

A Novel Maximum Neural Network with Stochastic Dynamics for N-Queens Problems

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Keywords : maximum neural network, N-Queens problems, stochastic dynamics, combinatorial optimization problems

We propose a novel maximum neural network with stochastic dynamics for solving NP-hard optimization problems, the N -Queens problems. A self-feedback term with stochastic characteristic is introduced into motion function of the maximum neural network, which increases the dynamics of the neural network to search for globally optimal solutions. Moreover, several new constraints having random selection character are presented and used in the proposed algorithm to drive the network to escape from local minima. With the stochastic dynamics and those new constraints, the proposed algorithm has a great ability to find optimal or near-optimal solution of N -Queens problems. The simulations show that the proposed algorithm is superior to other algorithms in light of successful rate, and it is especially suited to be used in practical system with parallel computing.

Based on maximum neural network, we introduce a stochastic negative self-feedback term into the motion equation to increase the dynamics of maximum neural network. The maximum neural network with stochastic dynamics would have more powerful energy to jump out local minima and search for the globally optimal solutions. The novel motion equation is described as following:

$$\delta = \text{random}(0 \sim 1) \dots\dots\dots (1)$$

$$u_{ij}(t+1) = u_{ij}(t) + \psi \Delta u_{ij}(t) - T(t)(v_{ij}(t) - \delta) \dots\dots\dots (2)$$

$$T(t) = T(t)(1 - \theta) \dots\dots\dots (3)$$

Where ψ is a positive scaling parameter for inputs, and $T(t)$ is a self-feedback connection weight ($T(t) > 0$). θ is a damping factor of the time dependent $T(t)$ ($0 \leq \theta \leq 1$). Parameter σ is a random variable producing rich dynamics by acting with the $v_{ij}(t)$. By embedding the random parameter σ , our improved maximum neural network has more efficient dynamics to skip local minima than original maximum neural network and the other improved maximum neural network methods. Being similar with transiently chaotic neural network, the self-feedback term would increase the dynamics of maximum neural network. The drastic dynamics is able to improve the ability of searching for optimal solutions. Because the novel maximum neural network utilizes the characteristic of N -Queens to build the competitive mechanism in each row, the row constraint of N -Queens problem is auto satisfied automatically. In addition, the neuron input U_{ij} is always confined within a constant range to encourage the state of neurons to escape from a local minimum:

$$\text{If } U_{ij} = U_{\max} \text{ then } U_{ij} = U_{\max} \text{ else if } U_{ij} < U_{\min} \text{ then } U_{ij} = U_{\min}$$

In order to increase the degree of competition, we introduce several random constraints into the network as follows:

$$\text{If } U_{ij} = U_{\min} \quad \forall j = 1, 2, \dots, N \text{ then } U_{ij} = \text{Random}(0 \sim U_{\max})$$

$$\text{If } U_{ij} = U_{\max} \quad \forall j = 1, 2, \dots, N \text{ then } U_{ij} = \text{Random}(U_{\min} \sim 0)$$

$$\text{If } U_{ij} = U_{\max} \quad \{ \forall j = 1, 2, \dots, M; M < N \} \text{ then } V_{ij} = 1 \{ j = \text{Random} \}$$

Fig.1 shows the powerful competition among the neurons and Fig.2 shows the evolution of energy function and the controlling temperature of 8 queens problems in our algorithm.

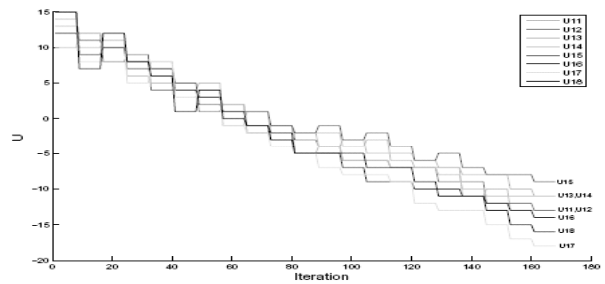


Fig. 1. The Competitive process of eight neurons when using our novel neural network to solve 8-Queens problem.

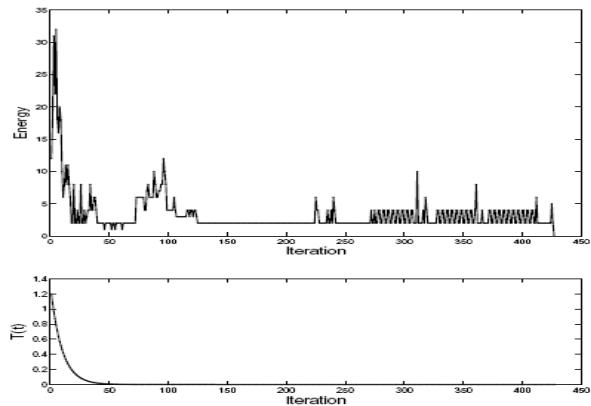


Fig. 2. The evolution of energy function and the controlling temperature of the 8 queens problems in our proposed algorithm.