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Embodying Cultured Networks with a Robotic Drawing Arm

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Abstract— **The advanced and robust computational power of the brain is shown by the complex behaviors it produces. By embodying living cultured neuronal networks with a robotic or simulated animal (animat) and situating them within an environment, we study how the basic principles of neuronal network communication can culminate into adaptive goal-directed behavior. We engineered a closed-loop biological-robotic drawing machine and explored sensory-motor mappings and training. Preliminary results suggest that real-time performance-based feedback allowed an animat to draw in desired directions. This approach may help instruct the future design of artificial neural systems and of the algorithms to interface sensory and motor prostheses with the brain.**

I. Introduction

How the basic principles of neuronal network communication can produce adaptive behavior and cognition is not understood. We grew cortical neurons multi-electrode arrays (MEAs) and embodied them with a simulated or robotic body (animat) situated within a controlled environment. Recorded action potentials determined the movement of the animat, and sensation determined the subsequent feedback of electrical stimuli delivered to the neurons [1]. Thus, behavior and learning could be observed in concert with the detailed and long-term electrophysiology available using a cultured network [2]. Here, we present progress on engineering the hardware, software, and wetware of a hybrid biological-robotic drawing machine.

Various neural systems have been previously embodied with robotics. Artificial *synthetic brains* controlling a mobile robot demonstrated object recognition, categorization, and behavioral conditioning [3]. Sensory feedback to an isolated lamprey brain stem caused adaptive behavior in a mobile robot [4]. Cultured neurons on MEAs commanded robots to avoid obstacles [5] or follow objects [6], but deterministically and without learning. In another case, although without goal-directed behavior, feedback was found to enhance the diversity of spatio-temporal activity patterns in a simulated environment [7], possibly facilitating learning by allowing the network to explore a greater range of synaptic weights [8].

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Here, we built a robotic drawing machine named Meart (Multi-Electrode Array aRT) and designed closed-loop training algorithms in order to achieve the goal-directed behavior of drawing geometrical shapes. The algorithms were optimized using a living network connected to a simulated body, whereby the animat repeatedly learned to draw in different desired directions. Encoding more detailed sensation and motor output could produce increasingly complex and interesting behaviors.

II. Methods & Preliminary Results

Three major topics need to be addressed when constructing embodied cultured networks: the hardware (or software) implementation of the body, the sensory-motor transformations and training algorithms, and the nurturing of the biological brain.

Behavior is constrained by the limitations of the brain and the body. With Meart, movement was confined to a 2 dimensional plane and constrained by the machine's speed and accuracy. The choice of how to map neuronal activity into motion and sensory feedback into electrical stimulation constrains which neuronal plasticity mechanisms could be observed behaviorally. This can be an advantage if investigating an individual mechanism or a disadvantage by limiting the neuronal computational capacity available to the animat. Here, we used a measure of network activity, incorporating spatial and firing rate information, that reflects accumulated changes in synaptic strengths [9].

A cortical culture lacks the 3D structure present in the brain and so lacks any computational advantages that this may have afforded. However, basic self-organizing principles and plasticity mechanisms, such as spike-timing dependent plasticity [10] and homeostasis [11], persist and were the objects of our study. Neurons spontaneously begin communicating electrically and chemically within a few days, demonstrating an inherent goal to network [12].

A. Neuronal cultures

We have developed techniques to maintain neuronal cultures and conduct experiments for many months. Cells from E18 rat cortices were dissociated and cultured at high density [2, 12] on MEAs (www.multichannelsystems.com). Electrically evoked activity was induced using biphasic voltage pulses of 400 µs duration and 500 mV magnitude per phase [13]. Data acquisition, visualization, artifact suppression, and spike detection were controlled using Meabench [14]. Experiments were conducted using sealed-lid MEAs inside an environmentally controlled

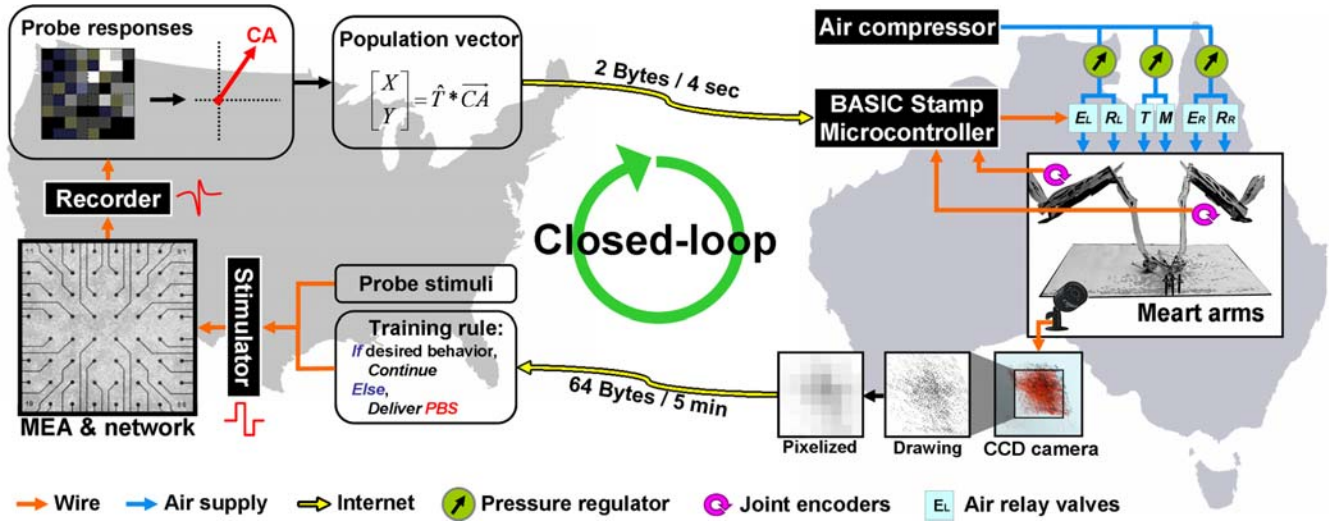

Fig. 1. Schematic of the bio-robotic software algorithms and hardware. ◆**Commanding movement.** The *Center of Activity* (*CA*) of neuronal action potentials was calculated from 100 ms of responses after a probe stimulation (*8x8 box* representing the MEA; increasing firing rate is black to white). Animat movement was instructed from a transformation (*T*) of the *CA* into a *Population vector*. The [*X*,*Y*] movement command was sent over the internet (*yellow arrows*) to the robotic arms every 4 sec. ◆**Movement.** The robotic drawing machine consisted of 2 perpendicular arms (aluminum & acrylic Perspex) hinged at their ends to a 2 m x 2 m table. Similar to biceps and triceps, McKibben braided pneumatic artificial *muscles* could contract individually, allowing the left (E_L/R_L) and right (E_R/R_R) arms to retract (*R*) or extend (*E*) within approximately a 30 cm by 30 cm workspace. Similarly, activation of smaller muscles pressed the pens to the paper; a dark pen marked the target location (*T*), while an optional lighter colored pen (not detected by the CCD camera) traced the movement trajectory (*M*). The supply line from an *air compressor* was split between 3 pressure regulators (*green circles*), 1 for each arm and 1 for the pens, to isolate pressure fluctuations. Air pressure and thus arm and pen movement was controlled by opening and closing 24 volt AC reticulation valves (*light blue rectangles*). Pneumatic muscles, while offering a high power to weight ratio, produce nonlinear motion difficult to predict. Therefore, arm location was tracked using joint encoders (*purple arrows*; 10k potentiometers), and a *BASIC Stamp microcontroller* (BS2SX-IC) modulated the relay valves to provide accurate movement. The muscles and other nonlinear components were not considered negatives. In fact the brain learns to compensate for the physics of the body, often in advantageous ways. For example, both here and for biological movement, the presence of friction improves precision and stability by damping overshoot. ◆**Sensory feedback.** A CCD camera located above the workspace captured images of the drawing. Fluctuations in light from shadows and clouds could strongly influence the images. Therefore, ambient and natural light sources were eliminated except for bright spotlights on the drawing itself. Vignetting was corrected by subtracting the captured images by an image of the sheet of paper when blank, prior to a drawing. The accumulation of markings were recorded every 5 min by retracting the arms out of view and capturing an image. To reduce internet bandwidth, 8 bit grayscale values of an 8 x 8 grid of pixels (isomorphic to the electrodes on the MEA) were sent back over the internet to command feedback stimulation of the neurons. ◆**Training.** Animat behavior was compared to the goal behavior to determine the choice or application of training stimulation (see Methods). Feedback stimuli could change neuronal activity, in turn varying subsequent animat movement and sensory feedback, thus forming a closed-loop system. TCP/IP sockets were used to communicate between the drawing machine and the neurons, which were often located in separate continents. In a sense, the internet served as an extended spinal cord.

incubator, allowing us to conduct long-term experiments [2].

B. Hardware development

The drawing machine consisted of two perpendicular, rigid, jointed arms actuating the *X* and *Y* positions of a group of pens over a sheet of paper. See Figs. 1 & 2 for details. We used a simulated body while improving the sensory-motor mappings and training algorithms. However in order to engineer biologically-based control systems, their performance must be tested in the real world where noise and non-linearity are commonplace. In the case of Meart, we tested the neuronal network's ability to learn the dynamics of its body as it was trained to achieve a goal-directed behavior.

C. Software development & Experimental design

Motor transformation - For an animat to behave, sequences of neuronal action potentials need to be transformed into body movements, but understanding how such sequences encode information is a subject of much scientific inquiry. Population coding [15] is one candidate method found to occur in the motor cortex, premotor cortex, and other cortical areas: the firing rates of a group of broadly tuned neurons taken together provide an accurately tuned representation (e.g., to a preferred direction of arm movement). We found that a related population calculation of the Center of neural Activity (*CA*, analogous to the *center of mass*) could reliably quantify neuronal network plasticity on a MEA by including spatial information [16], whereas measuring firing rates alone could not [17]. Therefore, animat movement was calculated from the CA of 100 ms of responses after a probe stimulus:

$$\begin{bmatrix} X \\ Y \end{bmatrix} = \hat{T} * \overrightarrow{CA} = \hat{T} * \frac{\sum \overrightarrow{W_e} * FR_e}{\sum FR_e} \qquad (1)$$

The *CA* is the vector summation of the firing rates of each electrode *e* (FR_e) weighted by the spatial location of the electrode (W_e). *T* transformed the *CA* from electrode space to the population vector in animat movement space: the range of CAs were found prior to the closed-loop experiment, offset by the mean, and scaled separately in the *X* and *Y* directions to produce a uniform distribution and the ability to move in all directions. However, spontaneous activity during the no-stimulation period between finding the transformation and beginning the closed-loop experiment caused the CA to drift, creating a movement bias; this should be avoided in the future. The responses to 1 Hz stimulation on a probe electrode were averaged between consecutive movements (every 4 sec) and used to command Meart location, while the responses to

1/4 Hz stimulation on a probe electrode were used to command the simulated animat. Only one probe electrode was used throughout an experiment.

Movement could be commanded by absolute location or in relative increments. For absolute location, the activity was normalized such that the set of possible movements would be distributed throughout the workspace. For incremental movement, the activity was normalized such that possible movements would be distributed throughout 180º. Absolute location was used initially with Meart because inadequate training algorithms could cause incremental movement exceeding the workspace, introducing discontinuities in behavior. Incremental movement was used for the simulated animat as workspace size was not physically limited.

Training and sensory feedback - The goal of Meart was to fill a square 12 cm x 12 cm area within the center of its 30 cm x 30 cm workspace. Successful behavior was determined from comparisons between consecutive feedback images. If a larger proportion of markings occurred inside the target geometrical area than outside, behavior was considered successful. Otherwise, plasticity of the probe response was desired. For training, plasticity was induced by repetitive stimulation of paired electrodes, termed Patterned Background Stimulation (PBS). A PBS was constructed by pairing the probe electrode with another active electrode (one that evokes network responses) at an inter-pulse-interval of 20 ms, repetitively stimulated for 3 sec. Bi and Poo [10] found that for mono-synaptically connected neurons firing within a few 10s of ms of each other, directional *spike timing dependent plasticity* occurred at the level of the synapse. The choice of PBS was behaviorally fixed for Meart. For example, if previous movements occurred below the target area, the probe was paired with an electrode at the top of the MEA.

Electrical stimulation can be an artificial source of neuronal plasticity. Jackson et al. [18], in a primate motor cortex, repetitively stimulated a neuron 5 ms after the occurrence of an action potential on a different neuron using an electronics implant. After halting the stimulation, subsequent activity of the recorded neuron caused an increase in the firing rates in the vicinity of the stimulated neuron. In this manner, we hypothesized the PBS would lead to potentiation of the probe response in the vicinity of the second paired electrode, modifying the CA and population vector such that arm movements approached the target area.

Meart's PBS did induce directional neuronal plasticity as evident in variations in the distribution of CAs (Fig. 3), but in an uncontrolled manner. We determined that since neurons at different electrodes can be connected through multiple intermediate neurons and pathways, the effect of a given PBS could not be predicted.

Therefore, we modified the training algorithms in 2 ways and conducted tests using the living cultures and a simulated animat, discussed in detail in [19]. To summarize, a pool of

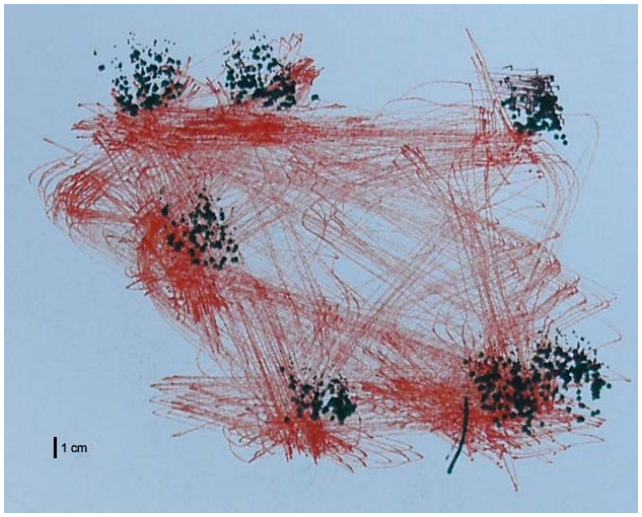

Fig. 2. Accuracy test of the robotic drawing machine. Movements between 7 locations were commanded 200 times in random order. A dark pen marked the target locations, while an offset lighter colored pen traced the movement trajectory. 3 cm x 3 cm resolution targets could be reached within 4 sec and a 1 cm x 1 cm target around 10 sec (not shown). For a 30 cm x 30 cm workspace, resolutions were 10 x 10 and 30 x 30 respectively.

candidate PBSs was formed by pairing the probe electrode with other electrodes (N_e = 58) and inter-pulse intervals {-80, -40, -10, 10, 40, 80 ms} (N_{PBS} = 58*6). The probabilities of choosing a given PBS were initially uniform and increased or decreased based on whether subsequent animat performance was successful or not. This allowed an iterative search for an appropriate training 'solution' to direct neuronal plasticity. Second, plasticity can arise from both the PBS stimuli and ongoing spontaneous activity occurring between probes. In a model network, a 20 Hz random stimulation stabilized neural synaptic weights [9]. Therefore, when animat behavior was successful (no PBS application), a random background stimulation was used between probes such that the plasticity accumulated from a series of PBSs was preserved.

The goal of the simulated animat was now to learn to move within ± 30° of a goal angle. Goal-directed behavior was achieved, and the animat learned to draw towards 3 different desired angles switched consecutively every 2 hr (Fig. 3).

III. Discussion

Experiments using embodied in vitro systems have been criticized for a lack of an inherent goal with which to direct behavior. Animals have many inherent goals that arise intermittently and often overlap in time. The neuromodulatory system is thought to regulate the saliency of these goals and subsequent behavior. However, learning how to reach a goal (and understanding the neuronal network correlates) remains an area of inquiry. Our approach defines a single goal and tests the behavioral consequence of various sensory-motor mappings and training algorithms. The confounding issues of competing goals, such as hunger or attention, must be accounted for during in vivo experiments but are absent here.

Meart had equal parts scientific, social, and philosophical motivations. One important aspect was public education of

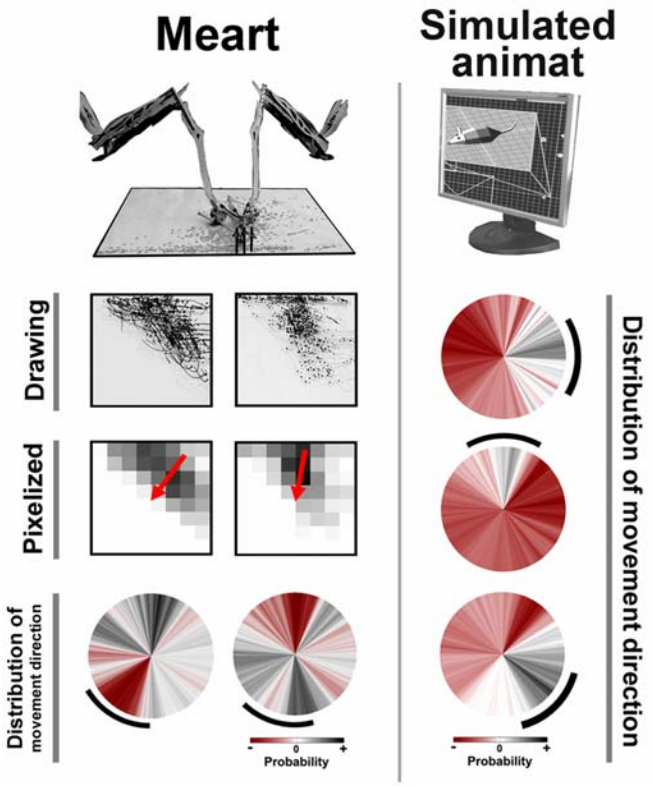

Fig. 3. Neuronal plasticity in response to unsuccessful and successful training of goal-directed animat behavior. **Meart**. Training with predetermined patterned background stimuli (PBS) caused a directional shift in the probability distribution of commanded movement directions in 2 experiments (*circles*, bottom row), but in an uncontrolled manner. Experiments were conducted during an exhibition at the First Moscow Biennale of Contemporary Art, 2005, where Meart's goal to fill a square at the center of the drawing was inspired by the Russian artist Malevich's 'Black Square'. The presence of a movement bias (see Methods) caused marks to accumulate on a side of the drawing's workspace (CCD camera image of the *drawing* and *pixelized* feedback), but successful PBS training should shift the markings back towards the center (*red arrow* middle row; *black arc* bottom row). The probability distribution of movement directions during 10 min at the start of 2 hr experiments was subtracted from that during the final 10 min, thus allowing negative values (*red*). **Simulated animat**. Iteratively updating the probability of selecting a given PBS for training allowed an animat to learn to move in multiple directions (*circles*; see Methods and discussed in detail in [19]). Desired angles of 0°, 90°, and -45° (*black arcs*) were applied in consecutive 2 hr periods. Successful behavior was considered to be movement within the desired angle ± 30°. Notice the change in probability distribution of movement directions was now in the appropriate direction and more focused than for Meart.

current biotechnology, and consequently experiments have been conducted in galleries throughout the world over the last 5 years. Meart promoted the need to critically examine the consequences of melding technology and biology. Furthermore, animats are a platform to continue philosophical and begin experimental inquiry into the fundamental makeup of intelligence and existence. What forms of intelligence can emerge from rat neurons connected to a mechanical body? Is Meart's drawing a product of creativity, a work of art? What are the implications for the internet and technology to expand our cognition? This question was dramatically framed by Meart's physical separation of brain and body.

The structure and function of neuronal networks provide unique computational abilities suited to behaving in the world. In particular, parallel processing and feedback loops on multiple scales allow efficient pattern recognition, real-time adaptability to changing input, and tolerance to noise or even to failure in parts of the circuit. Elucidating the role of environmental feedback in neuronal network processing can instruct the design of more robust computing methods and of neuronal prosthetic communication for sensory deprived or paralyzed patients. Our next step is to apply the algorithms developed with the simulated animat to control the drawings of Meart, creating a real-world biologically-based control system exhibiting goal-directed behavior.

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