The Cognitive Anteater Robotics Laboratory (CARL) at the University of California, Irvine

I. INTRODUCTION

Within our grasp is a deep scientific understanding of how the brain's mechanisms give rise to perception, cognition, emotion, action and social engagement with others. Such an understanding will have a revolutionary impact on science, medicine, economic growth, security, and social wellbeing. One way to understand this complicated system is through the construction of working models. Developing neural models that follow the architecture and dynamics of brain networks, combined with building robotic systems that physically ground these models, has great potential to solve one of the Grand Challenges posed by the United States National Academy of Engineering: *Reverse-Engineering the Brain*. Our laboratory attempts to meet this challenge in four complementary ways by: 1) Promoting the field of Cognitive and Brain-Based Robotics. 2) Developing adaptive action selection systems based on principles of vertebrate neuromodulation. 3) Data-mining neuroinformatic and gene expression databases. 4) Constructing large-scale, detailed models of cortical and subcortical processing on parallel computing platforms.

II. COGNITIVE AND BRAIN-BASED ROBOTICS

For over 10 years, we have been promoting the field of Cognitive Robotics, or Neurorobotics. These brain-based robots are physical devices whose control systems have been modeled after aspects of brain processing. The goals of these robots are to better understand cognition through the construction of physical artifacts, and to create practical systems that demonstrate cognitive capabilities. Neurorobotics is built on the notion that the brain is embodied in the body, which is, in turn, embedded in the environment, and that this coupling is necessary for an intelligent system. The field is small, but growing, due to technological advances and increased interdisciplinary research. Our group has developed a series of neurorobotic models that have successfully demonstrated perceptual categorization and conditioning [1], visual binding and scene segmentation [2], texture discrimination with artificial whiskers [3], adaptive motor control [4], spatial memory and navigation [5, 6], and neuromodulation as a general-purpose robot control system [7, 8]. These algorithms have several important features for autonomous robot control in general, such as fluid switching of behavior, gating in important sensory events, and separating signal from noise. Our algorithms and models have been tested on several robotic platforms in our laboratory, and we are currently working with other robotics laboratories around the world to demonstrate their applicability.

As an extension of our previous neurorobotic work in spatial memory and navigation, we are developing cognitive robots capable of contextual learning. A main goal of this research is to create a robot capable of constructing a cognitive map of its environment while foraging for different valued resources under varying environmental conditions. The system should lead to a better understanding of how areas of the medial temporal lobe interact with cortical areas to create flexible episodic memory. Such a system would be a major step forward for autonomous navigation by artificial systems.

Another research direction of our lab, which builds upon our cognitive robotics work, is to deploy teams of cognitive robots. These robot teams, or swarms, can be fairly large in size, and as a result, an inexpensive robot with strong communication capabilities is favourable. To that end, we have developed an open source robotic platform that leverages smartphone technology as a control system [9, 10]. The computing, communication, and sensing capabilities of current smartphones affords an inexpensive yet highly capable robotic platform that can be used for education and research. The platform, called leCarl, consists of an Android phone, R/C car platform, IOIO interface board, and additional sensors (see Figure 1). In the near future, our action selection, learning, and cognitive mapping algorithms will be deployed on a leCarl swarm in a Search and Rescue task.

Figure 1. Android based robotic platform. The Android phone serves as the computing and sensing device. The IOIO provides an interface to add additional sensors, such as IR range finders. The base is installed on the chassis of a R/C truck. The robotic head is composed of a rectangular tube, two servos for the pan and tilt unit, and a phone holder made of foam. Adapted from [9].

III. ADAPTIVE ACTION SELECTION SYSTEMS BASED ON PRINCIPLES OF VERTEBRATE NEUROMODULATION

The vertebrate neuromodulatory system plays a key role in regulating decision-making and responding to environmental challenges. In particular, the serotonergic system underlies control of stress, social interactions, and risk-taking behavior. The dopaminergic system has been implicated in the prediction of rewards and incentive salience. The cholinergic and noradrenergic systems are thought to play important roles in attention and judging uncertainty. We suggested that the behavior of an autonomous system

modeled after the vertebrate neuromodulatory system, might demonstrate the complexity and flexibility associated with higher order animals by monitoring its surroundings, adapting to change, and responding decisively to important environmental events [11]. Since the publication of this paper, our group has demonstrated how these systems can modulate attention in uncertain environments [12], shape decision-making in social situations [13, 14], and be used as an adaptive controller for autonomous robots [8, 15]. Our attentional study showed how the noradrenergic and cholinergic systems interact with each other, and suggested how this could lead to behavioral adaptation in the face of uncertainty [12]. We suggested that basal forebrain activity tracks expected uncertainty and that this shapes attentional search. We also suggested that the locus coeruleus tracks unexpected uncertainty, and this leads rapid responses to changes in the environment.

Game theory can be a powerful tool for testing models and discovering the neural correlates of decision-making in cooperative and competitive situations. In a set of human robot interaction studies using socioeconomic game theory, specifically the Hawk-Dove game, we showed that adaptive agents, whose behavior is guided by simulated dopaminergic and serotonergic systems, could evoke changes in strategy, reward/cost tradeoffs, and reciprocal behavior in subjects [14]. We also showed that division into two groups best described subjects' responses during these games [13]. Lowering subjects' serotonin levels through Acute Tryptophan Depletion caused some subjects to be more aggressive (as expected), but others to be less aggressive (unexpected). We suggest that individual variation, possibly due to genetic differences in serotonin and dopamine action, may be influencing this variability. To further understand this relationship, we turned to another socioeconomic game, called the Stag Hunt, which focuses on cooperation. In the Stag Hunt, subjects can either hunt a low valued hare on their own or form a social contract with another player to hunt a highly valued stag (see Figure 2). We constructed an adaptive agent, based

on the interaction between the dopaminergic and serotoninergic systems, which learned to play Stag Hunt and develop strategies based on the human player's tendencies [16]. In this study, we tested the performance of 40 subjects playing against five opponent types (the adaptive agent, and four other set strategies) in a spatiotemporal version of the Stag Hunt game. Subjects put more thought in their movements and in considering the movements of the agent when playing against the adaptive agent. Similar to our Hawk-Dove study, we observed differences between subjects on the individual level, with several responding to the adaptive agent by almost always cooperating, and several others remaining nearly exclusively uncooperative. In future work, we are interested in both the development of the agent strategy and the subjects' reaction to adaptive agents. Moreover, we plan to further investigate the neural correlates of these behaviors through brain imaging, pharmacological manipulations and genetic screening.
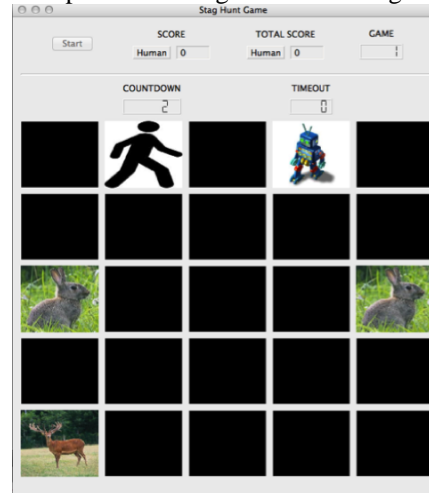

Figure 2. Screenshot of Stag Hunt game board. The game board included a 5x5 grid of spaces upon which the player (stick figure image), agent (robot image), stag (stag image), and hare (hare image) tokens resided. The screen included a button to start the experiment, the subject's score for the round, the subject's overall score for the experiment, the game number within the round, a 3-second countdown to the start of the game, and a 10-second counter monitoring the game's timeout. At the beginning of each game, the locations for the stag, player, and agent tokens were randomly placed along either the top row, bottom row, or middle column at least one square away from each other. The initial positions of the hares were fixed in the locations shown above for all games. The player and agent could move one square at a time

towards their goal at the start of the game, while the targets remain fixed. Adapted from [16].

IV. DATA-MINING NEUROINFORMATIC AND GENE EXPRESSION DATABASES.

In addition to our modeling work, we are taking a neuroinformatic approach to understanding cognitive function. Neuroinformatics is an emerging technique concerned with the management and sharing of neuroscience data. In recent work, we performed an exploratory survey of receptor gene expression associated with classical neuromodulatory systems (i.e., cholinergic, dopaminergic, noradrenergic, and serotonergic) within anatomical origins of these neuromodulatory systems, as well as in the amygdala [17]. Investigation of receptor gene expression in these regions was undertaken using the Allen Mouse Brain Atlas, a growing neuroinformatic resource that contains data sets of extensive mouse gene expression and neuroanatomical data. As a result, this type of exploratory analysis revealed many connectivity relations and receptor localization of these neuromodulatory systems that had not been previously reported (Figure 3). Currently, we are using this approach to understand the structural and functional underpinnings of reward processing by acquiring and analyzing expression data from dopamine and serotonin signaling genes across brain areas associated with the reward circuit.
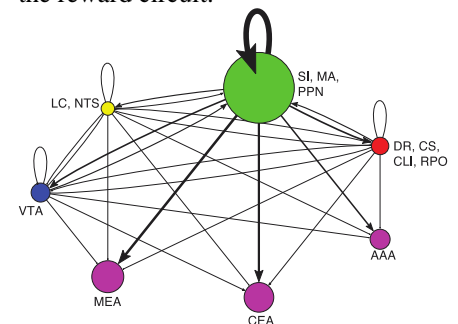

Figure 3. Network model showing overall expression of neuromodulatory receptors and their implied neuromodulatory projections to target areas. Vertices represent brain regions that are either standalone (purple = amygdala regions) or combined regions (yellow = noradrenergic, green = cholinergic, blue = dopaminergic, and red = serotonergic). Directed arcs represent projections going to and coming from a source. The pointed-arrow indicates the target location and the non-arrow end of the arc indicates the origin. The thickness of each arc, as well as the size of vertices,

is proportional to the amount of expression found in the target location. Adapted from [17].

V. DETAILED MODELS OF CORTICAL AND SUBCORTICAL PROCESSING ON PARALLEL COMPUTING PLATFORMS

Despite recent increases in computer power, constructing a neural model that approaches the size of a human-brain will require several orders of magnitude increases in computation, communication, and memory capacity. Conventional computer hardware may not be the appropriate architecture for modeling a brain. Unlike a conventional computer, the brain is a massively parallel, analog, fault-tolerant, selective system that does not rely on programmed instructions. Alternative computer architectures and programming paradigms, which are neurobiologically inspired, are in need of investigation [18, 19]. Our group has been developing tools to incorporate these brain features into computer models. Specifically, we have constructed large-scale network models that capture the dynamics of neural signaling at the microcircuit (i.e., within brain areas) and macrocircuit (i.e., between brain areas) levels. We have developed a highly efficient implementation of Spiking Neural Networks (SNN) by leveraging the parallel computing power of Graphical Processing Units (GPUs). Our publically available software program, called CARLsim (http://www.socsci.uci.edu/~jkrichma/CARLsim), is a C/C++ based SNN simulator that runs on both generic x86 CPUs and standard off-the-shelf GPUs. With our optimizations, we have demonstrated roughly 25X speedups over cutting edge desktop computers. This simulation environment was released to the modeling community so that researchers would have easy access to large-scale SNN simulations [20]. It has been very popular among computer scientists, neuroscientists, and engineers. Our latest release of simulator software extended this prior model to include more biologically plausible descriptions of synaptic connections and learning rules [21]. In particular, this new simulation environment facilitates the development of very large-scale spiking neural networks that follow the brain's

architecture. Using this simulator environment, we developed cortical models of visual form, color, and motion processing in which we replicated color opponency and motion perception results at both the psychophysical and neuronal level (see Figure 4). This simulation environment has also been used to replicate a recent and important finding on how basal forebrain activation can enhance cortical coding of natural scenes [22]. Our spiking neuron model, which included the basal forebrain, thalamus, and visual cortex, suggested that basal forebrain activation switches the firing mode of thalamic neurons, which in turn leads to an increase in within-cell reliability and a decrease in between-cell redundancy in LGN and visual cortex. In near future releases of our spiking simulator, we plan to introduce an automated parameter tuning framework, and a more extensive visual motion perception model. In addition, we are expanding our GPU-accelerated spiking neural network simulator (CARLsim) to run across many GPUs with the use of MPI. We believe this work in the spiking neural network domain will have a broad impact on the neuromorphic engineering community and will one day lead to practical applications deployed on specialized hardware.
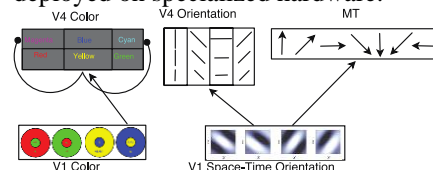

Figure 4. Architecture of the spiking neural network model of visual cortex. In the V1 color layer, there are four color opponent (center+/surround−) responses, which are combined in V4 to respond to six primary colors. The V1 motion energy model projects to edge detecting neurons in V4 and directionally selective neurons in cortical area MT Adapted from [21].

VI. SUMMARY

By combining computational modeling and neuroinformatics with autonomous robots and parallel computing techniques, our group has created a multi-disciplinary approach to understanding the inner workings of the brain and cognition. It is our hope that this approach will continue to benefit both the neuroscience and computer

science communities and move us closer to meeting the grand challenge of reverse-engineering the brain.

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