# Multiple Cell Assemblies and Multi-Step Computation in Neural Networks

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#### Abstract

The dynamics of a recurrent neural network model in which localized learning patterns and asymmetric interactions between the patterns are embedded is investigated. In the network, multiple cell assemblies exist at the same time, and the combination of assemblies changes step by step. The network dynamics exhibits characteristic behavior that the timings of each appearance and disappearance of assemblies vary much from trial to trial, while the sequential order of events does not. These features are probably due to the balance between two forces: the feedback within each assembly that stabilizes the network state and the asymmetric inter-assembly connections that keep computation go on. The computational meanings of this 'assembly of assemblies' framework as a mechanism of multi-step computation are discussed.

Key words Cell assembly, multi-step computation

## 1 Introduction

A cell assembly is a collection of neurons those cooperate temporarily as a functional unit. There are considered a few mechanisms of a cell assembly, i.e., reverberation of excitatory signals<sup>1</sup>, populational oscillation at a specific frequency<sup>2,3</sup>, and synchronous spiking<sup>4,5</sup>. Functional meanings of a cell assembly include the following. First, an assembly maintains information for a certain time after the input disappears, which is regarded as working memory. At another viewpoint, distant areas in the brain are dynamically interrelated by an assembly so that they can exchange information depending on the situation<sup>6–8</sup>.

It comes that the same neuron or connection has multiple meanings, because it may belong to different assemblies at different time. In general, assembly switchings are considered in many contexts. For example, associative thinking and mental imagery are believed to correlate with assembly switchings in the brain. Recently it is also experimentally observed that the ongoing activity in the visual area of cats exhibits spontaneous transitions between different patterns<sup>9</sup>. Theoretical models have also been proposed to explain the mechanism of the switching phenomena<sup>10,11</sup>.

By the way, multiple assemblies may coexist at the same time in the real brain. Switchings of multiple assemblies, however, have not been considered so far. Here we propose a framework in which assemblies cooperate to evoke or suppress other assemblies, and then the combination of assemblies in the network changes one after another (see Fig. 1).

In this paper, the above mechanism of multi-step computation is realized by a simple neural network model. In the next section, the model is explained. In section 3, the main results of test simulations are shown. The computational meanings of multi-step computation performed by multiple assemblies are discussed in section 4.



Fig. 1: Mechanism of multi-step computation. In the neural network, multiple cell assemblies exist at the same time. They cooperate to evoke or suppress other assemblies. This triggers subsequent changes, which may cause a chain of assembly switchings.

### 2 Model

As a single neuron model, the simplest threshold model with stochastic update is used:

$$y_i = \sum_{j=1}^N w_{ij} x_j - \theta_i, \qquad (1)$$

$$p_i = \frac{1}{1 + \exp(-\epsilon y_i)},\tag{2}$$

where  $x_i$  is the activity of neuron i (1 is spike and 0 is resting),  $w_{ij}$  is the synaptic weight from neuron j to neuron i,  $\theta_i$  is the threshold, and  $p_i$  is the probability of the neuron i being on. The order of updating is random.

Now we store in the network localized learning patterns  $s^1, \ldots, s^M$ ,  $s^\alpha \in \{-1, 0, 1\}^N$  (see Fig. 2). In addition to symmetric connections that make the patterns self-sustained, we also stored in the network asymmetric inter-assembly connections:

$$W = \sum_{\alpha=1}^{M} s^{\alpha} . (s^{\alpha})^{\mathrm{T}} + \lambda \sum_{(\alpha,\beta)\in A} s^{\beta} . (s^{\alpha})^{\mathrm{T}}, \qquad (3)$$

where A is a set of index pairs and  $\lambda \geq 0$  is a parameter that determines the strength of asymmetric connections.



Fig. 2: Localized learning patterns. Three templates of size  $10 \times 10$  are located in  $30 \times 20$  space with translation. Blank spaces are zero-padded. Templates are borrowed from Adachi and Aihara  $(1997)^{10}$ .

#### 3 Simulation Results

The default parameter values for the following simulations are shown in Tab. 1. The components of set A are manually decided so that more than two assemblies invoke one new assembly cooperatively, and as long chain of assembly switchings as possible occurs.

Table 1: Parameter settings for the simulations

Variable	Value	Explanation
N	600	number of neurons
M	18	number of patterns
L	18	number of index pairs in $A$
$\epsilon$	0.1	slope of sigmoid function
$ heta_i$	0	threshold
$\lambda$	0.2	asymmetry coe cient

Figure 3 shows the property of the weight matrix W. First, the average of  $|w_{ij}|$  against the distance in the two-dimensional space indicates that short-range connections are dominant in the sense of absolute value. On the other hand, the average of  $|w_{ij} - w_{ji}|$  indicates that long-range connections have higher asymmetry degree than short-range connections.



Fig. 3: Property of the weight matrix. (Left) Average of  $|w_{ij}|$  against the distance in the two-dimensional space, and (Right) Average of  $|w_{ij} - w_{ji}|$  against the distance.

Figure 4 shows an example of time sequence of the state of the network. Starting from the initial state (the top left edge), the combination of assemblies changed step by step. For example, at first the cross-shaped assembly at the bottom left region disappeared, and the triangle-shaped assembly emerged there. Subsequently, another change started at the bottom right region. Totally eight switchings of assemblies occurred. The last state remained stable for longer runs.

The stepwise dynamics is also clearly seen in the plot of the activity of each assembly measured by  $\langle s^{\alpha}, x \rangle / |s^{\alpha}|^2$  (see Fig. 5, Left). The time scale of the durations of assemblies was much longer than that of switchings.

Furthermore, the timings of each appearance and disappearance of assemblies varied much from trial to trial (see Fig. 5, right). On the other hand, the sequential order of the assembly switchings was roughly kept in most trials.

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Fig. 4: An example of time sequence of the state of the network. Black and white cells show the firing and resting states, respectively. Intervals between the snapshots are two steps.



Fig. 5: (Left) Activity plot of the trial in Fig. 4 , and (Right) 20 trials plot of the activity of an assembly (index = 17).

In the limitation of  $\epsilon \to \infty$ , where the system's dynamics becomes deterministic, the initial state and all the intermediate states were stable.

When the value of  $\lambda$  was increased to 0.5, the whole chain of switchings turned to take shorter time on average. However, the sequential order of switchings became vague, because more than one switchings were likely to occur simultaneously at different regions.

### 4 Discussion

The observed dynamical characteristics, large fluctuations of the timings of assembly switchings and high rate of reproduction of the similar sequential order, can be explained by the two points below. First, the property of the weight matrix shows that the effect of feedback connections within each assembly dominates the effect of asymmetric inter-assembly connections. Second, the result of the limitation of  $\epsilon \to \infty$  shows that each assembly switching is driven by stochastic fluctuations. From these evidences, it is thought that switchings may occur only when the stochastic fluctuations happen to largely overlap the inter-assembly influence, and any other perturbations are repaired by the dominant short-range connections. The balance of the two types of connections may control the speed and accuracy of assembly switchings, which is consistent with the result of larger  $\lambda$ 's case. In general, high reliability per step is particularly important for complex computation that needs many steps, because errors in computation accumulate in each step.

Next, it should be clarified what advantage the 'assembly of assemblies' framework has against the assembly of single neurons. The most critical thing is that in principle a single neuron cannot actively sustain the state of itself without continuous external input, while an assembly can do that. Accordingly, the neurons that are involved in a formation of an assembly will be able to be reused for other processing after the target assembly is completed. Of course, by behaving as a group, assemblies perhaps have more robustness against noise or uncertainty and can deal with much complex nonlinear interactions than single neurons. Furthermore, just as a single neuron possesses much more information than whether or not it is activated, an assembly is perhaps able to represent multi-modal information.

Although it is a di cult problem what should be regarded as the output of the network, this framework can be seen as a model that represents the inputoutput mappings. Given an initial state as an input, the network visits multiple intermediate states until the output is obtained. A benefit for neural networks to use this computational method may be that under a certain limitation of neuron number and wiring complexity, the method is e cient to embed in the network as many input-output correspondence relations as possible. To check this idea, it is necessary to investigate how much information processing ability networks of different structures have on average.

By the way, some of neuroscientists think that in a specific region in the brain information is explicitly coded, and a different region controls it  $^{12,13}$ . On the other hand, our standpoint is different because in our framework both representation and operation of information are performed in the same place. An explanation why this is possible is that 'drive system' assemblies, which make other assemblies switch, and 'response system' assemblies, which are switched, are separated at each moment, but the assignment changes depending on the context.

Finally, how can we measure the validity of this framework? In the first place, there is no strong evidence that neurons dynamically form functional clusters in the real brain. Many neuroscientists, however, predict that there must be neural activities that correlate with our conscious experiences, and that would be dynamically-formed cell assemblies consisting of a number of neurons<sup>13–15</sup>. Such assemblies may be still di cult to observe in the real brain. Furthermore, it is almost impossible to prove the causal relationships between sub-assemblies composing the principal assembly that correlates with the unified consciousness. Therefore, now we can only imply what computational meanings inter-assembly interaction may have.

## 5 Summary

In this paper, a new framework, multi-step computation performed by multiple cell assemblies, has been proposed, and we constructed a simple neural network model that realize the proposed mechanism and investigated its dynamical characteristics by numerical simulations. The network dynamics is subject to two types of connections, the feedback within each assembly and asymmetrical inter-assembly connections. The former dominates the latter, resulting in accurate transitions in each step.

Although the proposed model used continuous mutual excitations among neurons as a mechanism of cell assembly, the fundamental ideas are probably able to be shared with other mechanisms such as oscillation and synchronization. Even though it is di cult to show experimentally, the proposed mechanism could be used in some form in the real brain.

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