Mapping of Natural Patterns by Liquid Architectures Implementing Neural Cliques

Karina Odinaev, Igal Raichelgauz, and Yehoshua Y. Zeevi

Department of Bio-Medical Engineering, Department of Electrical Engineering,
Technion – Israel Institute of Technology, Haifa 32000, Israel
{karinao@tx.technion.ac.il, igal.raichelgauz@intel.com, zeevi@ee.technion.ac.il }

Abstract. Computational tasks related to processing and recognition of natural signal require identification of complex patterns and relationships in massive quantities of low precision, ambiguous noisy data. While state-of-the-art techniques and architectures fail to provide sufficient solutions, cortical neural networks have an inherent computational power in this domain. A recently-introduced Liquid-State-Machine (LSM) paradigm provides a computational framework for applying a model of cortical neural microcircuit as a core computational unit in classification and recognition tasks of real-time temporal data. In this study we apply the concept of "Neural Cliques" and extend the computational power of the LSM framework by closing the loop. By incorporating functions of readout, reward and feedback, we implement such a closed-loop framework of neural architecture in classification and recognition tasks of real-time temporal data. This approach is inspired by several neurobiological findings from ex-vivo multi-cellular electrical recordings and injection of dopamine to the neural culture. Finally, we illustrate the performance of the proposed architecture in word-recognition tasks.

1 Introduction

The lack of adequate interface between the natural environment and the computing devices constitutes a significant barrier to computer application in many real-world tasks. To incorporate computational means in the execution of day-to-day tasks, the physical world must be instrumental in the process, so that the computer systems will be exposed to, and linked with, the natural environment. The latter involves the transformation of data across the boundary between the real and the digital world, whenever a computer is sampling and/or acting on real world data. Examples of these "boundary transformation" problems include the computer recognition of human speech, computer vision, textual and image content recognition, robot control, OCR, ATR, and more. These are difficult problems to solve on conventional computers, since they require the computer to find complex structures and relationships in massive quantities of low precision, ambiguous and noisy data.

It has been proposed and supported by empirical evidences [5] that large, generic, random, massively connected cortical networks are not built specifically for each computational task but, rather, are used as a basic computational unit for diverse natural computational tasks in different cortical areas. Therefore, realistic models of these networks are good candidates for a core of biologically-motivated computational architectures. Moreover, even a relatively simple model composed of ~100 sparsely connected leaky-integrate-and-fire (LIF) neurons by dynamic synapses, with stochastic heterogeneous parameters, depicts powerful computational capabilities in a domain of parallel processing of temporal noisy data in real-time.

A new computational paradigm, called Liquid-State-Machine (LSM), recently introduced by Maass, Natschläger and Markram [1], provides a theoretical basis for applying a model of neural microcircuit to generic computational tasks. The LSM system is composed of two parts: *(1)* A liquid computational unit– a model of neural microcircuit is used as a "reservoir" of complex dynamics to transform the input time series $u(.)$ into "liquid states" $x(t)$, and to *(2)* A readout – a memoryless function which maps the liquid state $x(t)$ at time t onto the output $v(t)$. Readout may be implemented by a simple one-layer network of perceptron, trained by linear algorithm to build a function mapping liquid-states onto desired outputs. It was shown by means of simulations [2] that such a system is computationally effective in executing parallel tasks of recognition and classification of temporal data.

In the framework of computational LSM, a neural microcircuit is used as an efficient generic filter transforming different temporal inputs into significantly different liquid states. The task-dependent part is executed by the readout after being trained by supervised-learning algorithm to map these states onto predefined output. Obviously, neural systems are not composed of these two different components – liquid-states generators and readout layers. Thus the functions of both, Readout and Liquid should be incorporated into co-sets of the same generic neural ensemble. However, by this simplification and by emphasizing that recurrent neural ensemble, rather than individual neurons, should be viewed as basic computational units, the LSM computational framework suggests a radically different paradigm for neural computation. Moreover, the LSM framework enables the application of real cortical neural ensembles in real-world tasks by embodiment of cortical neural culture in artificial environments [15].

In this study we extend such a non-Turing paradigm for neural computations by incorporating biologically-motivated computational functions and components, such as reward-based feedback, observed in experiments performed on ex-vivo neural culture [10]. Several principles of computational neurobiology are assumed: (1) Computational tasks are carried out by spatio-temporal patterns, coined "Cliques", generated by generic neural ensembles which are vastly mutually communicated [16]. (2) Learning processes drive the generation of new subsets of cliques dictated by the environment through reward and/or penalizing signals. Reward signals are sent through a feedback from the environment and allow the success in computational tasks.

2 Neural Microcircuit as a Generic Computational Unit

The neocortex is characterized by precise structure of columns and layers. Within neocortical layers neurons are mapped into each other, where anatomical and physiological properties are unique for each type of pre- and post-synaptic combination. However remarkable morphological, electrophysiological and spatial stereotypy exists in these networks, in addition to very stereotypical connectivity and patterning of synaptic connections between neighboring cells. This clear stereotypy exists across different regions of the brain, suggesting that there is a generic template of microcircuit and that all neocortical microcircuits are merely subtle variations of that common microcircuit template. Such templates could subserve the apparent omnipotent functional capacity of the neocortical microcircuitry [5]. A computational model of generic neural microcircuit is inherently endowed with powerful and versatile information processing capabilities. We used a similar model to [2], composed of a 3-dimentional recurrent network of 150 Leaky-Integrate-and-Fire (LIF) neurons with random connectivity, and similarity to generic cortical microcircuit, 20% of the neurons are randomly chosen to be inhibitory and, accordingly, 80% excitatory. The probability of connection between two neurons depends on the distance between them according to,

$$C \cdot \exp(-D(i,j)/\lambda^2), \tag{2.1}$$

Where in λ and C are parameters that determine the average number of connections for a certain Euclidean distance D between the neuron i and neuron j. This connectivity characterization by primary local connections and a few longer connections is biologically realistic. Long range connections will be incorporated, and their functional effects on the computational properties of the network will be investigated within a context of a different study.

Random, heterogeneous parameters of NM model fit neurobiological data from rat somatosensory cortex [2]. Synaptic short-term plasticity of the NM is implemented by dynamic synapses in which the amplitude of each post-synaptic-current depends on the spike train that is impinging on the synapse [6], and causes facilitation and depression processes. The model was implemented using CSIM simulator [7].

3 Computing with Neural Cliques

Spatio-temporal firing patterns may be considered as basic information units of neural ensemble's response; however it seems that there is no unique information encoded in the dynamics characteristics of these firing patterns, but rather in the timing and specificity of the firing/non-firing neurons [17]. These spatio-temporal patterns are sensitive to input signals and are indicative of network states. "Synfire-chains", a concept originally introduced by Abeles [18], [11], and recently confirmed in neural culture activity by Yuste and associates [12], [19], emphasize the importance of correlated spatio-temporal firing patterns generated by neural ensembles with relevance to their connectivity characteristics. For this reason, we introduce and define the concept spatio-temporal patterns produced by neural ensembles' "Cliques". A clique does not directly depend on the connectivity characteristics of the firing/non-firing neurons and therefore may be composed of several synfirechains active in the same or even different brain loci and structures. Figure 1 illustrates the meaning of a clique by means of a spatio-temporal cube with finite temporal length, determined by short-term dynamics of the neural ensemble. The selection of subsets of neurons participating in the "clique" is determined by subsequent neuronal layers through closed-loop interaction with the environment and, thus, is a function of the defined computational task.

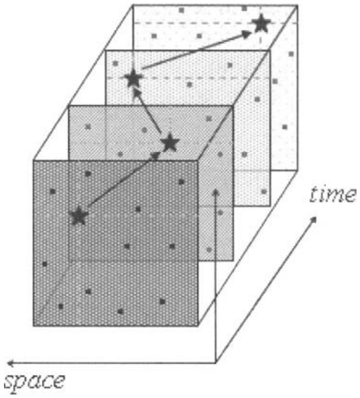

Fig. 1. Spatio-temporal representation of neural clique depicted as a sliding cube with finite temporal length. Points indicate neural responses that do not participate in the clique, stars indicate neural responses that participate in the clique.

Learning process drives a neural microcircuit to the desired cliques defined by configuration of sets of associations between stimuli and responses. This dynamical process begins with exploration of various network's cliques through modification of neuronal correlations. Two mechanisms which may be responsible for changing neuronal correlations are driving stimuli and neuromodulation by dopamine. Experiments on ex-vivo culture have shown [8], [4] that both mechanisms enhance changes in neuronal correlations by dispersing existing correlations, i.e. decorrelating previously acquired correlated activity. It is assumed that both mechanisms that cause decorrelation (dispersion) are mediated by a biophysical jittering of the synaptic strengths at polysynaptic level.

The second phase of learning, the recognition, is responsible for "freezing" the NM state by stopping the exploration process after the desired cliques were obtained. In recent years, a major effort has been devoted to mapping of the behavioral concept of reward to neural mechanisms that change the functionality of a given NM based on its past performance [9]. The regulation of exploration process, driven by dopamine neuromodulation, is enabled by reward prediction error (RPE) signals. Learning by reward can occur by associating a stimulus or an action with a reward [3]. In this type of learning known as "Learning by Dispersion" [4], [14], the synaptic efficacies are jittered according to the RPE values, i.e. the higher the error in the computational task, the larger the amplitude of jittering. The process continues until the error converges to zero and the system "freezes". In other words, the mechanism of jittering the synaptic efficacies, discovered by Eytan and Marom, is instrumental in avoiding trapping into a fixed point. When the best clique dictated by the environment is found, the system reaches the recognition phase, and by stopping the dopamine emission, network's associations are "frozen".

A mathematical model of this process, in which the synaptic efficacies are randomly jittered by regulation of RPE is formulated by:

$$\Delta W = \psi(W_0 \cdot K \cdot RPE), \tag{3.1}$$

wherein ψ is uniform distribution in the range of the argument, $W0$ is the previous value of the synaptic strength, K is a constant, and ΔW is the change in the strength of the synapse. The model illustrates exploration and recognition processes, by dispersion of the NM synaptic strengths, regulated by the success in achieving the task of the overall system.

The overall framework is described in Fig. 2. Time-varying stimuli from the environment excite NM with a continuous input stream $(P_i(t))$. At any time t_0, the clique of the microcircuit $(C_i(t_0))$ holds a substantial amount of information about recent inputs $P_i(t < t_0)$. Memoryless function maps the cliques $C_i(t_0)$ onto discrete predefined values (j). Discrete value j is a decision/action of the system in its environment.

If the system succeeds in the task, i.e. $i = j$ for classification task, reward signal is sent by the environment to the system. Reward signals, injected by the environment, are determined by system's performance and activate the Decorrelator by setting the value of RPE. Decorrelation mechanism modifies the NM synaptic strengths according to previously defined algorithm and drives the exploration phase of learning. When system's performance is sufficient, RPE is low, the recognition phase is reached and NM state is “frozen” by stopping the dispersion of the synaptic strengths.

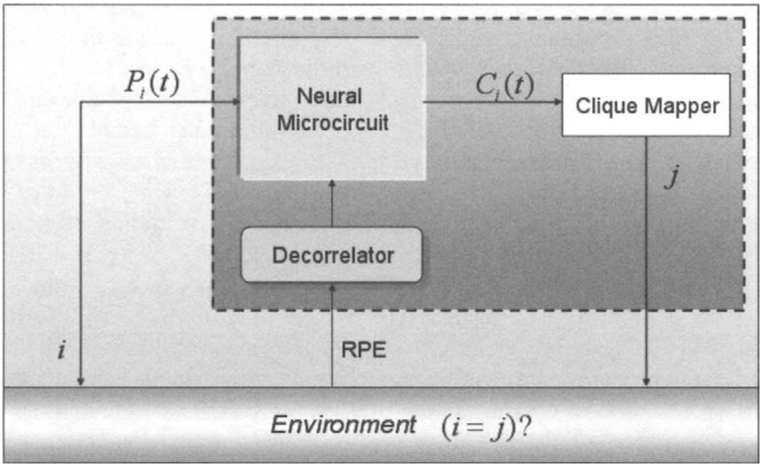

Fig. 2. Closed-loop liquid architecture implemented in a classification task of time-varying inputs. NM is composed of 135 LIF neurons. Time-varying stimuli *Pi(t)* are transformed by NM onto cliques, $C_i(t_0)$, defined as firing patterns of NM at time t_0. Memoryless function maps the cliques $C_i(t_0)$ onto discrete output to the environment (*j*). A feedback on system's performance is sent by the environment in form of reward signals to determine the RPE. Decorrelation, regulated by RPE, enables the exploration process of the NM until a desired performance is obtained.

4 Word Recognition Task

Closed-loop liquid architecture was applied in a well-studied computational benchmark task – an isolated word recognition task. The dataset consists of 230 input files: 40 samples of the word "one", 40 samples of the word "zero" by different speakers, and 150 samples of other words by 10 different speakers. The task was to recognize the word "one" out of 190 other words. To verify that the system can be extended to recognition of words other than "one", similar experiment was done for recognition of the word "zero".

The waveforms of the input sound were preprocessed by performing Fourier transform. Each of the frequency bands was composed of one or more of the following three events: onset (the start of the phase of significant energy), offset (the end of this phase), and peak (the first maximum of energy). The entire waveform is normalized to have maximum amplitude of 0.7, the sampling rate used in this case is 12000 samples/sec. The running average power and its second derivative are subsequently used in identification of events in the sound's spectrogram. This sound preprocessing converts the sound signal into a spatiotemporal sequence of events, suitable for recognition. Monosyllabic words are encoded into such sequences by retrieving features in different frequency bands in their spectrogram. Finally, sound waveform is converted into a list of 40 single events that are converted in turn into their respective times of occurrence [13].

For recognition of the word "one" 20 signals were randomly chosen out of 40 as a training data and the other 20 as a testing data, in addition to other 150 samples of different words. A previously described, randomly generated NM was implemented in a in a closed-loop setup. The mapping function from the NM cliques onto the output of the system was implemented by a simple algorithm identifying the stable neuronal spikes within the spatio-temporal firing pattern of the NM, after each step of exploration process. The average error in this classification task, achieved by this closed-loop system, was 0.065, as depicted in Fig. 3.

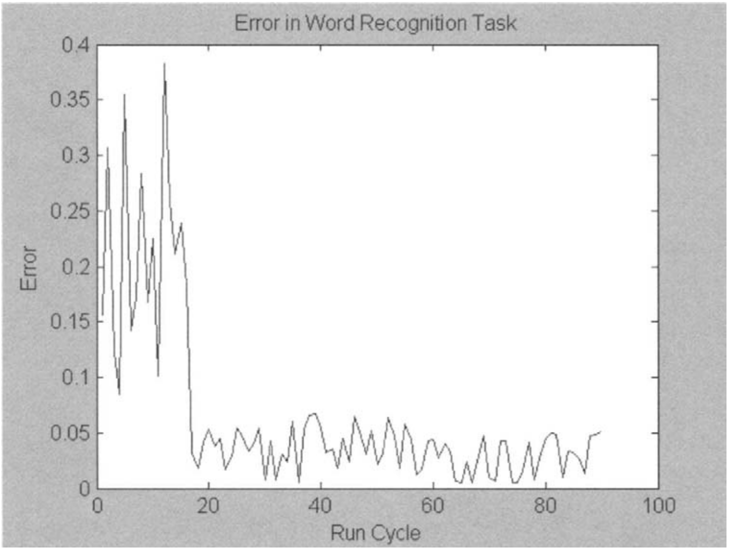

Fig. 3. Error-in-task of closed-loop liquid architecture vs. time.

5 Discussion

The liquid architecture paradigm, motivated by the cortical NM model, enhances the computational and learning capabilities characteristic of neural networks. On the one hand, the liquid architecture paradigm depicts a rich behavior that can be tested experimentally on the ex-vivo tissue setup. These emerging architectures are motivated by neurobiological findings obtained in experiments with neural culture [4], [8], [10]. On the other hand, the liquid architecture paradigm inspires the development of new computational hardware, suitable for processing and mapping of natural signals. We selected speech as an example of physiologically generated natural signal, and demonstrated that indeed such architecture is suitable for accomplishing relatively complicated processing tasks. Lastly, and most interestingly, is the possibility of coupling a real NM tissue and a liquid architecture. Such a hybrid computational system is likely to provide further insight into the rules that govern the functioning of brain tissue and its computational capacity. Such a hybrid system can also serve as a closed-loop model of a brain interaction with its environment.

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