

Spatial memory based on an STDP-driven neural network

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Abstract—We propose a model of spatial memory implemented in a Spiking Neural Network (SNN) and test it on a robot moving in an environment with neutral and harmful regions. Neurons in the SNN play the role of place cells, and their population dynamics determines the robot movements. We show that STDP rearranges the couplings in the SNN and forms spatial memory similar to cognitive maps associated with the negative experience. Then, the robot learns to avoid harmful zones.

Keywords—SNN, cognitive maps, place cells, vector field of synaptic connections, vector field of functional connections, neurorobotics

I. INTRODUCTION

All biological systems at different organization levels have a memory, which can be broadly defined as an ability to preserve and reproduce their past adaptive states. Neurobiological studies of memory are mostly focused on the problems of its formation, storage, and representation [1]. Synaptic plasticity has been identified as one of the main mechanisms of memory and learning at the cellular level. However, its extrapolation to the network level has been less addressed in the literature.

Spike-Timing Dependent Plasticity (STDP) can be considered as an experimentally discovered [2], [3] type of Hebbian plasticity. According to the STDP rule, the synaptic coupling is potentiated if a presynaptic spike goes ahead of a postsynaptic one and depressed otherwise [4]. There is also an anti-STDP rule, whose effect is opposite to STDP [5]. The implication of STDP rules to the emergence of cognitive maps, i.e., of mental representation of the environment, is a hot topic in modern Neuroscience [6]. Pioneering works by O'Keefe provided the neurobiological basis for cognitive maps. For example, it has been discovered that the activity of the so-called place cells depends on the position of an animal in the environment [7].

Nowadays there exist a number of mathematical models simulating cognitive maps by associating external stimuli with their internal (neuronal) representation [8], [9]. In such models, synaptic plasticity yields the emergence of spatial memory in a spiking neural network (SNN). For example, in the Ponulak-Hopfield model, the anti-STDP rule leads to the ability to “remember” the localization of a “positive” stimulus [5]. Synaptic couplings in an SNN directed to the

stimulation point are potentiated and the synaptic vector field converges to this point. As a result, the activation of a neuron in the SNN causes a wave of spikes traveling to the neurons encoding a positive spatial stimulus.

Our recent studies have shown that stimulation of an STDP-driven SNN potentiates synaptic couplings directed outwards the stimulus locus [10]–[12]. Thus, in the case of STDP, the synaptic vector field diverges from the stimulation point. Then, one may hypothesize that STDP can be responsible for the codification of “negative” or harmful stimuli.

To study the emergence of negative spatial memory, here we emulate the movement of a wheeled robot exploring an environment. We propose an STDP-driven SNN capable of encoding regions in the environment associated with the harmful experiences of the robot. We show that neurons in the SNN play the role of place cells and the direction of the robot’s movement is determined by the waves of spikes running from the stimulation site. Then, the robot can learn to avoid harmful zones.

II. SNN STRUCTURE AND VECTOR FIELDS

The SNN model has been described elsewhere [10], [11]. The neuronal dynamics follows the Izhikevich model [13]. The external current for each neuron includes an uncorrelated white Gaussian noise and a sequence of pulses at a 10 Hz frequency rate, with an amplitude sufficient to excite a neuron. The synaptic (internal) current induced by other neurons was modeled the Tsodyks-Markram model, taking into account the effects of short-term synaptic plasticity [14]. The SNN included 400 excitatory and 100 inhibitory neurons, randomly distributed on a 1.2×1.2 mm square. The probability of interneuron connection decreased with distance.

To construct a vector field of interneuronal connections, we used the method described elsewhere [10]–[12]. At the first step, the network was divided into square cells. Then, each synaptic connection passing through a specific cell makes a linear contribution to the total connectivity vector associated with this cell. In addition to the vector field of synaptic connections, we also used the vector field of neural activity or, in other words, fields of functional connections (functional connectome). In this method, the direction of a unit vector of the neural activity coincides with the direction

of synaptic connections, and its length is determined by the history of spikes that passed through this connection and caused spikes on postsynaptic neurons:

$$\frac{dl_{ij}}{dt} = cy_{ij}\delta(t - t_{sp}^i) - \frac{l_{ij}}{t_l}$$

where l_{ij} is the length of a unit vector of connection activity from neuron j to neuron i , c is a constant, y_{ij} is the output of presynaptic neuron j , and t_{sp}^i is the time instant of postsynaptic spike i .

III. EMERGENCE OF STDP-MEDIATED SPATIAL MEMORY

The SNN generates noise-induced spontaneous population bursts with an average frequency of 1 Hz. Under external periodic stimulation (Fig. 1A), STDP-mediated neural connections arriving from the stimulated site are potentiated. Such a rearrangement of coupling weights changes the direction of the synaptic vector field (Fig. 1B). The potentiation of centrifugal connections facilitates the passage of traveling waves from the stimulated region. Each stimulus causes a population bursts of the same type, while the frequency of the bursts tunes to the stimulation frequency. We note that such a synchronization occurs at a high-enough stimulation frequency only, whereas low-frequency stimulation (i.e., of 1 Hz) competes with the spontaneous activity with approximately the same characteristic frequency and fails to synchronize waves of bursts [10].

The vector field of functional connections evaluated according to the direction of propagating activity generally coincides with the vector field of synaptic connections (Figs. 1C and 1B). The differences appear mainly in areas with

small vector lengths (Fig. 1C, areas marked by magenta color). Thus, the network functionality in the form of waves of spikes reflects the structure of interneuron connections. Then, the SNN represents the external world from the allocentric viewpoint.

Neurons or place cells undergo stimulation of their receptive fields when the robot goes through the corresponding areas in the arena. Receptive fields overlap in such a way that each location of the robot in the environment corresponds to a circle of radius $r = 40 \mu\text{m}$ in the network space that receives stimulation. The stimulation frequency is set to 1 Hz, while the robot is in the neutral zone of the environment, but if the robot gets into the zone of negative reinforcement, the frequency increases to 10 Hz (Fig. 1D).

The spiking activity of the SNN determines the robot behavior. The robot moves in the direction corresponding to the activity vector (the vector of the functional connectome). The speed of the robot is proportional to the length of the activity vector. Thus, the direction and speed of the robot movement in the arena reproduce the direction and intensity of the traveling waves of spikes in the network space.

In computer experiments, the harmful zone occupied 25% of the total area (Fig. 1D). Without STDP the average time the untrained robot spent in the harmful zone was $48.1\% \pm 2.8\%$ of the total time ($n = 11$). The discrepancy between these figures was caused by different robot velocities. When the robot was in the harmful zone the stimulation frequency was high. Then, the functional connections change, and their length decreases. Accordingly, the mean robot velocity in the harmful zone was significantly lower than in the neutral environment, and hence the robot spent a long time in this zone.

To test the learning abilities, we performed simulations in three consecutive steps: (i) an untrained robot explored the environment without STDP, (ii) the robot was trained by switching STDP on, and (iii) STDP was turned off again in order to measure the learning performance. The average time spent by the robot in the harmful zone decreased from $48.1\% \pm 2.8\%$ at step (i) to $7.6\% \pm 0.8\%$ at step (iii), whereas it was $25.2\% \pm 2.3\%$ during the training phase (Fig. 2).

IV. CONCLUSIONS

In this work, we have proposed an SNN driving the behavior of a neurorobot. Neurons in the SNN play the role of place cells, and the direction and velocity of the robot movement are determined by the population dynamics. The external stimulation of the SNN depended on the robot environment. In a neutral zone, the stimulation frequency was low, whereas in a harmful zone it was high. STDP rearranged the SNN couplings and formed a spatial memory associated with the structure of the arena. Such behavior mimics the emergence of spatial cognitive maps earlier discussed [15], [16].

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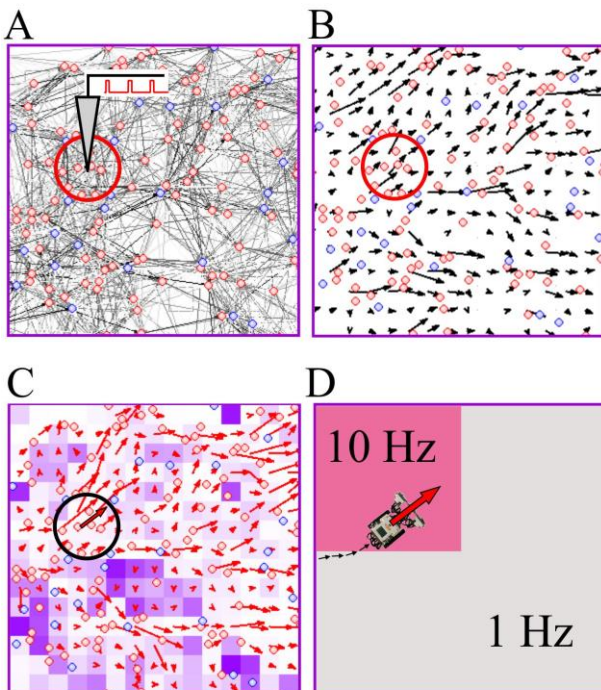


Fig. 1. Structure of the SNN controlling the robot. A) Stimulation of the network corresponding to the location of the robot in the arena. B) Vector field of synaptic connections. C) Vector field of the spike propagation. The resulting vector at the robot position drives the robot. D) Stimulation frequency is 1 Hz in the neutral area (gray) and 10 Hz in the harmful zone (magenta).

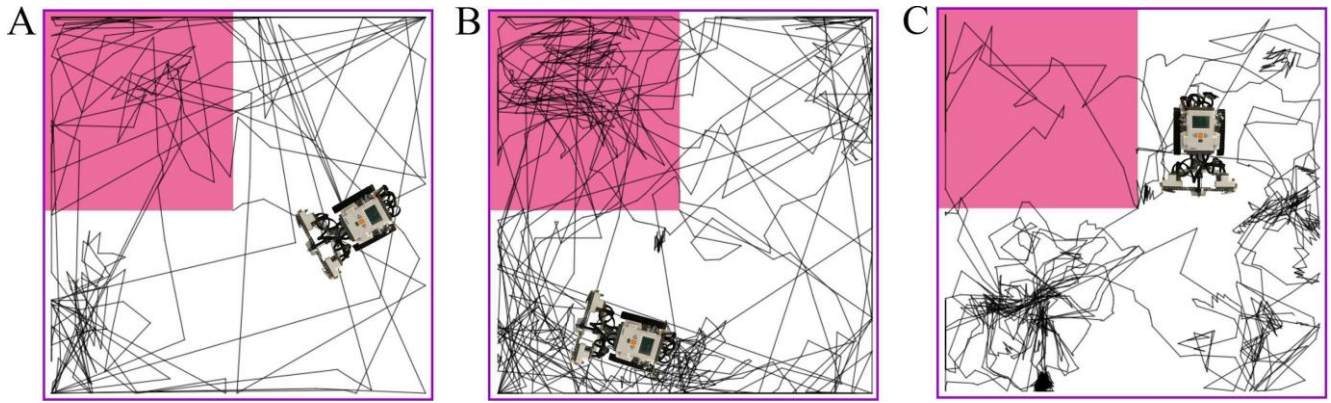


Fig. 2. Traces of the robot movement in the arena before (A), during (B), and after (C) learning (the harmful region is marked by magenta).

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