically later) to evaluate future actions given the states because they reside in two separate systems and embodiments (neural activity and computer code). In the RL framework, the true value of an action is specified by the mean reward received when that action is selected. At every instance in time, the brain generates new states, the agent selects actions, and the environment gives rise to new rewards, which are numerical values that the agent tries to maximize over time and, as stated, coincide with the user's goal in the environment. The update of the state-to-action mapping is based on the past history of rewards and the estimation of future rewards. The distribution of rewards in the environment defines the task, which is a great advantage for reaching tasks in the external world because the experimenter can completely specify the task through the distribution of rewards in the environment without having to develop ad-hoc correlations among the variables (i.e. requesting the user to "imagine" moving to a particular location and observing the neuromodulation). The CA finds an optimal control strategy based on the user's neuronal state and prosthetic's actions, which we define as movement direction [54]. In preliminary studies, we have quantified in brain control that animals can used their neural modulation and rewards that are projected on the external world to achieve control of a robotic arm [55]. The system involved the integration of improved real-time signal processing methods that capture global computation on multiple spatial, temporal, and behavioral scales [56, 57].

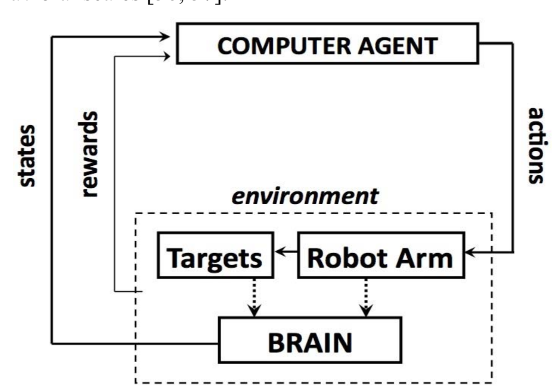

Figure 2. Symbiotic BMI architecture.

IV. Conclusion

We have introduced here a transformative framework for goal-directed behavior that enables the co-adaptation between two learning systems; a computer agent and a user's brain. This framework is based on well-established concepts that include the perception-action cycle and value-based decision making. However, unlike traditional computational modeling or neurobiological study of these systems, we have presented a method that enables a direct, real-time dialogue between the biological and computational systems. An important design element of the architecture is that neither the user nor the CA can solve the task independently, therefore the entities become by design symbiotically related to each other: The user's brain has no direct access to the external space where the reward is located and the CA states cannot be updated without neuromodulation so it cannot solve the evaluation of rewards alone either. Both need to learn how to symbiotically cooperate and use the prerequisites of value-based decision making to solve the task. One of the enablers to this process is the sharing of goals, which facilitates brain-computer dialogue and symbiosis. We seek to perform additional study of this framework in closed-loop brain control mode to test its implications as a general architecture to study causation between biological and computational systems.

References

[1] J. C. R. Licklider, "Man-Computer Symbiosis," *IRE Transactions on Human Factors in Electronics,* vol. HFE-1, pp. 4-11, 1960.

[2] S. Arimoto, "What are the Fundamentals of Bio-Mimetic Control?," *Robotics and Biomimetics, 2004. ROBIO 2004. IEEE International Conference on,* pp. 26-33, 2004.

[3] S. B. Banks, M. R. Stytz, and E. Santos, "Towards an adaptive man-machine interface for virtual environments," *Intelligent Information Systems, 1997. IIS '97. Proceedings,* pp. 90-94, 1997.

[4] J. C. Barca and R. K. Li, "Augmenting the Human Entity Through Man/Machine Collaboration," *Computational Cybernetics, 2006. ICCC 2006. IEEE International Conference on,* pp. 1-6, 2006.

[5] N. Hagita, "Symbiosis between humans and networked communication robots," *Electrical Machines and Systems, 2007. ICEMS. International Conference on,* pp. 1-5, 2007.

[6] L. I. Perlovsky, "Neurodynamics of Consciousness and Cultures," *Integration of Knowledge Intensive Multi-Agent Systems, 2007. KIMAS 2007. International Conference on,* pp. 359-364, 2007.

[7] R. Brooks, *Cambrian intelligence: The early history of the new AI* Cambridge, MA: MIT Press, 1999.

[8] S. Nolfi and D. Floreano, *Evolutionary robotics: The biology, intelligence, and technology of self-organizing machines*. Cambridge, MA: MIT Press, 2000.

[9] R. Kozma and T. Fukuda, "Intentional dynamic systems: Fundamental concepts and robotics applications," *Int. J. Intelligent Systems,* vol. 21, pp. 875-879, 2006.

[10] J. Schmidhuber, "Developmental robotics, optimal artificial curiosity, creativity, music, and the fine arts. ," *Connection Science,* vol. 18, pp. 173-187, 2006.

[11] J. L. Krichmar and G. M. Edelman, "Brain-based devices for the study of nervous systems and the development of intelligent machines," *Artificial Life,* vol. 11, pp. 63-77, 2005.

[12] J. K. Chapin, K. A. Moxon, R. S. Markowitz, and M. A. Nicolelis, "Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex," *Nature Neuroscience,* vol. 2, pp. 664-670, 1999/7 1999.

[13] K. V. Shenoy, D. Meeker, S. Cao, S. A. Kureshi, B. Pesaran, C. A. Buneo, A. P. Batista, P. P. Mitra, J. W. Burdick, and R. A. Andersen, "Neural prosthetic control signals from plan activity," *NeuroReport,* vol. 14, pp. 591-597, 2003.

[14] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain-computer interface technology: A review of the first international meeting," *IEEE Transactions on Rehabilitation Engineering,* vol. 8, pp. 164-173, Jun 2000.

[15] G. Buzsáki, *Rhythms of the Brain*. New York: Oxford University Press, 2006.

[16] S. P. Kim, J. C. Sanchez, Y. N. Rao, D. Erdogmus, J. C. Principe, J. M. Carmena, M. A. Lebedev, and M. A. L. Nicolelis, "A Comparison of Optimal MIMO Linear and Nonlinear Models for Brain-Machine Interfaces," *J. Neural Engineering,* vol. 3, pp. 145-161, 2006.

[17] E. N. Brown, R. E. Kass, and P. P. Mitra, "Multiple Neural Spike Train Data Analysis: State-of-the-art and Future Challenges," *Nature Neuroscience,* vol. 7, pp. 456-461, 2004.

[18] M. D. Serruya, N. G. Hatsopoulos, L. Paninski, M. R. Fellows, and J. P. Donoghue, "Brain-machine interface: Instant neural control of a movement signal," *Nature,* vol. 416, pp. 141-142, 2002.

[19] J. Wessberg, C. R. Stambaugh, J. D. Kralik, P. D. Beck, M. Laubach, J. K. Chapin, J. Kim, S. J. Biggs, M. A. Srinivasan, and M. A. L. Nicolelis, "Real-time prediction of hand trajectory by ensembles of cortical neurons in primates," *Nature,* vol. 408, pp. 361-365, 2000.

[20] S. I. Helms Tillery, D. M. Taylor, and A. B. Schwartz, "Training in cortical control of neuroprosthetic devices improves signal extraction from small neuronal ensembles," *Reviews in the Neurosciences,* vol. 14, pp. 107-119, 2003.

[21] D. W. Moran and A. B. Schwartz, "Motor cortical representation of speed and direction during reaching," *Journal of Neurophysiology,* vol. 82, pp. 2676-2692, 1999/11 1999.

[22] D. M. Taylor, S. I. H. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," *Science,* vol. 296, pp. 1829-1832, 2002.

[23] W. Wu, M. J. Black, Y. Gao, E. Bienenstock, M. Serruya, and J. P. Donoghue, "Inferring hand motion from multi-cell recordings in motor cortex using a Kalman filter," in *SAB Workshop on Motor Control in Humans and Robots: on the Interplay of Real Brains and Artificial Devices*, University of Edinburgh, Scotland, 2002, pp. 66-73.

[24] Y. Gao, M. J. Black, E. Bienenstock, W. Wu, and J. P. Donoghue, "A quantitative comparison of linear and non-linear models of motor cortical activity for the encoding and decoding of arm motions," in *The 1st International IEEE EMBS Conference on Neural Engineering*, Capri, Italy, 2003.

[25] J. C. Sanchez, S. P. Kim, D. Erdogmus, Y. N. Rao, J. C. Principe, J. Wessberg, and M. A. L. Nicolelis, "Input-output mapping performance of linear and nonlinear models for estimating hand trajectories from cortical neuronal firing patterns," in *International Work on Neural Networks for Signal Processing*, Martigny, Switzerland, 2002, pp. 139-148.

[26] M. Velliste, S. Perel, M. C. Spalding, A. S. Whitford, and A. B. Schwartz, "Cortical control of a prosthetic arm for self-feeding," *Nature,* vol. 453, pp. 1098-1101, 2008.

[27] N. P. Holmes, G. A. Calvert, and C. Spence, "Extending or projecting peripersonal space with tools? Multisensory interactions highlight only the distal and proximal ends of tools," *Neuroscience Letters,* vol. 372, pp. 62-67, 2004.

[28] J. M. Carmena, M. A. Lebedev, R. E. Crist, J. E. O'Doherty, D. M. Santucci, D. F. Dimitrov, P. G. Patil, C. S. Henriquez, and M. A. Nicolelis, "Learning to control a brain–machine interface for reaching and grasping by primates," *PLoS Biology,* vol. 1, pp. 1-16, 2003.

[29] L. R. Hochberg, M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, A. Branner, D. Chen, R. D. Penn, and J. P. Donoghue, "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," *Nature,* vol. 442, pp. 164-171, 2006.

[30] J. Moody, "The effective number of parameters: an analysis of generalization and regularization in nonlinear learning systems," in *Advances in Neural Information Processing Systems*, San Meteo, California, 1992.

[31] D. M. Taylor, S. I. Helms Tillery, and A. B. Schwartz, "Information conveyed through brain-control: Cursor versus robot.," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 11, pp. 195-199, 2003.

[32] S. I. H. Tillery, D. M. Taylor, and A. B. Schwartz, "Training in cortical control of neuroprosthetic devices improves signal extraction from small neuronal ensembles," *Reviews in the Neurosciences,* vol. 14, pp. 107-119, 2003.

[33] J. del R. Millan, "Adaptive brain interfaces," *Comm of the ACM,* vol. 46, pp. 75-80, 2003.

[34] D. J. McFarland, D. J. Krusienski, and J. R. Wolpaw, "Brain-computer interface signal processing at the Wadsworth Center: mu and sensorimotor beta rhythms," in *Event-Related Dynamics of Brain Oscillations*. vol. 159, 2006, pp. 411-419.

[35] N. Birbaumer, A. Kubler, N. Ghanayim, T. Hinterberger, J. Perelmouter, J. Kaiser, I. Iversen, B. Kotchoubey, N. Neumann, and H. Flor, "The thought translation device (TTD) for completely paralyzed patients," *IEEE Transactions on Rehabilitation Engineering,* vol. 8, pp. 190-193, 2000.

[36] W. H. Calvin, "The emergence of intelligence," *Scientific American,* vol. 9, pp. 44-51, 1990.

[37] J. M. Fuster, "Upper processing stages of the perception-action cycle," *Trends in Cognitive Sciences,* vol. 8, pp. 143-145, 2004.

[38] A. Rangel, C. Cramerer, and P. R. Montague, "A framework for studying the neurobiology of value-based decision making," *Nature Reviews Neuroscience,* vol. 9, pp. 545-556, 2008.

[39] G. M. Edelman, V. B. Mountcastle, and Neurosciences Research Program., *The mindful brain : cortical organization and the group-selective theory of higher brain function*. Cambridge: MIT Press, 1978.

[40] P. Dayan, Y. Niv, B. Seymour, and N. D. Daw, "The misbehavior of value and the discipline of the will," *Neural Networks,* vol. 19, pp. 1153-1160, 2006.

[41] A. Jackson, J. Mavoori, and E. E. Fetz, "Long-term motor cortex plasticity induced by an electronic neural implant," *Nature,* vol. 444, pp. 56-60, Nov 2006.

[42] J. A. Kleim, S. Barbay, and R. J. Nudo, "Functional reorganization of the rat motor cortex following motor skill learning," *Journal of Neurophysiology,* vol. 80, pp. 3321-3325, Dec 1998.

[43] M. S. Rioult-Pedotti, D. Friedman, G. Hess, and J. P. Donoghue, "Strengthening of horizontal cortical connections following skill learning," *Nature Neuroscience,* vol. 1, pp. 230-234, Jul 1998.

[44] W. Schultz, "Multiple reward signals in the brain," *Nature Reviews Neuroscience,* vol. 1, pp. 199-207, 2000.

[45] R. S. Sutton, Andrew G. Barto, *Reinforcement learning: an introduction*. Cambridge: The MIT Press, 1998.

[46] K. Doya, Samejima, K, Katagiri, K, and Kawato, M., "Multiple model-based reinforcement learning," *Neural Computation,* vol. 14, pp. 1347-1369, 2002.

[47] F. Rivest, Y. Bengio, and K. J., "Brain Inspired reinforcement learning," in *NIPS*, Vancouver, CA, 2004.

[48] N. Jong and P. Stone, "Kernel Based models for reinforcement learning," in *Workshop on Kernel machines for Reinforcement Learning, Proc. ICML* Pittsburgh, PA, 2006.

[49] N. Brannon, J. Seiffertt, T. Draelos, and D. Wunsch, "Coordinated Machine Learning and Decision Support for Situation Awareness," *Neural Networks,* vol. in press, 2009.

[50] R. S. Sutton and A. G. Barto, *Reinforcement learning: an introduction*. Cambridge: MIT Press, 1998.

[51] F. Worgotter and B. Porr, "Temporal sequence learning, prediction, and control: a review of different models and their relation to biological mechanisms," *Neural Computation,* vol. 17, pp. 245-319, 2005.

[52] M. Kawato and K. Samejima, "Efficient reinforcement learning: computational theories, neuroscience and robotics," *Current Opinion in Neurobiology,* vol. 17, pp. 205-212, 2007.

[53] J. DiGiovanna, B. Mahmoudi, J. Fortes, J. C. Principe, and J. C. Sanchez, "Co-adaptive Brain Machine Interface via Reinforcement Learning," *IEEE Transactions on Biomedical Engineering (Special issue on Hybrid Bionics),* vol. in press, 2008.

[54] A. P. Georgopoulos, A. B. Schwartz, and R. E. Kettner, "Neuronal population coding of movement direction," *Science,* vol. 233, pp. 1416-1419, Sep 26 1986.

[55] J. DiGiovanna, B. Mahmoudi, J. Fortes, J. C. Principe, and J. C. Sanchez, "Co-adaptive Brain Machine Interface via Reinforcement Learning," *IEEE Transactions on Biomedical Engineering (Special issue on Hybrid Bionics),* vol. 56, pp. 54-64, 2009.

[56] M. Zhao, P. Rattanatamrong, J. DiGiovanna, B. Mahmoudi, R. J. Figueiredo, J. C. Sanchez, J. C. Principe, and J. C. Fortes, "BMI Cyberworkstation: Enabling Dynamic Data-Driven Brain-Machine Interface Research through Cyberinfrastructure," in *IEEE International Conference of the Engineering in Medicine and Biology Society* Vancouver, Canada, 2008, pp. 646-649.

[57] B. Mahmoudi, J. DiGiovanna, J. C. Principe, and J. C. Sanchez, "Neuronal Tuning in a Brain-Machine Interface during Reinforcement Learning," in *International Conference of the IEEE EMBS* Vancouver, 2008.