# A Robust Energy Artificial Neuron Based Incremental Self-Organizing Neural Network with a Dynamic Structure

Hao Liu, Haruhiko Sato, Satoshi Oyama, Masahito Kurihara
Graduate School of Information Science and Technology
Hokkaido University
Sapporo 060-0814, Japan
liuhao@complex.eng.hokudai.ac.jp, haru@complex.eng.hokudai.ac.jp, oyama@ist.hokudai.ac.jp, kurihara@ist.hokudai.ac.jp

***Abstract*—Self-organizing neural network which is an unsupervised learning algorithm is to discover the inherent relationships of data. Such technique has become an important tool for data mining, machine learning and pattern recognition. Most self-organizing neural networks have a difficulty in reflecting data distributions precisely if data distributions are very complex. And meanwhile, it is also hard for these algorithms to learn new data incrementally without destroying the previous learnt data. In this paper, we propose a robust energy artificial neuron based incremental self-organizing neural network with a dynamic structure (REISOD). It can adjust the scale of network automatically to adapt the scale of the data set and learn new data incrementally with preserving the former learnt results. Moreover, several experiments show that our algorithm can reflect data distributions precisely.**

***Keywords-self-organizing; unsupervised learning; neural network; incremental learning; SOM; REISOD;***

## I. INTRODUCTION

Over the past decade, neural networks, especially self-organizing neural networks, have become one of important techniques in data mining, machine learning, pattern recognition and some other related fields. Self-organizing map (SOM) [1] is one of most well-known algorithms in self-organizing neural network. A standard SOM has a predefined scale of the network which usually consists of a set of neurons arranged in a 2-D structure. Each neuron is attached to a weight that is adjusted during training process by a learning strategy called simple competitive learning (SCL), which means an input data is assigned to the neuron that is the closest to the input data [2]. The weight of the winner and weights of its neighborhoods will be updated. When the training is finished, SOM divides the input space into several regions which represent clusters in the original input space. The topology of input data is preserved in the corresponding low dimensional structure. These advantages let SOM achieve a huge success in the development of neural network.

However, most classical self-organizing neural networks are generally facing two problems at the same time. The first one is the fixed structure of the network, which let them to be weak on adapting complex distributions of data. The second one is the so-called stability and plasticity dilemma that means learning new data will also destroy the previous learnt data [19], which results in a difficulty in implementing an incremental algorithm.

In this paper, we propose a new self-organizing neural network to solve these two problems which are mentioned above. The proposed algorithm called Robust Energy artificial neuron based Incremental Self-Organizing neural network with a Dynamic structure (abbreviated as REISOD). REISOD is realized based on energy artificial neuron (EAN) model, which is a generalized artificial neuron model. EAN is usually used to facilitate establishing a neural network with a dynamic network. The main contributions of REISOD are summarized as follows:

1) Data can be learnt incrementally and robustly, which means the sequence of inputting data will not affect the result of learning and previous learnt structure will not be destroyed by learning a new data.
2) It is not necessary to predefine the scale of the network, because REISOD can change the scale of network dynamically.
3) The data distributions with complex structures can be reflected precisely with almost no dead neurons appearing in the result.

The rest of this paper is organized as follows: the related work is described in Section II. The energy artificial neuron is proposed in Section III. We present the new algorithm, REISOD, in Section IV. Experimental results are presented in section V. Finally, we give the conclusions and discussions about the future work briefly in Section VI.

## II. RELATED WORK

Most self-organizing neural networks are unsupervised learning algorithms, which indicate that the only available information is a data set and there is no any external information about the desired output. The aim of this learning framework is to find the inherent relationships of the data. Self-organizing map (SOM) is an unsupervised learning algorithm

and it is designed on the simple competitive learning (SCL) to learn the relationships of data [1], [2], [6]. But some limitations still exist in SOM. First, dead neurons, neurons which will not learn in any case, may appear in the zero-density area of the original data distribution if the data distribution is complex (such as a non-convex shaped data distribution). Second, SOM can't overcome the so-called stability-plasticity dilemma. Third, SOM must predefine the scale of the network before training, which results in a difficulty of selecting an appropriate parameter for the network. To improve the limitation of a fixed structure, self-growing and self-organizing networks have been attracted by many researchers. This improved approach usually has a feature of growing, which means that they can dynamically increase their structure according to the input vector. Some of those techniques are considered as follows: growing cell structures (GCS) is an improved algorithm based on the concepts of SOM [3]. The network of GCS is organized by triangles, which is defined by the nodes and the connections between nodes. Each triangle cover the area of input space of nonzero distribution, and the whole network try to cover all over those areas. But it has some problem with visualizing high-dimensional data into a low dimension space with their topology, because the whole process is performed in the input space whose dimension might be very high, which is very hard to understand. Growing neural gas (GNG) an algorithm based on neural gas (NG), which begins with two neurons. During the training procedure, new nodes are added as a similar way as GCS and two nodes with the highest activity are moved together with a link created between them. The algorithm ends when the stopping criterions are reached. Because of preserving the topology in the input space, GNG also has the visualizing problem as GCS [4], [5]. Cell-splitting grid (CSG) is a new approach of self–growing network, which simulate the mechanism of cell splitting in biological organ. Each neuron has an activation level which is decreased when its weight is adjusted. A neuron is split into four neurons when its activation level equals zero. The algorithm starts with one neuron and split existing neurons during the process of algorithm. The algorithm results in a regular square structure which can easily reflect the density in the input space [7]. Growing self-organizing map (GSOM) is an algorithm based on SOM. In contrast to SOM, after each training step, neurons can be added. Many neurons are added in the same time, as an entire row or a column, even a new dimension, so that GSOM can keep its regular shape [8]. More algorithms are also to be considered [9], [10], [11]. These algorithms overcome or partially overcome the limitation of fixed structure of SOM. However, some of them may have the limitation of slow growing which due to using local error as the condition of growing, or mean quantization error (MQE) as the convergence condition of the network. Besides, for some growing networks, how to reflect the distribution precisely and how to learn new data as an incremental way are still to be settled.

## III. Energy Artificial Neuron Model

### A. Motivation of Energy Artificial Neuron Model

EAN model is motivated by a biological cell called glial cell. Actually, the central nervous system (CNS) can be separated into two kinds: neurons and glial cells. In the past biologic researches, neurons were regarded as the active and main objects in the neural activities. And glial cells were viewed as passive elements which just provide structural and metabolic support to the neurons. However, recent studies show that glial cells play a very important role in the information processing and it has been proved that glial cells are related to the growth of neurons. These biologic researches demonstrate that glial cells are responsible to complex and important functions in nervous system, such as growing of synapse, constructing nervous system, learning and memories [12], [13], [14], [15], [16]. So, in a brief conclusion, the brain should be regarded as a system consisted of both neurons and glial cells, not only neurons [17]. The main feature of biological glial cell is its physical structure supporting and energy supplement. So the important thing is how the glial cell affects the synaptic activities by energies which are in the form of adenosine triphosphate (ATP) [18]. These biological features are surely heuristic to set up an artificial network with a dynamic structure.

### B. Energy Artificial Neuron Model

In this part, we introduce a new artificial neuron model called energy artificial neuron (EAN) model, which brings the concept of energy to the traditional M-P artificial neuron model. The main contribution of EAN model is providing the threshold of network growing. However, to avoid increasing the complexity of the network system, only the energy feature is extracted and implemented in the artificial neural networks.

**Definition 1** Given an *n*-dimensional data set, EAN model is defined by a 7-tuples:

$$\boldsymbol{EAN} = \langle \boldsymbol{X}, \boldsymbol{O}, \boldsymbol{M}, \boldsymbol{I}, \boldsymbol{F}, \boldsymbol{E_{AN}}, \boldsymbol{L_{AN}} \rangle,$$

where:

X is a vector $\mathrm{X} = (\mathrm{x_1}, \mathrm{x}, \dots, \mathrm{x_n})^{\mathrm{T}}$, called input vector.

O is the output.

M is a unit of local memory which has two components: $\mathrm{M} = \mathrm{M_w} \cup \mathrm{M_L}$,where $\mathrm{M_w}$ is the STM (Short Term Memory) and $\mathrm{M_L}$ is the LTM (Long Term Memory).

I is the integrated mapping.

F is the activation function which can be: $\mathrm{O} = \mathrm{F}(\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{X_i W_i} - \theta)$, where θ an activation threshold.

$\mathrm{E_{AN}}$ is the total energy of the current neuron.

$\mathrm{L_{AN}}$ represents the generalized Hebb learning rule.

EAN model is a generalized artificial neuron model which can be extended to a specific situation in designing a network with a dynamic structure. A simplified figure is shown in Fig. 1a. The main difference of EAN model from the classical neuron model is considering energy when the connection of two neurons is going to be created.

**Definition 2** Given an $EAN_i$, the total energy of this neuron, denoted as $\boldsymbol{E_{AN}^{(i)}}$, is defined as:

$$\boldsymbol{E_{AN}^{(i)}} = \boldsymbol{E_{AN}^{consumption(i)}} + \boldsymbol{E_{AN}^{surplus(i)}},$$

where $E_{AN}^{consumption(i)}$ is the energy consumption and $E_{AN}^{surplus}$ is the energy surplus in $EAN_i$ currently.

The energy consumption means energy reductions are produced when two EANs establish a connection between each other. $E_{AN}^{consumption(i)} = \{e_{ij} | j = 1,2,\dots,m\}$, where $e_{ij}$ is the energy consumption when $EAN_i$ connects to another $EAN_j$ and $m$ is the total number of such connected $EAN$s.

**Definition 3** The total energy consumption of $EAN_i$ can be calculated by this formula below:

$$\boldsymbol{E_{AN}^{consumption(i)} = \sum_{j=1}^{m} e_{ij} = \sum_{j=1}^{m} \bar{e} \cdot \varepsilon_{ij}}$$

Further, each $e_{ij}$ is calculated by $e_{ij} = \varepsilon_{ij} \cdot \bar{e}$, where $\bar{e}$ is a fixed natural number that represents the average expectation of the energy consumption when a connection is created between $EAN_i$ and $EAN_j$, and $\varepsilon_{ij}$ is a factor of this energy consumption.

According to Definition 1 and Definition 2, energy is required when a connection is going to be created. So, given $EAN_i$ and $EAN_j$, EAN model has two features:

- **Feature 1** if $e_{ij} = \varepsilon_{ij} \cdot \bar{e} > E_{AN}^{surplus}$, the connection cannot be created.
- **Feature 2** When two EANs are disconnected, the energy surplus will recover to the amount of energy before the connection is created.
- **Feature 3** The energy in EAN model provides a threshold in the network growing. However, if the connection has been established, the connection-strength is determined by their connection weights, not the energy consumption.

## IV. Robust Energy Artificial Neuron Based Incremental Self-growing and Self-Organizing Neural Network with a Dynamic Strucure

In this section, we propose the robust energy artificial neuron based incremental self-growing and self-organizing neural network with a dynamic structure (abbreviated as REISOD). First, we introduce some basic concepts of REISOD, which construct the structure of network. Then, we give the training algorithm.

### *A. Concepts of REISOD*

**Definition 4** Neuron Unit (NU) is defined as a triplet:

$$\boldsymbol{EAN^{unit} = \langle G^{unit}, W_G, \Delta H_G^{unit}(t+1) \rangle},$$

where:

- $G^{unit}$ is a graph that is composed of six EANs placed as hexagon structure in 2-D. A $G^{unit}$ can be detailed as: $G^{unit} = \langle V_c, E_c \rangle$, where $V_c = \{EAN_i | i = 1,2,\dots,6\}$ is a set of EANs and $E_c = \{e_{ij} | i,j = 1,2,\dots,6\}$ is a set of connections.
- $W_G$ is a matrix of weights which are attached to the corresponding neurons.

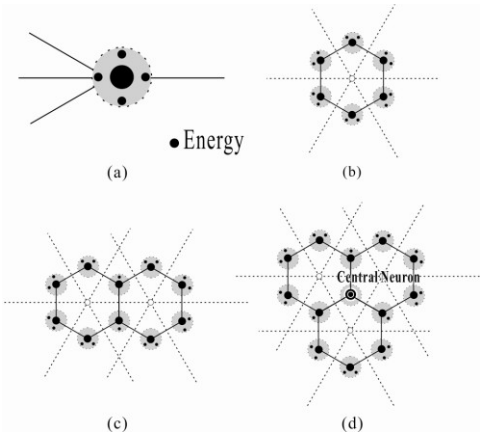


Fig. 1. (a) A Simplified EAN Model. The solid black points represent the energy surpluses. (b) A neuron unit (NU) topological graph. (c) Two connected NUs . (d) A treble neuron unit (TNU) topological graph with a central neuron (CN) locating in the topological center.

- $\Delta H_G^{unit}(t+1)$ is the entropy production of $EAN^{unit}$ at the moment of t+1, however, $\Delta H_G^{unit}(t+1)$ is a property of $EAN^{unit}$ at the moment of t.

Since the REISOD is an implementation of using EAN model as its basement, a NU has two features below:

- The total energy in each EAN is four, the average expectation of energy consumption, is defined as one and every factors of energy consumptions is one (i.e. $E_{AN} = 4, \bar{e} = 1, \ \varepsilon = 1$ ).
- The incremental entropy production in $EAN^{unit}$ can be calculate by Shannon Entropy:

  $$\boldsymbol{\Delta H_G^{unit}(t+1) = -\sum_{R \in S(R)} P(R_{t+1}) \log_2 P(R_{t+1})}$$

  where the $P(R_{t+1})$ is determined by the $E_{AN}^{surplus}$ at the moment of t.

Further, the structure of NU (See Fig. 1b) can be extended under the condition of energies. Let two NUs connect to each other with a public border and two public nodes, and then we can get a structure like what Fig. 1c shows. If three NUs connect with each other like what Fig. 1d shows, we can get a triple neuron unit structure. Similarly as the definition of NU, we give the definition of the triple neuron unit.

**Definition 5** Triple Neuron Unit (TNU) is defined as:

$$\boldsymbol{EAN^{unit3} = \langle G^{unit3}, W_G, \Delta H_G^{unit3}(t+1) \rangle}$$

The graph of a TNU has 13 nodes and 15 connections in total.

**Definition 6** Central Neuron (CN) is an EAN which locates at the central of topological graph of TNU.

Since the network which has a dynamic structure is designed as graph, $G_N = \langle V_N, E_N \rangle$, we define a graph called growing point for extending the current network.

**Definition 7** Growing point (GP) is defined as a graph:

$$\boldsymbol{GP = \langle V_G, E_G \rangle}$$

where:

- $V_G = \{EAN_i | i = 1,2, \dots, n\}$ is a set of EANs in GP.
- $\mathrm{E_G} = \{\mathrm{e_{ij}} | \mathrm{i, j} = 1,2, \dots, \mathrm{m}\}$ is a set of connections existing in GP.

Moreover, a GP must meet two conditions as follows:

- To get a regular shape for the network, the topological graph of a GP must be a proper sub-graph of NU; the nodes existing in GP and the new nodes must be placed in a hexagon-topology strictly. In another word, each EAN in GP must meets: $\mathrm{GP} \subset \mathrm{G_t}$ and $\mathrm{GP} \subsetneq \mathrm{G^{unit}}$

  where $\mathrm{G_t}$ is the current network topology.
- Each EAN in GP must have enough energy. So, according to the feature1 of EAN model, $\forall \mathrm{EAN_i} \in \mathrm{GP}$ must meet: $\sum_{\mathrm{i=1}}^{\mathrm{n}} \bar{\mathrm{e}} \cdot \varepsilon_{\mathrm{ij}} < \mathrm{E_{AN}^{surplus}}$

A GP has two following features:

- When the network is growing, a new NU must be created based on a GP. Due to the structures, existing nodes in GP will become public nodes after grown.
- The energies in EAN will reduce when the network is growing because new connections have been established. The energy decrement $\Delta \mathrm{E_{AN}^{unit}}$ can be calculated by:

  $$\Delta \boldsymbol{E_{AN}^{unit}} = \sum_{i=1}^{n} \Delta \boldsymbol{E_{AN}^{consumption(i)}} = \sum_{i,j=1}^{n} \bar{\boldsymbol{e}} \cdot \boldsymbol{\varepsilon_{ij}}$$

  where $\Delta \mathrm{E_{AN}^{consumption(i)}}$ is each energy decrement, and according to the definition of NU, the $\Delta \mathrm{E_{AN}^{unit}}$ can be simply calculated by the amount of nodes in GP:

  $$\Delta \boldsymbol{E_{AN}^{unit}} = \sum_{i=1}^{n} \Delta \boldsymbol{E_{AN}^{consumption(i)}} = \boldsymbol{n}$$

  where n is the amount of nodes in GP.

It is possible that there are many GPs when the network is growing. However, the network must know which the best GP is. Here, the best GP is called the optimal growing point (OGP). We give a competition rule to find the OGP, which is described as below:

- The GP which will become OGP must insure that the production entropy of current network must be the minimum one among all the GPs in time t+1.
- At least one neuron which has the max similarity with the current input data, $X$, must exists in OGP.

Based on this competition rule, the optimal growing point is defined as:

**Definition 8** Optimal growing point (OGP) is a GP which meets:

$$\Delta \boldsymbol{H_{G'_{optimal}}^{unit}}(\boldsymbol{t+1}) \leq \Delta \boldsymbol{H_{G'_i}^{unit}}(\boldsymbol{t+1})$$

and

$$\left\| \boldsymbol{X} - \boldsymbol{W_{C^{optimal}}} \right\| \leq \left\| \boldsymbol{X} - \boldsymbol{W_{C_i}} \right\|.$$

where $G'_i$ is any GP in time t, and $W_{C_i}$ is the weight of any neuron in $G'_i$ in time t.

**Definition 9** Given the current input data, $X_i$, the cover domain neuron (CDN) is a neuron whose weight meets:

$$\|\boldsymbol{W} - \boldsymbol{X_i}\| \leq \boldsymbol{\xi},$$

Where $W$ is the weight of this neuron, $\boldsymbol{\xi}$ is a user parameter and $\|\boldsymbol{W} - \boldsymbol{X_i}\|$ means calculating the Euclidean distance between $\boldsymbol{W}$ and $\boldsymbol{X_i}$.

The CDN is used to describe a hyper-sphere in the high-dimension space. The weight $\boldsymbol{W}$ and the parameter $\boldsymbol{\xi}$ are the centre and the radius of this hyper-sphere, respectively.

*B. Training Algorithm*

Given a $n$-dimensional data set, $R^n$, the training algorithm of REISOD is described as follow:

**Step 1** Input a data $X_i$ from $R^n$ randomly.

**Step 2** Initialize the network by generating a TNU structure, $EAN_{first}^{unit3}$, which has to meet:

$$\forall \boldsymbol{EAN_i} \in \boldsymbol{EAN_{first}^{unit3}} \rightarrow \boldsymbol{W_i} = \boldsymbol{X_i}$$

**Step 3** Obtain an OGP according to Definition 8.

**Step 4** If a neuron becomes a CDN or the count of learning steps has reached to a threshold $\boldsymbol{\sigma}$, the network will generate a new NU structure at the OGP in time t. the weights of EANs added in new generated NU can be calculated by:

$$\boldsymbol{W_{new}} = \begin{cases} \boldsymbol{W_c} & EAN_{new}\ is\ diagonal\ to\ CN \\ \boldsymbol{W_{adjacent}} & EAN_{new}\ is\ adjacent\ to\ OGP \end{cases}$$

where $W_c$ is the weight of CN in the new formed TNU and $W_{adjacent}$ is the weight of neurons in the OGP, which is adjacent to the new EAN in time t+1.

If the neuron in the central topological graph becomes a CN in time t+1, the weights of neurons in OGP will be adjusted by:

$$\boldsymbol{W_{(t+1)}} = \begin{cases} \boldsymbol{W_{(t)}} + \boldsymbol{\eta_{max}} \cdot \Delta \widehat{\boldsymbol{W}}_{\boldsymbol{it}} & \boldsymbol{V_t} = \boldsymbol{V_c} \\ \boldsymbol{W_{(t)}} + \boldsymbol{\eta_{topo1}} \cdot \Delta \widehat{\boldsymbol{W}}_{\boldsymbol{it}} & \boldsymbol{V_t} = \boldsymbol{V_{topo1}} \\ \boldsymbol{W_{(t)}} + \boldsymbol{\eta_{topo2}} \cdot \Delta \widehat{\boldsymbol{W}}_{\boldsymbol{it}} & \boldsymbol{V_t} = \boldsymbol{V_{topo2}} \end{cases}$$

where $V_{topo1}$ and $V_{topo2}$ are two neurons which are adjacent to the CN. In addition, $\boldsymbol{\eta}$ is the learning-efficiency, where $\eta_{topo1}$, $\eta_{topo2}$ and $\eta_{max}$ are three different learning-efficiency corresponding to $V_{topo1}$, $V_{topo2}$ and $V_c$. Make sure that $\eta_{max}$ is the biggest one. The $\Delta \widehat{W}_{it}$ is a normalized vector towards the data $X_i$, which can be calculated as below:

$$\Delta \widehat{\boldsymbol{W}}_{\boldsymbol{it}} = \frac{\boldsymbol{X_i} - \boldsymbol{W_t}}{\|\boldsymbol{X_i} - \boldsymbol{W_t}\|}$$

$$= \left( \frac{X_i^1 - W_t^1}{\sqrt{\sum_{j=1}^{n} \left(X_i^j - W_t^j\right)^2}}, \frac{X_i^2 - W_t^2}{\sqrt{\sum_{j=1}^{n} \left(X_i^j - W_t^j\right)^2}} \dots, \frac{X_i^k - W_t^k}{\sqrt{\sum_{j=1}^{n} \left(X_i^j - W_t^j\right)^2}} \right)^{\boldsymbol{T}}$$

**Step 5** If a neuron becomes to a CDN, reserve its weight and generate a new NU, then input next data until all the data have been input into the network, or go back to the Step3.

**Step 6** if a neuron did not become to a CN and no adjacent neurons are CDNs, deletes this neurons and its adjacent neurons. By deleting operating, the network could form clusters by the connectivity of neurons.

**Step 7** Combine $\mathrm{CDN}_i$ and $\mathrm{CDN}_j$, if $\left\|\mathrm{CDN}_i - \mathrm{CDN}_j\right\| < \boldsymbol{\xi}$

**Step 8** Finally, combine all the adjacent neurons and calculate the decision domains, $D_c$ , which are the volumes of corresponding hyper-spheres in the corresponding dimensional space:

$$\boldsymbol{D_c = \cup_{i=1}^{n} Vol_{EAN_i}}$$

Check whether all the data in $R^n$ have been input into the network, or go back to the Step 2.

## V. Experimental Results

### A. Robustness of Adpating Complex Distributions of Data.

In this experiment, two artificial data sets are designed to verify whether REISOD is robust when it deals with data which distribute in a complex structure. Two data sets are illustrated in Fig. 2. The experiments are compared with a variant of SOM. It uses link-distance instead of using Euclidean distance. Additionally, for the winning neuron, $n_i$, its neighborhood is defined by $N_i(d) = \{j, d_{i,j} < d\}$ . Neighborhood $N_i(d)$ contains the indices for all of the neurons that lie within a radius *d* of the winning neuron.

Data set 1 has 998 data, which is shown in Fig. 2a. There are two ring-shaped clusters with the smaller one locating in the bigger one. Besides, there is also a band-shaped cluster inserting into two ring-shaped clusters. The dimension of data is two.

Data set 2 has 1386 data in total and each data is two-dimensional. There are four clusters in data set 2. A cluster on the top represents a twisty shape and another three smaller clusters locate below the top one (See Fig. 2b).

In the experiment on the data set 1, SOM uses a 20-by-20 hexagonal topological network. Let the initial value of neighbor radius equals 3, the steps for shrinking of neighborhood is 100 and global max iteration is 1000. The result on data set 1 by SOM is shown in Fig. 3a. We can see that there a lot of dead neurons appearing in the gaps of each cluster, where are the zero density areas. Besides, all the neurons are connected with each other, which we cannot read any information about the clusters directly by the connectivity of neurons. We can observe a similar result on the data set 2, which is shown in Fig. 3c. The parameters are selected as: 20-by-20 scale for the network, initial value for the radius of neighborhood is 5, 100 for the shrinking step and 1000 for max number of iteration. On the other side, REISOD can reflect the distributions of data set 1 more precisely than the result of SOM. Moreover, we can see there three clusters in this data set, which is directly shown by the connectivity of neurons (See Fig. 3b). For data set 2, REISOD get a similar result of the previous one, which is shown in Fig. 3d.

Experiments on these two data sets show REISOD could reflect the data distributions precisely and almost no dead neurons appear in the result.

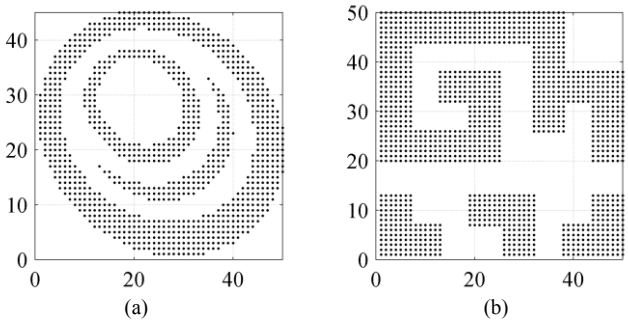

Fig. 2. Artificial datasets. (a) data set 1. (b) data set 2.

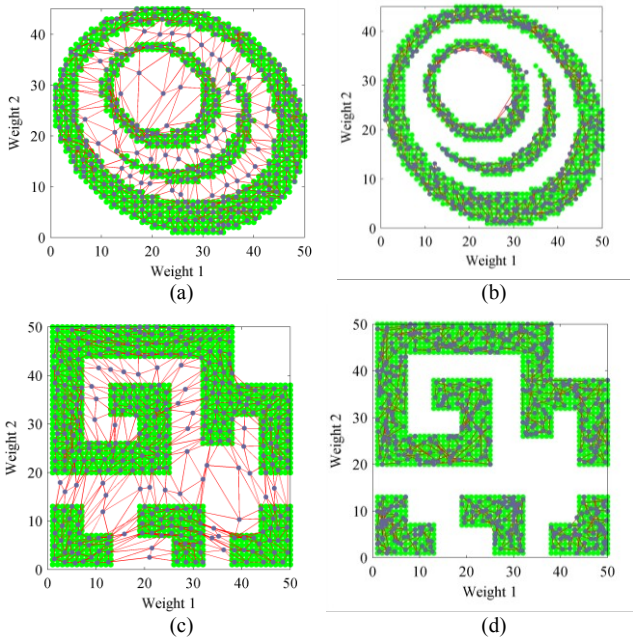

Fig. 3. Experimental results. (a) SOM on data set 1. (b) SOM on data set 2. (c) REISOD on data set 1. (d) REISOD on data set 2.

### B. Incremental Learning

In this part, we use data set 2 as the testing data to verify whether REISOD can get a good performance in the incremental learning. Here, data is selected randomly and input one by one into the algorithm. We select six snapshots from the procedure of learning in this experiment, which is shown in Fig. 4. At the early steps of learning, there are many groups of neurons in the result, because REISOD gives a result only according to the current data. Since the data is given randomly, is possible that the amount of given data may not sufficient to represent the global distribution of the data set. But with more data given in the later, the number of groups is reduced and some small groups are combined to form a large group. Finally, REISOD successfully reflects the global distributions of the data set precisely.

This experiment shows that learning a new data will not bring damage to the previous leant structures and the sequence of the inputting will not affect the result of learning, because the data is input randomly.

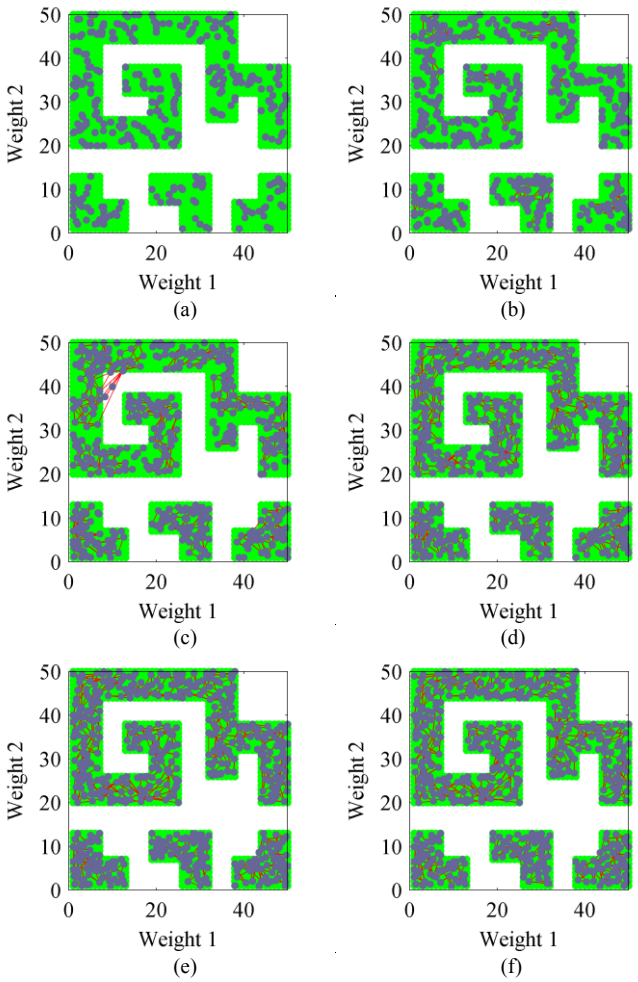


Fig. 4. Snapshots in incremental learning by REISOD. Let n is the number of data which have been learned. (a) n =250. (b) n = 500. (c) n =750. (d) n = 1000. (e) n =1250. (f) n = 1386 (final).

## VI. CONCLUSIONS

In this paper, we propose a new self-organizing neural network called REISOD, which is the robust energy artificial neuron based self-organizing neural network with a dynamic structure. The main contributions of REISOD are summarized as follows:

4) REISOD can learn data incrementally and robustly, which means the sequence of inputting will not affect the result of learning and the algorithm can learn new data without destroying the structures of the current network.

5) REISOD can change the scale of network dynamically, which means it is no need to predefine the scale of the network.

6) REISOD could reflect the data distributions precisely and it is robust to adapt complex distributions of data with almost no dead neurons in the result.

The application of this work can be applied in clustering, classification, data mining and some other related subjects. But so far it can only deal with numeric data and the basic structure of the network is hexagon. However, it may be possible to implement with other kinds of structures, such as grid or triangle structure. We will do further researches on these topics.

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