

MODULAR NETWORK SOM (MNSOM): A NEW POWERFUL TOOL IN NEURAL NETWORKS

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Abstrak

Pada paper ini diperkenalkan suatu arsitektur baru dalam jaringan syaraf tiruan, yang disebut sebagai modular network SOM (mnSOM). mnSOM adalah suatu generalisasi dari Self Organizing Maps (SOM) yang dibentuk dengan mengganti unit-unit node pada SOM dengan modul-modul fungsi. Modul fungsi ini dapat berupa suatu multi layer perceptron, recurrent neural network atau bahkan SOM itu sendiri. Karena memiliki fleksibilitas yang sangat tinggi, maka mnSOM menjadi tool yang sangat bermanfaat dalam bidang jaringan syaraf tiruan.

Kata kunci: modul-modul fungsi, generalisasi dari SOM, mnSOM

Abstract

In this paper, a new powerful method in artificial neural networks, called modular network SOM (mnSOM) is introduced. mnSOM is a generalization of Self Organizing Maps (SOM) formed by replacing each vector unit of SOM with function module. The modular function could be a multi layer perceptron, a recurrent neural network or even SOM itself. Having this flexibility, mnSOM becomes a new powerful tool in artificial neural network.

Keywords: function modules, generalization of SOM, mnSOM

1. INTRODUCTION

Artificial Neural Networks, commonly referred as "Neural Networks" is one of the major research areas in artificial intelligence. Using neural networks, scientists try to solve many problems by mimicking learning mechanism of human brain. Generally speaking, there are two major learning strategies of neural networks. First is supervised learning. Multilayer perceptron and Radial Basis Function are examples of famous neural networks architecture which are trained in supervised way. The later is unsupervised learning. The most successful unsupervised learned network is Kohonen model of Self Organizing Maps (SOM) [1].

SOM can only deal with vectorized data. To cope with this difficulty, many modifications to the standard algorithm have been proposed [1]. Most of the modification is by changing competitive process or adaptive process in the standard SOM algorithm. In 2003, Tokunaga et.al. [2] proposed a generalization of SOM algorithm called modular network SOM (mnSOM). The idea is quite simple: replace each nodal unit in SOM by a function module. By choosing an appropriate function module according to the task, the mnSOM deals with not merely vector data but also deals with functions, systems and manifolds. By employing a multi layer perceptron (MLP) for example, the mnSOM learns input-output relations as a set of function and simultaneously generates feature maps representing the relations.

This paper aims to introduce mnSOM and discuss its further application. The rest of this paper is organized as follows. Section II briefly explains architecture and algorithm of mnSOM. Successful applications of mnSOM are given in Section III. Finally Section IV concludes the paper by discussion of future research direction on mnSOM.

2. THE MNSOM

mnSOM is an extension of SOM in which each vector unit is replaced by function module. Studying the mnSOM means studying SOM more deeply. In this section theoretical

aspect of mnSOM will be discussed briefly, starts from brief explanation on SOM theory followed by discussion on mnSOM.

2.1. Self Organizing Maps [1]

The principal goal of self-organizing maps is to transform an incoming signal pattern of arbitrary dimension into one or two dimensional discrete map and to perform this transformation adaptively in a topologically ordered fashion, as shown Fig. 1.

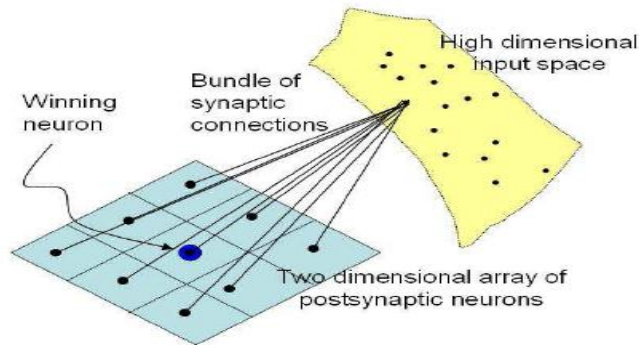


Fig.1 Kohonen model of SOM

There are two ways to train SOM, on-line learning and batch learning. From weight adaptation point of view, on-line learning always make weight adaptation on every single data being presented to the network, on the other hand batch learning SOM make weight adaptation after all of data being presented to the network.

SOM algorithm consists of 4 processes [1]:

1. Evaluative Process

After initializing synaptic weights in the network, for each input pattern, the neuron in the network compute their respective values of a discriminant function.

$$E_i^k = \frac{1}{2} \|x_i - w^k\|^2 \quad \text{for all } k \quad (1)$$

In this equation, x_i and w^k are input pattern and synaptic weight, respectively

2. Competitive Process

Using the discriminant function in equation (1) as the basis for competition among the neurons, the particular neuron with the largest value of discriminant function is declared as winner of the competition. Using Euclidean criterion, the winner of the competition is neuron which gives minimum Euclidean distance to the particular input pattern.

$$k_i^* = \arg_k \min E_i^k \quad (2)$$

3. Cooperative Process

Using the topological neighborhood centered at the winning neuron, a set of excited neurons is determined.

On-line learning:

$$\phi_i^k = h(k, k_i^*) \quad (3)$$

Batch learning:

$$\psi_i^k = \frac{h(k, k_i^*)}{\sum_{i'} h(k, k_{i'}^*)} \quad (4)$$

using Gaussian neighborhood function :

$$h(k, k_i^*) = \exp\left[-\frac{l^2(k, k_i^*)}{2\sigma^2}\right] \quad (5)$$

where $l^2(k, k_i^*)$ is lateral distance to the winning neuron. The parameter σ is the effective width of the topological neighborhood. Usually the size of topological neighborhood shrinks with time. In this case, σ can be chosen in the form of:

$$\sigma(t) = \sigma_{\min} + (\sigma_{\max} - \sigma_{\min}) \cdot \exp(-t/\tau) \quad (6)$$

where τ is time constant.

4. Adaptive Process

In adaptive process each synaptic weight of the network were updated using the following equations:

On-line learning:

$$\Delta w^k = \eta \sum_i \phi_i^k (x_i - w^k) \quad (7)$$

η is learning rate parameter, and this parameter can be decreasing with time such as

$$\eta(t) = \eta_{\min} + (\eta_{\max} - \eta_{\min}) \cdot \exp(-t/\tau_1) \quad (8)$$

Batch learning:

$$\Delta w^k = \sum_i \psi_i^k x_i \quad (9)$$

where ψ_i^k is normalized neighborhood function stated in equation 4.

2.2. Modular Network SOM (mnSOM)

The mnSOM consist of an array of function modules on a lattice. Type of function module is determined by designer. For dynamical system, a recurrent neural network (RNN) is a good candidate [3]. An example of the architecture of mnSOM with RNN modules is shown in Fig. 2.

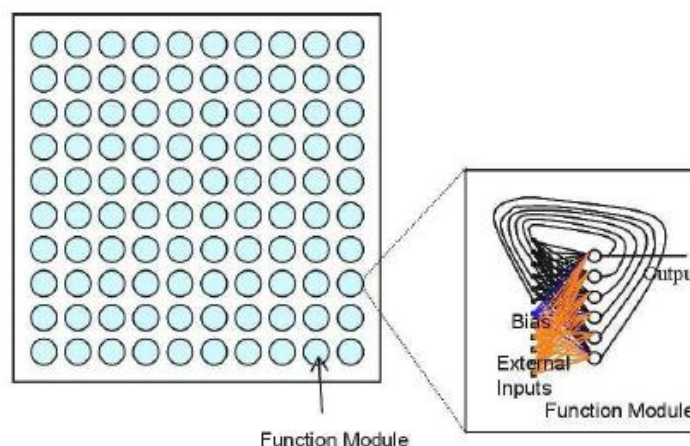


Fig 2. mnSOM architecture [4]

A learning algorithm of mnSOM is similar to that of the batch learning SOM. It consists of four processes [2][3]: evaluative, competitive, cooperative and adaptive processes. Let a set of input-output signals of a dynamical system be $\{x_{ij}, y_{ij}\} (i = 1, \dots, M; j = 1, \dots, L)$, where M and L are the number of data classes and the number of each data in each class, respectively.

1. Evaluative process

Inputs $\{x_{ij}\}$ are entered to all modules, and the corresponding outputs $\{\tilde{y}_{ij}^{(k)}\}$ are evaluated by:

$$E_i^{(k)} = \frac{1}{L} \sum_{j=1}^L \left\| \tilde{y}_{ij}^{(k)} - y_{ij} \right\|^2 \quad (10)$$

$$k = 1, \dots, K; i = 1, \dots, M; j = 1, \dots, L$$

where k stands for the module number, K stands for the number of modules, i stands for the number of data classes, and j stands for the data number in each class.

2. Competitive process

The module with the minimum $E_i^{(k)}$ with respect to k is the winner for data class i .

$$k_i^* = \arg_k \min E_i^{(k)} \quad (11)$$

3. Cooperative process

Learning rates of the modules are determined by the following normalized neighborhood function:

$$\Psi_i^{(k)}(t) = \frac{\phi(r(k, v_i^*); t)}{\sum_{i'=1}^M \phi(r(k, v_{i'}^*); t)}; t = 1, \dots, T \quad (12)$$

$$\phi(r; t) = \exp\left[-\frac{r^2}{2\sigma^2(t)}\right] \quad (13)$$

$$\sigma(t) = \sigma_{\min} + (\sigma_{\max} - \sigma_{\min})e^{-\frac{t}{\tau}} \quad (14)$$

where $r(k_1, k_2)$ stands for the distance between module k_1 and module k_2 , t is the iteration number in mnSOM, T is the number of iterations in mnSOM, σ_{\min} is the minimum neighborhood size, σ_{\max} is the maximum neighborhood size, and τ is a neighborhood decay rate. mnSOM terminates when no significant change is observed in the resulting map.

4. Adaptive Process

Suppose that RNN is employed as function module, connection weights are modified by Backpropagation Through Time (BPTT) learning as follows,

$$\Delta \mathbf{w}^{(k)} = \sum_{i=1}^M \Psi_i^{(k)}(t) \left(-\eta \frac{\partial E_i^{(k)}}{\partial \mathbf{w}^{(k)}} \right) \quad (15)$$

where $\mathbf{w}^{(k)}$ is the connection weights in module k . Fig. 3 summarizes a learning algorithm of mnSOM.

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Initialization and Initial evaluative process
for t=1 to T
  Competitive process (Eq.(11))
  Cooperative process (Eqs.(12), (13) and (14))
  for p=1 to P
    for i=1 to M
      for j=1 to L
        for k=1 to K
          BPTT learning (Eq. (15))
        end
      end
    end
  end
end
end
end

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Fig. 3 Summary of mnSOM Training Algorithm [4]

3. SUCCESSFUL APLICATIONS OF mNSOM

Since introduced in 2003, mnSOM has applied in wide areas. Tokunaga et.al.[3] used mnSOM with MLP modules to generate map of weather of Japan based on meteorological data: atmospheric pressure, temperature, humidity and sunshine hours. Using the resulting map, they can predict weather characteristic of unknown places.

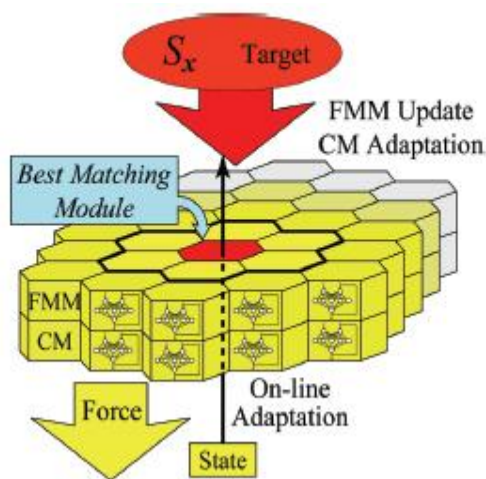
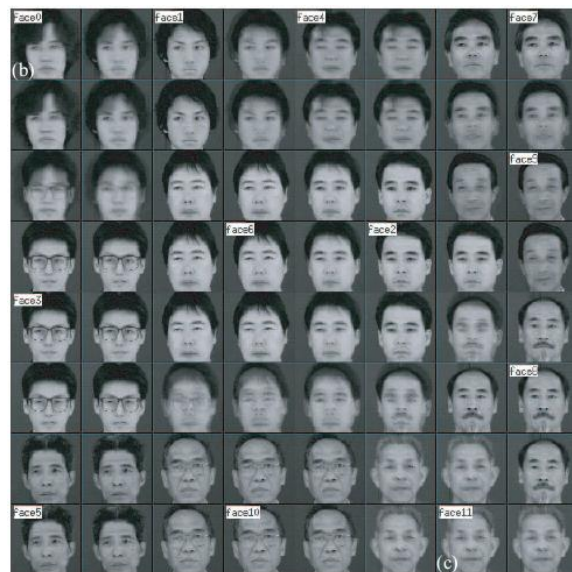


Fig. 4 Controller for AUV[9] based on mnSOM.

Fig. 5 Face Maps Generated by SOM² [11]

T. Minatohara et.al.[13] first applied mnSOM in control with their proposal of Self Organizing Adaptive Controller (SOAC) for controlling inverted pendulum. One year later, S.Nishida et.al. [9] proposed mnSOM to control their "Twin Burger" Autonomous Underwater Vehicle (AUV). Fig.4 depicts the structure, and Face Maps Generated by SOM² in Fig.5 stand for Forward Model Modules and Controller Modules, respectively. M. Aziz Muslim et.al. [4-8] proposed task segmentation in mobile robot by mnSOM followed by a graph-map approach. Accordingly complex navigation task of mobile robot can be simplified to some extent.

Special mnSOM class, called SOMⁿ, has been proposed by T.Furukawa [10]. Here, the function module is SOM itself. This is followed by the proposal of Self Organizing Homotopy [11] claimed as a foundation for brain-like intelligence. Application of SOMⁿ can be found in [12]. In that paper, SOM² is used for face recognition.

4. CONCLUDING REMARKS

As a generalization of SOM, mnSOM inherits all of advantageous and disadvantageous of SOM. In addition it also has advantageous over conventional SOM, since mnSOM can deal with un-vectorized data.

Many function modules have been tried successfully, such as Elman networks, fully connected RNN, MLP, Neural Gas and SOM itself. However, still so many neural networks architecture remain untouched, for example radial basis functions family. It is also interesting to include stochastic process in the function module of mnSOM.

Recent application of mnSOM deals with off-line data only. It is challenging to use mnSOM in real-time. Although current version of mnSOM algorithm does not provide with this capability, we believe that by minor modification on the standard algorithm, mnSOM can deal with real-time data. As a relatively new approach, mnSOM still has many open questions to answer and has wide application area which is remain untouched. Hence, extensive research on mnSOM is our common task.

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