Creating Self-organization Maps by Cooperative Information Control

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Abstract

This paper proposes a novel information theoretic approach to self-organization called cooperative information control. The method aims to mediate between competition and cooperation among neurons by controlling information content in neurons. Competition is realized by maximizing information content in neurons. In the process of information maximization, only a small number of neurons win the competition, while all the others are inactive. Cooperation is implemented by having neurons behave similarly to their neighbors. These two processes are unified and controlled in the framework of cooperative information control. We applied the new method to a political analysis. In the analysis, experimental results confirmed that cooperation and competition are flexibly controlled. In addition, controlled processes can yield a number of different neuron firing patterns, which can be used to detect macro as well as micro features in input patterns.

1 Introduction

In this paper, we propose a new type of selforganization method called cooperative information control. In this method, competition among neurons is realized by maximizing information content in neurons. In addition, this information maximization process synchronizes with the process of cooperation in which neurons behave similarly to their neighbors. Cooperative information control can mediate between competition and cooperation, which cannot be implemented by the conventional self-organization methods. The new method can contribute to unsupervised neural computing in the following three respects: (1) competition among neurons is realized by directly controlling neurons without approximating input patterns; (2) competition and cooperation are realized by maximizing information content in competitive neurons, and simultaneously by having neurons behave similarly to their neighbors; and (3) the method can mediate between the processes of competition and cooperation in self-organization. Let us discuss these three points in more detail.

First, competition is realized by directly controlling neurons. Thus, competition in cooperative information control is considerably different from that by the conventional competitive self-organization methods [1]. Competitive learning [2] is one of the most successful techniques for self-organization. However, because these traditional competitive methods must realize appropriate competitive neuron firing rates indirectly by approximating input patterns, the methods need to be sensitive to detailed parts of input patterns [3]. On the other hand, by directly controlling neuron firing rates, the new information theoretic method can produce the same kind of connections as the traditional competitive method does. This direct control permits networks to discover some salient features which cannot be detected by approximating input patterns.

Second, competition and cooperation in the new method are realized by maximizing mutual information between input patterns and competitive neurons and by having neurons behave similarly to their neighbors. Information theoretic methods have provided promising possibilities to neural computing in various ways [4], [5], [6]. However, the limitations of these approaches have severely constrained their range of application. The methods have not reached a stage in which they can replace the simple and practical conventional self-organization. Contrary to these traditional information theoretic methods, the new method [7] is easy to implement in any neural network architecture, and the process of information maximization and final internal representations can be intuitively interpreted. The theoretical framework of the new method is derived from the previous research on information theoretic learning methods, [8], [9], [10]. In these methods, information was defined directly
by hidden unit activation, and activation patterns could be flexibly controlled; however, the methods were all based upon supervised learning methods, and thus could not simulate self-organization processes. On the other hand, the new method uses competitive unit activation as a neuron firing rate. By maximizing information, only one neuron wins the competition, and all the other competitive neurons are turned off, which is used to simulate competition. In addition, to realize cooperation, we introduce a procedure in which neurons behave similarly to their neighbors. Connections are updated to increase information and at the same time to have neurons behave similarly to their neighbors.

Third, cooperative information control is used to mediate between competition and cooperation in self-organizing processes. Self-organization maps developed by Kohonen [11], [1], [12] have been used in a variety of fields because of their simplicity and powerful visualization. However, in the Kohonen maps, because neurons’ firing rates are automatically given in the process of approximating input patterns, and there are no ways to control cooperation and competition, final neuron firing patterns and accompanying internal representations are sometimes ambiguous, uncertain and dependent upon detailed parts of input patterns. For this reason, a great number of theoretic and heuristic techniques have been proposed to enhance internal representations obtained by the conventional self-organization maps [13], [14], [15], [16], to cite a few. If it is possible to control and mediate between competition and cooperation flexibly, final neuron firing patterns and obtained internal representations can be more easily interpreted. Our method can create appropriate final neuron firing patterns by controlling information content in neurons, and thus by coordinating competition and cooperation.

2 Cooperative Information Control
2.1 Competitive Information Control
We realize competition by controlling information content in neurons. In this paper, we focus upon information stored in neural systems [17], [9]. Information is defined as the decrease in uncertainty from an initial state to another state after receiving input patterns. The initial uncertainty $H_1$ is described by first order entropy:

$$H_1 = - \sum_j p(j) \log p(j),$$  

where $p(j)$ denotes the probability of firing of the $j$th neuron in a neural system. First order entropy $H_1$ may be further decreased to second order uncertainty $H_2$, that is, uncertainty after receiving input signals:

$$H_2 = - \sum_s \sum_j p(s)p(j \mid s) \log p(j \mid s),$$  

where $p(s)$ represents the probability of input signal $s$, and $p(j \mid s)$ denotes the conditional probability of the $j$th neuron after receiving the $s$ input signal. This uncertainty or the information gained is defined by

$$I = H_1 - H_2 = - \sum_j p(j) \log p(j)$$

$$+ \sum_s \sum_j p(s)p(j \mid s) \log p(j \mid s).$$  

As information is increased, a neuron tends to fire in response to some input patterns, as shown in Figure 2(a). Thus, information maximization is used to simulate competition among neurons.

![Figure 1: A network architecture for self-organization.](image1)

![Figure 2: Competition (a) and cooperation (b).](image2)

Next, we apply information gain to actual neural networks. As shown in Figure 1, a network architecture is composed of input neurons $x^i_k$ and competitive neurons $v^j_s$. Let us define information for competitive neurons and try to control the neuron firing
patterns. The \( j \)-th competitive neuron receives a net input from input neurons, and an output from the \( j \)-th competitive neuron can be computed by

\[
v_j^i = f(\sum_k w_{jk} x_k^i),
\]

where \( w_{jk} \) denotes a connection from the \( k \)-th input neuron to the \( j \)-th competitive neuron, and \( f(t) = 1/(1 + \exp(-t)) \). In modeling competition among neurons, one of the easiest ways is to normalize the outputs from the competitive neurons as follows:

\[
p_j^i = \frac{v_j^i}{\sum_m v_m^i}.
\]

The conditional probability \( p(j \mid s) \) is approximated by this normalized competitive neuron output, that is,

\[
p(j \mid s) \approx p_j^i.
\]

Since input patterns are supposed to be uniformly given to networks, the probability of the \( j \)-th competitive neuron is approximated by

\[
p(j) = \sum_s p(s) p(j \mid s)
\approx \frac{1}{S} \sum_s p_j^s,
\]

\[
= p_j.
\]

Using these probabilities, first order entropy is approximated by

\[
H_1 \approx - \sum_j p_j \log p_j.
\]

Second order entropy \( H_2 \) is approximated by

\[
H_2 \approx - \frac{1}{S} \sum_s \sum_j p_j^s \log p_j^s.
\]

As second order entropy becomes smaller, the specific pairs of input patterns and competitive neurons are strongly correlated. By using these two types of entropy, the information is approximated by

\[
I \approx - \sum_j p_j \log p_j + \frac{1}{S} \sum_j p_j^s \log p_j^s.
\]

In the process of information maximization, neurons compete with each other, and finally one neuron wins the competition. Figure 2(a), shows this process. At the initial stage of learning, no information is given to a network, meaning that all competitive neurons are almost uniformly distributed. When information is maximized, only one competitive neuron is turned on, while all the others competitive neurons are off. By maximizing the information, we can simulate competitive learning.

2.2 Cooperated Information Control

Cooperation is realized by having neurons behave similarly to the neighboring neurons. In living systems, it has been well known that a group of neurons fire to a specific input pattern [18], [19]. This phenomenon is a best example of cooperation among neurons in living systems. For example, Figures 2 (b) shows an example of this cooperation process. In (b), the surrounding neurons' firing rates around the target neuron in the center are relatively high. The target neuron must increase its firing rate up to the level of the neighboring neurons.

Now, let us consider update rules to realize this cooperation. Following the conventional self-organization maps, we define a topological neighborhood function \( \phi_{jm} \) between the \( j \)-th and \( m \)-th neuron. For this purpose, we introduce the lateral distance \( d_{jm} \) between the \( j \)-th and \( m \)-th neurons as follows:

\[
d_{jm}^2 = ||r_j - r_m||^2,
\]

where the discrete vector \( r_j \) denotes the \( j \)-th neuron position in the two dimensional lattice. By using this distance function, we have the topological neighborhood function:

\[
h_{jm} = \exp \left( \frac{d_{jm}^2}{2\sigma^2} \right),
\]

where \( \sigma \) denotes a parameter, representing the effective width of the topological neighborhood. For realizing cooperation, we consider the following modified topological neighborhood function:

\[
\phi_{jm} = p_m h_{jm},
\]

where \( p_m \) denotes the \( m \)-th neuron's firing rate. This neighborhood function becomes stronger, as the distance becomes smaller and at the same time the neighboring neurons' firing rate becomes higher. By using this topological function, we can simulate cooperation by making connections into the \( j \)-th neuron similar to those into the \( m \)-th neuron. This is achieved by updating the following rule \( G \):

\[
G = \theta \sum_m \phi_{jm} (w_{mk} - w_{jk}),
\]

where \( \theta \) is the parameter.

Differentiating information function \( I \) with respect to connections \( w_{jk} \) and adding the cooperation term \( G \), we have the final update rules:

\[
\Delta w_{jk} = \beta \frac{\partial I}{\partial w_{jk}} + \theta \sum_m \phi_{jm} (w_{mk} - w_{jk})
\]

\[
= -\beta \sum_s \left( \log p_j - \sum_m p_m^s \log p_m \right) Q_{jk}
\]

\[
+ \beta \sum_s \left( \log p_j^s - \sum_m p_m^s \log p_m^s \right) Q_{jk},
\]

\[
+ \theta \sum_m \phi_{jm} (w_{mk} - w_{jk}),
\]

(15)
where

\[ Q_{jk} = \frac{1}{S} p_j^s (1 - p_j^s) x_k. \] (16)

3 Medical Data Analysis

In this experiment, we attempt to demonstrate how cooperative information maximization can infer the physical states of different people. In the experiment, we used data on heart functions for 32 healthy and unhealthy people in which features such as the heart rate, systolic blood pressure, diastolic blood pressure, mean blood pressure, pulse pressure, and the ejection time of the left ventricle of the heart were incorporated. The first 13 and the latter 19 persons were classified as healthy and unhealthy, respectively. The numbers of input and competitive neurons were 20 and 36, respectively, according to the guideline of SOM.

Figure 3 shows average information for the medical data. Information is almost zero before the number of epochs reaches 7,000, and then information rapidly increases up to about 80 percent. Figure 4(a) and (d) show neuron firing patterns when the number of epochs is 7,500 for healthy and unhealthy people, respectively. We can clearly see that neurons on the upper right hand side respond strongly to the healthy people (a), while neurons on the lower left hand side respond strongly to the majority of the unhealthy people (d). However, the firing patterns of the unhealthy people (30) and (31) are slightly ambiguous.

When the number of epochs is increased to 10,000, there appears a clear difference between healthy and unhealthy persons. Figure 4(b) and (e) show firing patterns for healthy and unhealthy persons, respectively. As can be seen in the figure, a smaller number of neurons tend to fire for the healthy and unhealthy persons. When the number of epochs is further increased to 15,000, a different neuron tends to respond to a different person, as shown in Figure 4(c) and (f). For the healthy persons, different neurons on the upper right hand side fire. On the other hand, for each unhealthy person, different neurons on the lower side fire or on the diagonal position fire.

Finally, we plotted neuron firing patterns by the conventional self-organization maps. We can see a tendency that some neurons on the lower left hand side fire relatively more strongly than others for the healthy persons. For those unhealthy, a situation is complicated. Though neurons on the upper side tend to fire strongly, many other patterns can be seen. This means that no clear neuron firing patterns can be obtained by the conventional method. Because the conventional method does not have techniques to control firing patterns, it is impossible to enhance firing patterns without additional heuristic methods.

4 Conclusion

We have proposed a new type of self-organization method called cooperative information control. In this method, competition has been realized by maximizing information content in competitive neurons. In addition, information control is accompanied by the process of cooperation in which neurons behave similarly to their neighbors. When information is zero, all neurons cooperate with each other and there are no special competitive neurons at this stage. As information becomes larger, several neurons form a group, and cooperation can be more clearly seen. When information is completely maximized, only competition is realized in which one neuron wins the competition and all the other neurons lose. Thus, cooperative information control can adjust neuron firing patterns flexibly, which is not possible in the traditional self-organization methods. Experimental results have confirmed that our method can generate different neuron firing patterns. When information is relatively small, firing patterns obtained show macroscopic features of input patterns. As information becomes larger, microscopic features such as relations among input patterns can be detected.

For further development of our method, some elaborations are needed. First, in the present model, cooperation is implemented by having neurons behave similarly to their neighbors. However, if other types of neuron cooperation behaviors can be taken into consideration, different types of firing patterns will be obtained. Second, in cooperative information maximization, competition and cooperation must compromise with each other. Without setting parameters appropriately, compromise between two processes cannot be flexibly controlled, as demonstrated in the present experiments. More sophisticated approaches to parameter setting are necessary.
Figure 4: Competitive neuron firing patterns $p^*_j$ for 32 people. The number of epochs was 7,500.
Though further research in competition and cooperation is needed, the present study has shown the possibility of the new method for flexible self-organization.

References


