Pattern Languages: A New Paradigm for Neurocomputation

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Abstract

Existing neurocomputation models do not describe very faithfully biological neural systems. Here we offer a new look at neural activity data, by introducing the paradigm of pattern languages. Biological examples are presented to provide the biological grounding, and an artificial neural network is described as a simple example of how to interpret neural activity data in terms of pattern languages. The new approach places the emphasis on internal processing within the neural system, instead of the input/output processing, and offers a good balance between the consideration of individual neural activity and of the activity of large numbers of neurons.

Key words: dynamics, neural model; neural networks; pattern language

1 Introduction

Many theories about how biological neural systems work emphasize the input / output processing of information in such systems (e.g., [5]), ignoring the internal processes that transform the data and blend it with a priori knowledge existing within the system. The theory of pattern languages [8] emerged recently as a new computational paradigm, which fits very well to the description and analysis of complex systems and which can be used to highlight the importance of internal processing in neural systems. Examples of complex neural activity patterns, e.g., crab stomatogastric nucleus [6], olfactory bulb [3], are cases where classic theories were so far not very successful in explaining the behaviour of the neural systems. In these cases the pattern languages approach offers a fresh look at the data with the promise of providing faithful explanations and robust predictions about the behaviour of the neural system.

In this paper we describe a simple model neural system, that performs neural computation by interacting activity patterns, and discuss how the pattern languages approach can help in understanding neural systems. The system that we describe can be viewed as an example of how neural computation is interpreted in terms of pattern languages.

The rest of the paper is structured as follows. First, we look at examples of biological neural systems which show complex neural activity that is hard to explain using classical models of neural systems. Second, we briefly introduce pattern languages. Third, we introduce the Sierpinski brain [1]. Fourth, we discuss the application of pattern languages in the context of understanding neural systems. We close the paper by a conclusion section.

2 Neural activity patterns

There is considerable indirect experimental evidence (e.g., [3], [7]) that indicate that neural activity patterns play an important role in the processing of information, and mere consideration of individual neurons alone cannot reveal the whole story of neural information processing.

The crab stomatogastric ganglion contains between 30 - 40 neurons and these neurons are organized into two sub-networks, one regulating the activity of the gastric mill and the other the pylorus [6]. These networks produce a wide range of rhythmic output activity patterns, and in some cases they combine their activities. Although the knowledge about individual neurons of the networks, their electrical and chemical synapses, and effects of modulatory substances is very extensive [6], it is still unknown how the output rhythms emerge, and how do the networks join and separate their activities depending on their incoming stimuli.

In the case of the olfactory bulb researchers reported the emergence of complex activity patterns [3], which can be captured by analysing high spatio-temporal resolution surface EEG recordings. These activity patterns characterize the perception, storage and recall of olfactory information, and highlight the importance of joint activity of many neurons in such processes. So far, models based on individual neurons (i.e., in which individual neurons acts as independent complete computational units; e.g., [4]) were unable to explain fully how such activity patterns emerge, and how neural computations happen by these patterns.

3 Pattern languages

Ideas related to pattern languages were organized into a coherent theory recently by Wolfram [8]. Essentially pattern languages can be described as sets of basic patterns and sets of pattern transition rules. A simple example is a cellular automaton, where configurations of cell states are the patterns and rules of changes of cell states describe the pattern transition rules. Figure 1 shows an example of one dimensional cellular automaton.

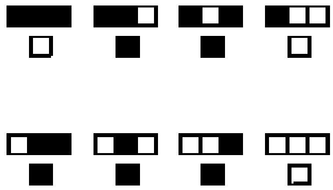

Fig. 1. A simple pattern language expressed as a set of transcription rules. Each rule consists of an input pattern of three black / white squares and the transcription of the middle square into a black or white square. The upper triplets show the input pattern, while the square below the triplets show the new color of the middle square.

Pattern languages can be viewed as information processing tools, where the input information is specified in terms of the initial pattern. Such information processing is a computational process where input information is transformed into output information. Wolfram [8] describes examples of such pattern languages that can execute simple computations like addition, multiplication and others.

An important feature of pattern languages is that the amount of input/output computation is much smaller than the amount of internal processing. This implies that looking purely at their input/output computations may reveal very little about the pattern language and for a true understanding of it we need to observe and understand the internal processing of the language.

4 The Sierpinski brain

The Sierpinski brain was introduced by Andras [1] as a relatively simple neural system that performs universal approximation by computing with neural activity patterns. This neural system is based on the Sierpinski neural networks, an example of which is shown in Figure 2.

The Sierpinski network contains an excitatory - inhibitory complex that selects one pair of excitatory neurons to fire at any time out of three such excitatory neuron pairs $((ax, ay), (bx, by), (cx, cy))$. Each pair of neurons represents by

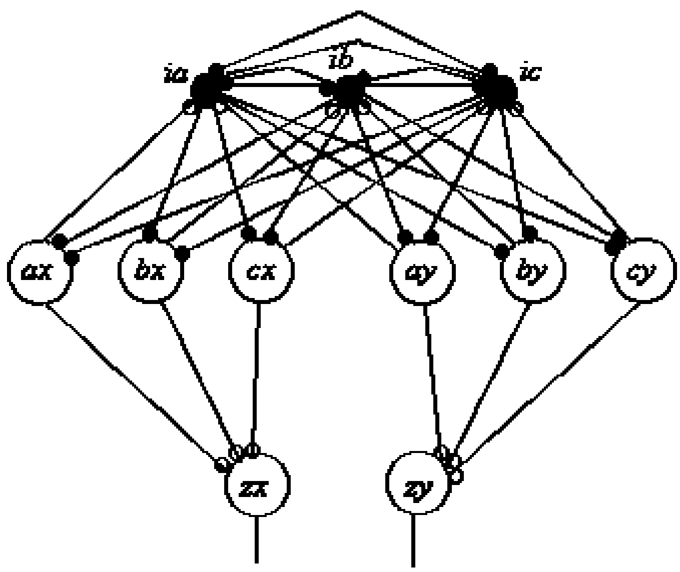

Fig. 2. Sierpinski network: inhibitory neurons (ia,ib,ic) are in the upper row, periodic burster neurons (ax,bx,cx,ay,by,cy) are in the middle row, integrate-and-fire neurons (zx,zy) are in the lower row.

their firing rate the coordinates of one vertex of a triangle. The integrating neurons (zx, zy) calculate a weighted combination of a random series of these coordinates. In this way the firing rates of the output neurons of the network represent at each time a point from within the triangle. The sum of points that can be generated in this manner constitute the Sierpinski triangle corresponding to the triangle determined by the vertices represented by the pairs of excitatory neurons in the excitatory - inhibitory complex. The spatio-temporal output pattern of a Sierpinski neural network is shown in Figure 3.

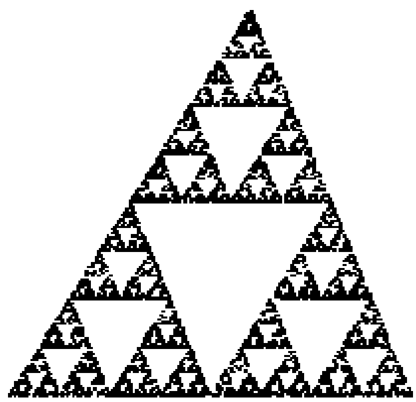

Fig. 3. The spatio-temporal output pattern of a Sierpinski neural network

Calculating the number of intersections between two Sierpinski triangles with the vertex coordinates $\{(0,0),(1,0),(t,1)\}$ and $\{(0,1),(1,1),(x,0)\}$ gives the values of the Sierpinski basis function $s(t,x)$ [2]. The set of these functions can be used to perform universal approximation with respect to the closure of the set of continuous functions [1]. Using two Sieprinski neural networks that represent such triangles we can compute an approximation of any $s(t,x)$ value, by employing synchrony detector neurons that count the synchronous firings of the corresponding output neurons of the two networks.

The Sierpinski brain is a combination of many such Sierpinski neural networks. The summed output of the synchrony detector neurons will be the output of the Sierpinski brain. This output is given in form of the firing rate of a final output neuron of the Sierpinski brain. Due to the blurred representation of the input values the output of the Sierpinski brain is an average of the actual approximations of the function values. Having an appropriate combination of networks representing basis functions the output of the Sierpinski brain can approximate a particular input - output function. Considering that the Sierpinski basis functions can be used for universal approximation, this means that the neural system of the Sierpinski brain can perform the approximation of many input - output functions by adjusting the numbers of the basis functions represented by the component networks of the brain. Such adjustments can be performed by a learning process [1],[2].

5 Discussion

In the case of pattern languages the internal processing of information is usually much more important than the simple input/output processing. The example of the Sierpinski brain shows the amount of activity that is not directly related to the received input or to the produced global output is far more than the amount of directly related neural activities. The internal processing represents the knowledge encoded in the rules of the system. This knowledge is used to interpret the input data and to produce some output. The use of this knowledge means many times long sequences of pattern transitions making up a large amount of internal processing.

If complex neural systems can be best described in terms of pattern languages, this implies that the role of internal processing in these systems must be much higher than it is supposed by current theories focused on input/output transformations. Ignoring the internal processing ignores the majority of the processing and prevents the understanding of the whole system. Adopting pattern languages for the description and analysis of complex neural systems implies that the research of these systems should focus to a large extent on the proper recording, analysis, interpretation and explanation of internal processing by activity patterns in these neural systems. Although, inputs and outputs are very important, and without them the system would not work and we could not observe it, their importance should not shadow the importance of internal processes that are independent of inputs and outputs to a large extent. The proper analysis of the internal processes will allow the search for the transition rules of the corresponding pattern language, and consequently will allow a faithful description and analysis of the full system.

6 Conclusions

Understanding simple biological neural systems with complex behaviour is crucial for the understanding of more complicated neural systems. While, classical neural models have only very limited explanatory and predictive power in such cases, the pattern languages paradigm offers a new way to look at these neural systems. By switching the focus from input / output processing to internal processing, and by having a balanced approach between considering only individual neurons or only large groups of neurons, the pattern languages paradigm is likely to be able to capture to a good extent the behaviour of complex neural system. Consequently it is likely that it can provide better explanations and predictions about such neural systems with complex behaviour.

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