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Sensory Decoding in a Tactile, Interactive Neurorobot*

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Abstract— **We present a novel neuromorphic robot that interacts through touch sensing and visual signaling on its surface. The robot's form factor is a convex, hemispheric shell containing trackballs for sensing touch, and LEDs for communication with users. In this paper, we explore tactile sensory decoding by constructing a spiking neural network (SNN) of somatosensory cortex. The SNN uses a biologically inspired, unsupervised learning rule, known as spike timing dependent plasticity, to classify a user's hand movements. In an evaluation of the network's ability to categorize hand movements, both rate and temporal neural coding performed well. Because of its unique form factor and means of interaction, this robot, which is called CARL-SJR, may be useful for exploring the neural coding of touch, and also for Human-Robot Interaction studies.**

I. Introduction

The ability to engage the world through tactile sensing is prevalent in all organisms. In humans, touch is used to manipulate and categorize objects, react to stimuli, and to perceive and control the body [1, 2]. Tactile sensing in robotics is often inspired by biology and neuroscience. For example, whiskered robots have been developed to sense the borders and shape of objects [3-5]. Fingers and hands have been developed for humanoid robots to enable grasping and detecting surfaces [6-8]. Most of these humanoid robots are constructed from custom-made materials and sensing circuits for touch [9-11].

Rather than concentrating on touch sensors to manipulate objects, we have designed a neuromorphic robot that encourages tactile interaction with people. In contrast to many other robots that use custom-made sensors, we incorporated trackballs, which are typically found in cellphones and other devices, to signal the direction and velocity of tactile stimuli. Moreover, the robot has the capability to signal or communicate by flashing different colors in response to touch or other stimuli.

Our robot, which is called the Cognitive Anteater Robotics Laboratory – Spiking Judgment Robot (CARL-SJR), falls under the class of robotics known as Socially Assistive Robotics or SARs. SARs may aid in diagnosis and treatment of developmental disorders by providing consistent behavioral evaluations and standardized stimuli in diagnostic settings [12]. Children tend to form social bonds during interactions with robots [13]. Children with Autism Spectrum Disorders (ASD) or Attention Deficit Hyperactivity Disorders (ADHD) respond well to robot artifacts and this might be a form of therapy for these subjects [12, 14-17]. Most of these systems focus on eye contact (e.g., shared attention, or shared gaze). However, these systems tend to ignore tactile interaction, which is impaired in many children with developmental disorders. One exception is the robot KASPAR, which has an artificial skin on its face [18, 19]. KASPAR has been shown to facilitate tactile engagement with autistic children [20]. Another exception is the Roball [21, 22], which has been developed for playing games with autistic children. Similar to CARL-SJR, Roball flashes colors and has panels that respond to touch, but Roboall has limited tactile sensing capability, cannot collect and store data, and lacks learning capabilities.

Having a platform that can be handled and that can respond to contact has been shown to have therapeutic value for dementia and Alzheimer's disease patients [23-25]. However, this form of robot therapy is purely reactive. There may be advantages in having a SAR paradigm in which the robot can adapt to the patient's needs or challenge the patient by playing an interactive game where the subject must learn the robot's needs or desires, and vice versa. This fits nicely with the goals of Sensory Integration Theory (SIT).

SIT is intended to focus directly on the neurological processing of sensory information as a foundation for learning of higher-level (motor or academic) skills [26]. Treatment goals centers on improving sensory processing to either (a) develop better sensory modulation as related to attention and behavioral control, or (b) integrate sensory information to form better perceptual schemas and practical abilities as a precursor for academic skills, social interactions, or more independent functioning. SIT has shown benefits for children with ASD and ADHD [27-30].

Figure 1. CARL-SJR. Top left. Rendering shows the trackballs protruding the surface. Top right. Transparent view shows electronics, camera, and drive system. Bottom. Example movements and color patterns on the prototype shell. Right movement produces blue, upward produces red, and left produces green.

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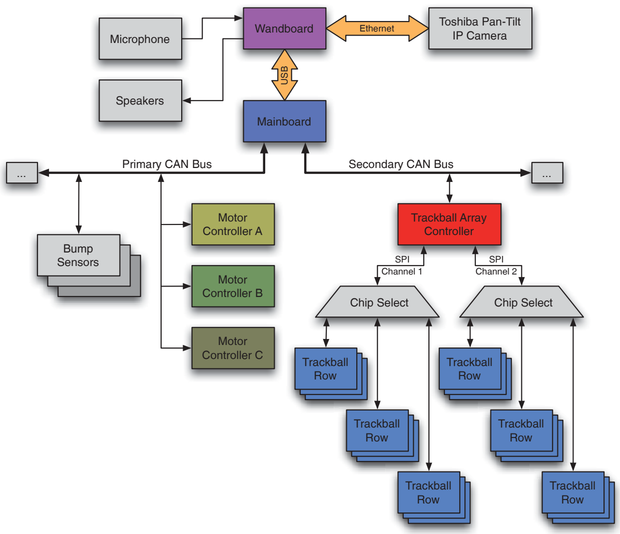

Figure 2. System overview of CARL-SJR's components.

CARL-SJR is in the prototype stage. The components of the robot are described below and the tactile shell is demonstrated. However, the main goal of the present article is to show that a spiking neural network (SNN) is sufficient to learn different hand movements across the robot's surface. This will become necessary when the robot is used in learning paradigms where a spatiotemporal pattern of activation is associated with positive or negative reinforcement.

In particular, this paper compares the performance of a rate code versus temporal code for classifying different movements. The spatiotemporal nature of tactile stimuli, as well as noisy sensors and environments, make the perception of touch a complex problem. To encode tactile signals in the nervous system, there is evidence for both a rate code and a temporal code [2, 31]. A rate code is simpler and not as susceptible to noise [32]. However, a temporal code has a larger capacity for encoding patterns [33, 34].

The outline of the paper is as follows: Section II.A. describes the overall robot design, Section II.B. describes the construction of a SNN that gets input directly from a trackball array, Section III describes the ability of the SNN to learn and decode real hand movements, and Section IV discusses these results and how they will be used in the complete robot system.

II. Methods

A. The CARL-SJR Neurorobot Platform

CARL-SJR is an autonomous, mobile robotic platform, which has the ability to interact with users in a novel way. There is a convex shell covering CARL-SJR, which has an array of trackball sensors and light emitting diodes (LEDs) (see Fig. 1). Inputs to the trackballs, such as sweeps of a hand across the shell, are coded into neural spikes that retain temporal information. The LEDs may be used to display colors and patterns which can communicate behaviors, desires, or other useful information to a user or subject.

The inside of the hemispherical shell contains an array of 67 circuit boards each containing a PIC16LF1827 microcontroller, red, green and blue LEDs, and a miniature trackball (Sparkfun.com COM-09308) which is accessible from the outside of the shell. When a user runs their hand along the shell they swipe the trackballs, which have independent magnetic encoders for each direction: up, down, left, and right. A group of trackball boards are joined into a row and are daisy chained by an SPI bus (see Fig. 2).

The complete robot carries a suite of sensors including a pan-tilt-zoom camera, microphones, speakers, wheel encoders, and bump sensors. The robot also employs a holonomic drive system using three, triangularly oriented omni wheels in order to allow for mobility within the confined spaces of an office building. Fig. 2 shows a system overview of CARL-SJR's electronic components.

CARL-SJR has an onboard computer that runs the SNN algorithms and behavioral control. The board also handles the input and output of the robots sensors and actuators. Controller Area Network (CAN) busses handle motor output commands and the trackball array inputs.

CARL-SJR can express itself by signaling visually through changes of its skin or shell (i.e., the LEDs surrounding each trackball). In Fig. 1 and the supplementary materials video accompanying this paper, we demonstrate how different movements can trigger different color responses. As one can see from the movie, the response is bright and vibrant, and movements in diagonal directions result in a mixing of colors (e.g., purple, teal, etc.).

B. Prototype Trackball Array

The main goal of the present paper is to explore different decoding methods for hand movements. Rather than use the complete robot for these decoding experiments, we constructed a smaller prototype trackball array to test the usefulness and accuracy of the trackball system. The prototype contained a 4 by 4 array of trackballs that was built with a PIC16F1824 monitoring each trackball board (see Fig. 3). The row controllers of the trackball array were connected to a PC via a CAN bus. CAN messages were converted to serial (RS-232) format and transmitted to a PC running the SNN simulation. When the PC received a message, it

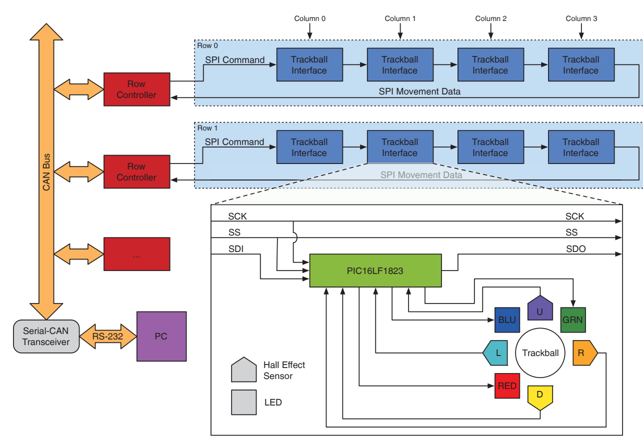

Figure 3. The architecture of the prototype trackball array. Each row contains four trackballs and their interface chips daisy chained using an SPI bus with a row controller as the master. The row controllers communicate through a CAN bus to a transceiver which converts spike data to a serial (RS-232) format which is then transmitted to the PC running the spiking neural network.

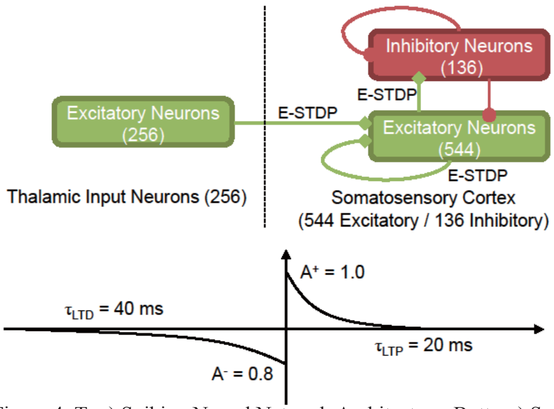

Figure 4. Top) Spiking Neural Network Architecture. Bottom) Spike Timing Dependent Plasticity Learning Rule.

translated the information into spike events that were input to the neural network simulation. Each message contains spike data for a single direction on a single trackball and only for one 8 ms window.

Although these trackball messages contain directional information, the sensory data is noisy, making movement categorization difficult. Thus, a SNN with unsupervised learning was constructed to categorize different hand movements.

C. Spiking Neural Network (SNN) Simulations

A SNN was constructed to learn hand movement patterns across the trackball array, and to evaluate the ability of the network to discriminate different movements. The SNN simulation was composed of three populations of neurons as shown in Fig. 4. A population of 544 excitatory neurons and 136 inhibitory neurons form a spiking neural network that loosely corresponds to primary somatosensory cortex, and a population of 256 excitatory input neurons that simulates thalamic neurons relaying touch information to the simulated cortex. Each neuron in the somatosensory cortex received 100 synapses, which were randomly chosen from both input neurons and other somatosensory cortex neurons. These connections had delays ranging from 1 ms to 20 ms to mimic the variation in axonal conduction observed in cortex [35]. Excitatory connections labeled by *E-STDP* in Fig. 4 were subject to Spike Timing Dependent Plasticity [36, 37].

1) Neuron Model

The current-based version of the Izhikevich neuron model was used to govern the dynamics of the spiking neurons [38]. The dynamics of inhibitory and excitatory neurons in the Izhikevich neuron model can be described as the following equations:

$$dv/dt = 0.04v^2 + 5v + 140 - u + I \quad (1)$$

$$du/dt = a(bv - u) \quad (2)$$

$$\text{if } v = 30, \text{ then } v = c,\ u = u + d \quad (3)$$

The variable v is the membrane potential, u is the recovery variable, I is the total current injected into a post-synaptic neuron, and a, b, c, d are parameters chosen based on the neuron type. For regular spiking, excitatory neurons, we set $a = 0.02, b = 0.2, c = -65.0, d = 8.0$. For fast-spiking, inhibitory neurons, we set $a = 0.1, b = 0.2, c = -65.0, d = 2.0$.

The total current I injecting into a neuron in somatosensory cortex is described in the following equation.

$$I = \sum s_j + I_{background\_noise} \quad (4)$$

The variable s_j is the synaptic weight of synapse j, which had an initial value of 6.0 and could range from 0.0 to 12.0. The weights of inhibitory synapses are fixed at -4.0. The summation of all s_j presents the total current contributed by all firing pre-synaptic neurons. $I_{background\_noise}$, which was set to 15.0 for one randomly selected neuron per ms, caused the somatosensory cortex to have spontaneous activity.

The total current injected into an input neuron was the summation of I_{input_noise} and I_{input}. We set I_{input} to 100 when the corresponding trackball was moving in the preferred direction; otherwise the current was set to 0. I_{input_noise}, which was set to 16.5 for one randomly selected neuron per ms, caused the input area to have spontaneous activity.

$$I = I_{input\_noise} + I_{input} \quad (5)$$

2) Sensory Input

The stimuli to our SNN simulation came directly from the trackball movement messages described above. Each of the 16 trackballs gave a velocity signal for up, down, left, and right. These 64 input signals were connected to 4 neurons resulting in the 256 input neurons shown in Fig. 5. Because signals from the trackball array can arrive so rapidly that the input neuron's firing rate is unnaturally high, the current was injected (see equation 5) in a round robin fashion to the 4 neurons that respond to the same trackball and direction.

3) Training and Testing Procedures

To train the SNN, we recorded the input pattern of 100 left moves and 100 right moves across the trackballs. Each movement was a manual sweep of the hand and the duration of a move ranged from 900 ms to 1600 ms with the average movement lasting 1285.4 ms ± 133.6 sd. These recorded inputs were fed into the input layer of the SNN by randomly choosing an input pattern and presenting it to the SNN every 2000 ms.

During training, excitatory connections were subject to STDP. The STDP function is depicted on the right side of Fig. 4. A^+ and A^- are 1.0 and 0.8 respectively. τ_{LTP} and τ_{LTD} are 20 ms and 40 ms respectively. The learning rate for STDP was set to 0.005. We trained the SNN for 6400 seconds. At this time, the distribution of synaptic weights became U-shaped, where most weights were either close to zero or near the maximum value of 12.0, and the minimum point was lower than 1% of maximum point.

During testing, we presented an additional 100 left moves and 100 right moves to a trained SNN. These 200 moves were repeated 5 times. We developed a decoding algorithm to compare firing rate coding to temporal coding, specifically the reliability of polychronous groups [33].

For firing rate decoding, we recorded the firing rate of each neuron in the simulated somatosensory cortex and generated firing rate distributions for left and right movement trials. If the peak of the distribution for right moves was higher than that of left moves, we referred to this neuron as a *right-responsive neuron*, otherwise it was considered a *left-responsive neuron*.

For temporal decoding, we identified polychronous groups by the following criteria: 1) The group started with an anchor neuron, that is, an input neuron spike. 2) A group member had to be connected to that anchor neuron and fire a spike within 4 ms of its axonal delay. 3) From this set of neurons, a downstream neuron needed to receive at least two spikes from the upstream neuron within 4 ms of its axonal delay. This algorithm proceeded as a breadth-first search until criterion 3 no longer could be met. A polychronous group was considered a *left-predictor* if $P(L \mid pg) > 0.5$ and a *right-predicator* if $P(\mathrm{R} \mid pg) > 0.5$).

III. RESULTS

A. SNN Activity During Movements

The SNN took input directly from the trackball array and responded to hand movements. Fig. 5 shows firing activity from a representative left to right hand sweep (Fig. 5, top) and spontaneous activity with no input (Fig. 5, bottom). In the top chart of Fig. 5, the trackballs of the fourth column are contacted with a hand at 20 ms and then the third, second and first columns are contacted at 240 ms, 460 ms, and 670 ms, respectively. The duration of touching a column is roughly 600 ms. The hand contacts the fourth column at 20 ms and leaves it at 660 ms. We recorded 200 left moves and 200 right moves for training and testing spiking neural networks. The interval between two message events from the trackball array in our recording ranged from 5 ms to 20 ms, which could generate firing rates from 12.5Hz to 50Hz. The average number of message events for a left move was 443.7 with a standard deviation 80.9 ms, while the average number of message events for a right move was 340.2 ms with a standard deviation 54.8 ms. The lower raster diagram shows spontaneous activity of a SNN when there is no stimulus from the trackballs. The spikes are results of background noise and input noise (i.e., I_{input_noise} and $I_{background\_noise}$).

The simulated somatosensory cortex showed repeatable patterns of firing in response to left and right hand movements. Fig. 6 shows the correlation of firing activity between 8 right (rows and columns 1-8) and 8 left (rows and columns 9-16) movements before training (Fig. 6, left) and after training (Fig. 6, right). Note that after training through unsupervised STDP, similar classes of movements are highly correlated, whereas different classes are not.

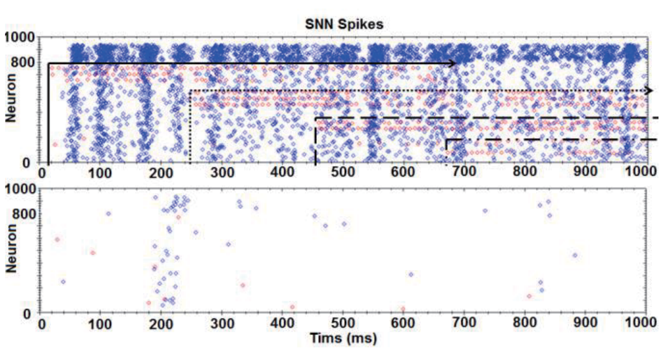

Figure 5. Top) Response of neurons to a left movement. Each dot represents a spike from a neuron. Rows 0-799 are excitatory and rows 800-935 are inhibitory. Red dots represent the 256 input neurons. Bottom) Same network in the absence of a movement.

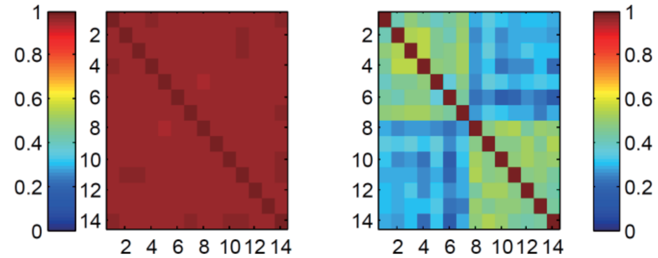

Figure 6. Correlation of firing activity between movements. Rows and columns 1-8 are left movements. Rows and columns 9-16 are right movements. Left) SNN before training. Right) SNN after training.

B. Rate versus Temporal Coding of Movements

We used Receiver Operator Characteristic (ROC) curves to evaluate the performance of rate decoding and polychronous group decoding. Fig. 7 shows the ROC curves for rate decoding left and right movements using left and right responsive neurons and for temporal decoding using left and right polychronous groups. For the rate code, we varied the firing rate threshold from 0.0Hz to 6.0Hz by steps of 0.1Hz. For the temporal code we varied the number of repeating polychronous groups threshold from 0 to 100 by steps of 2. Over five different simulations, the average number of polychronous groups was 382±75sd, and the reoccurrence of a polychronous group across all trials ranged from 5% to 38% with a median value of 10%.

Both firing rate and polychronous group decoding were

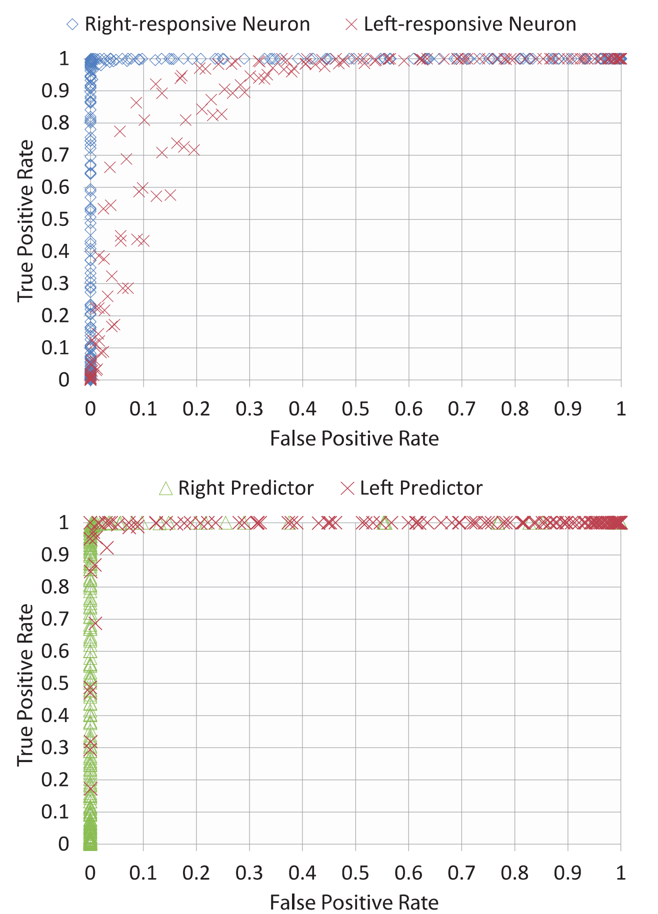

Figure 7. ROC curves for rate decoding (top) and polychronous group decoding (bottom).

near perfect with the area under the ROC curve approaching 1. The upper left region of the ROC curve is the desired case where there is a high true positive rate and a low false positive rate. To better understand the classification performance, we looked at the number of points that had a true positive rate above 90% and a false positive rate less than 10%. For rate coding, only right-responsive neurons fit this criteria, where there were 38 points with the thresholds ranged from 2.7 to 3.8 Hz. For polychronous groups, there were 45 points for right predictors, and 11 points for left predictors that met this desirable decoding criteria. The threshold ranged from 4 to 30 groups.

It is interesting that the temporal coding outperformed firing rate coding. The inputs were noisy, real world signals that differed from trial to trial due to user variability. Although these polychronous groups were anchored to a specific trackball direction, it is still impressive that these tightly coupled spike orders repeated over multiple trials. It suggests that both types of coding can be used for learning and recalling tactile patterns.

IV. Conclusion

We presented a novel robot platform, CARL-SJR that is interactive and expressive. Its mode of communication is through changing its skin pattern or coloration. CARL-SJR's main sensory input was tactile. Unlike many tactile robots [7, 10], which focus on grasping and manipulation, CARL-SJR's tactile sensing was designed to facilitate interaction with a person. Rather than using custom-made tactile sensors, we decided to use off-the-shelf trackballs. Therefore, the size of the tactile region could be very large and manufactured fairly inexpensively. At this time, CARL-SJR is in a prototype stage. Most of the components have been designed, but only the trackball array and interactive shell are currently operational.

The present study examined the feasibility of using a SNN to categorize and decode hand movements with the trackball array. A SNN was constructed to learn hand movement patterns across the trackball array, and to evaluate the ability of the network to discriminate different movements. Both firing rate and polychronous group decoding were near perfect with the area under the ROC curve approaching 1 (see Fig. 7). These results demonstrate that a SNN with STDP is sufficient to learn spatiotemporal patterns related to hand movements.

Although decoding hand movements might be possible by sampling the trackballs directly, having a SNN that can associate tactile movements with other environmental signals can support reinforcement learning. In the future, dopamine modulated STDP [39, 40], will be used to reinforce CARL-SJR tactile interactions with valence. For instance, positive interactions, such as petting the robot in a desired speed and desired direction, could be reinforced with a color pattern on CARL-SJR's shell. Similarly, negative reinforcement could be used to shape CARL-SJR's behavior. Future neural models for CARL-SJR will take advantage of these additional learning rules to exploit two way learning or behavior shaping, where CARL-SJR learns from the user, and the user learns from CARL-SJR.

By providing a surface that encourages touch, CARL-SJR could be a standardized form of SIT, and would address impairments in tactile sensitivity and social interaction observed in children with developmental disorders [41-44]. In the future, we intend for users to play interactive games with CARL-SJR, in which the robot learns a pattern of interaction with the child, and the child learns how to best interact with the robot. We believe such interaction will transfer to play with others and lead to behavioral improvements.

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