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Associative memory by incremental learning using chaotic neural networks

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Research Fields

Neural Networks

Keywords

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Research Outline

Incremental Learning

The incremental learning was developed by using the chaotic neurons and provided an associative memory. The network type is an interconnected network, in which each neuron receives one external input, and is defined as follows:

$$x_i(t+1) = f(\xi_i(t+1) + \eta_i(t+1) + \zeta_i(t+1))$$
(1)

$$\xi_i(t+1) = k_s \xi_i(t) + v A_i(t) \tag{2}$$

$$\eta_i(t+1) = k_m \eta_i(t) + \sum_{j=1}^n w_{ij} x_j(t)$$
 (3)

$$\zeta_i(t+1) = k_r \zeta_i(t) - \alpha x_i(t) - \theta_i(1-k_r) \tag{4}$$

where $x_i(t+1)$ is the output of the *i*-th neuron at time t+1, f is the output sigmoid function described as $f(x) = 2/(1 + \exp(-x/\varepsilon)) - 1$, k_s, k_m, k_r are the time decay constants, $A_i(t)$ is the input to the *i*-th neuron at time t, v is the weight for external inputs, n is the size—the number of the neurons in the network, w_{ij} is the connection weight from the j-th neuron to the i-th neuron, and α is the parameter that specifies the relation between the neuron output and the refractoriness.

The parameters in the chaotic neurons are assigned in Table 1.

Table 1: Parameters

$$v = 2.0, k_s = 0.95, k_m = 0.1, k_r = 0.95,$$

 $\theta_i = 0, \varepsilon = 0.015$

In the incremental learning, each pattern is inputted to the network for some fixed steps before moving to the next. When a pattern is inputted, a neuron which satisfies the condition of (5) changes the connection weights as in (6).

$$\xi_i(t) \times (\eta_i(t) + \zeta_i(t)) < 0 \tag{5}$$

$$w_{ij} = \begin{cases} w_{ij} + \Delta w, & \xi_i(t) \times x_j(t) > 0 \\ w_{ij} - \Delta w, & \xi_i(t) \times x_j(t) \le 0 \end{cases} \quad (i \ne j) \quad (6)$$

where Δw is the learning parameter.

Capacity

Here, a capacity is a number of the patterns which the network memorizes all together. After the incremental learning with $\alpha=2.0$ and Δw changing along the network size, the capacity was turned out to be Fig. 1. The capacity of the auto-correlative learning is also shown in Fig. 1.

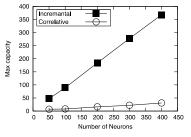


Figure 1: Capacity of Network at $\alpha = 2.0$

Through the simulations like the one shown in Fig. 2 which tell the fact that not only Δw but also α strongly affects the number of learned patterns, the capacity increases with the finely tuned parameters as shown in Fig. 3

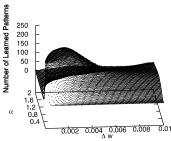


Figure 2: Number of Success with α and Δw

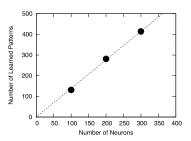


Figure 3: Capacity of Networks