Neuronal Self-Regulation Networks for Subspace Decomposition

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***Abstract*— We propose a new learning paradigm of neural network and apply it to solve the subspace decomposition problem for feature analysis. In this proposed network, each neuron learns about the environment through a process of self-regulation which actively controls the neuron's own learning by perceiving its status in overall learning effectiveness. Based on this concept of self-regulation, we derive the primary learning rules of the synaptic adaptation in the network. The self-regulative neural network is utilized to explore significant features of the environment data in an unsupervised way and to implement subspace decomposition of the data space. Numerical simulations demonstrate the efficiency of the learning model and verify the practicability of the concept of individual neuron's self-regulation for learning control.**

***Index Terms*—Neural Networks, Subspace Decomposition, Dimensionality Reduction.**

I. Introduction

Most unsupervised neural networks utilize the Hebbian learning rules [1] to adapt their synaptic weights such that the output can reflect features of the input. Usually, various competitive learning models [2][3][4] are also employed in these networks. A representative example with wide-spread applications is the self-organization networks [5][6]. In the competitive learning models, the winner-take-all mechanism and the lateral inhibition are used for synaptic adaptation. Only the weights corresponding to the best-matching neuron or winning neuron clusters are changed responding to input with the Hebbian learning rules. However, the competitive process which decides the best-matching neuron for each learning involves intensive search and comparisons among all the neurons in the whole network. It implies that we need global arbitrators to perform such decision tasks for the competitive learning networks. Different to the Hebbian rules, there is no strong physiological evidence for the arbitrators. This encourages us to introduce new applicable neural network paradigm based on the Hebbian rules in a neurobiological manner.

To establish the paradigm, we utilize a concept of neuron's self-regulation. Considering an individual neuron in the learning process, we think a neuron learns about the environment through a process of self-regulation which actively controls this neuron's own learning not by expecting the arbitration feedback, but by perceiving its status in overall learning effectiveness. There are various self-regulation theories which have been proposed in many different aspects, for example, [7][8][9]. From these concepts, we attempt to construct a self-regulative learning model for individual neuron in accordance with the Hebbian learning. And further, we apply this model to develop the feature-analyzing networks.

Feature analysis refers to explore the intrinsic information contents of a set of input data. The effective features are found through different dimensionality reduction or subspace decomposition techniques. There are many well-studied neural networks proposed for this purpose, for example, [10]-[16]. Many applications, for example, face recognition, image coding, and robotics, are also reported. However, the arbitration among neurons in the lateral inhibitory process is usually needed in these networks. To implement the lateral process without arbitration, some of these networks employ decreasing number of outgoing connections which are pre- determined for different neurons. This leads to the results that the neurons with more specified lateral connections will have more impacts upon feature analysis in the learning process. Neurons hold different significance for the learning. The capability for fault tolerance, which is one important benefit of neural networks, will be diminished.

In this paper, we propose the self-regulation learning model and apply it to solve the subspace decomposition problem for feature analysis. The networks are constructed on the basis of fundamental neuronal models. Without arbitration process or varying-number connections for different neurons, the networks have the potential to be inherently fault tolerant. More importantly, this model is effective to solve the feature analysis problems. The simulation results will be presented in the paper to verify its effectiveness. This paper is organized as follows. In Section II, the concept of self-regulation is introduced. The primary learning rules of the synaptic adaptation in the networks are derived in Section III. Applications of the model to the subspace decomposition problem are described in Section IV. Experimental results and comparisons are shown in Section V. Finally, Section VI gives the conclusions and some discussions.

II. Neuron's Self-Regulation

Considering an individual neuron in network, all its synaptic weights are excitatory to the stimulus input. There are no inhibitory connections to other neurons. The concept of neuron's self-regulation, rather than competition or arbitration among neurons, is utilized to achieve overall cooperative learning in the whole network.

To a certain stimulus, one neuron has its own output responding to the input. Our primary interest is focused on the learning process without global arbitration and the synaptic adaptation to the stimulus using Hebbian learning. The real issue is how to know one's learning effectiveness in overall learning results. To an individual neuron, the learning effectiveness reflects its familiarity status with the stimulus. Without arbitrators, information about the status is completely out of conscious awareness.

The concept of neuron's self-regulation refers to one's control over the learning process according to its status with the activation to stimulus. The status information is obtained in an individual manner and evaluated from its environment. With certain learning goals, the evaluated status information can be utilized to control one's learning actively. While its status is superior, the synaptic weights are strengthened, but on the other hand, they are weakened for inferior status. After self-regulation of each neuron, the network will be trained to form an organized output mapping to all input stimuli.

Notations in the concept are formulated as follows. Given a set of n-dimensional data with zero mean, the m neurons in the self-regulation networks are employed to learn the features of the input space. Let $\mathbf{x} = [x_1, x_2, ... x_n]^t$ represents the input vector. The synaptic weight vectors are $\mathbf{W}= \{\mathbf{w}_1, \mathbf{w}_2, ... \mathbf{w}_m\}$ for the m neurons, respectively. Suppose that the overall output of the network responding to the input $\mathbf{x}$ is $\mathbf{u} = [u_1, u_2, ... u_m]^t$. Each neuron regulates its learning by perceiving the status in overall effectiveness. We introduce the learning status vector of the network $\mathbf{r} = [r_1, r_2, ... r_m]^t$. The status vector **r** will be a function of **x**, **u**, and **W**. Utilizing the vector **r** to indicate the learning status, the neuron's self-regulation model is constructed and the cooperative learning rules without arbitration are also derived.

III. Learning Model

A. The Network

Consider the network model used for the self-regulation. Figure 1 shows the basic network structure. The input vector **x** and the synaptic weight vectors $\{\mathbf{w}_1, \mathbf{w}_2, ... \mathbf{w}_m\}$ of all neurons have the same dimension *n*. Generally, the value of *m* is not greater than that of *n*. Note that the synaptic weight vectors of neurons in the network are all excitatory.

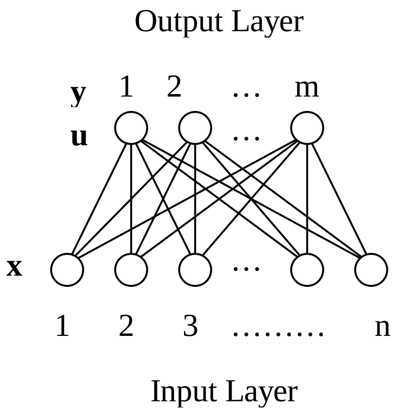

Fig. 1. A self-regulative neural network.

The output vector of neurons and the output vector of the network are denoted in **u** and **y**, respectively. The output vector of the network $\mathbf{y} = [y_1, y_2, ... y_m]^t$ can be regarded as the feature vector extracted for the input vector **x**. The relationship between **u** and **y** can be described with a rescaling form using the status vector **r** as follows

$$y_i = u_i r_i \tag{1}$$

or

$$\mathbf{y} = \mathbf{u}^t \mathbf{r}\,. \tag{2}$$

The rescaling extent varies in different processing neurons.

The synaptic weight vectors of neurons are $\{\mathbf{w}_1, \mathbf{w}_2, ... \mathbf{w}_m\}$, onto which the input vector **x** is to be projected using the inner projection

$$u_i = \mathbf{w}_i^t \mathbf{x} = \sum_j w_{ij} x_j \tag{3}$$

And all the synaptic weight vectors $\{\mathbf{w}_1, \mathbf{w}_2, ... \mathbf{w}_m\}$ are subject to the constraint of normal vectors with norm 1.

B. The Objective Function

To derive the learning rules, we use the objective function as a measure of learning performance for the network. The similarity between the input vector and the constructed vector can be measured by

$$E = \sum_{\mathbf{x}} \mathbf{x}^t \sum_i y_i \mathbf{w}_i\,. \tag{4}$$

The learning process is to adapt the synaptic weight vectors of the network to maximize the objective function *E*.

To maximize the function *E*, we can derive the learning rules for the synaptic weight vectors using

$$\mathbf{w}_i = \mathbf{w}_i + \Delta \mathbf{w}_i\,, \tag{5}$$

where

$$\Delta w_{ij} \propto \frac{\partial E}{\partial w_{ij}}\,. \tag{6}$$

C. The Status Vector

As described above, the status vector **r**, which indicates the neuron's learning effectiveness, plays a key role in the self-regulation model. Without global arbitration, only the parameters of neurons, **u**, **y**, and **W**, are available to evaluate it. Based on the concept of neuronal self-regulation, we thus define the status vector $\mathbf{r} = [r_1, r_2, ... r_m]^t$ as

$$r_i = \frac{u_i^2}{\sum_j u_j^2}. \quad (7)$$

Note that the denominator in (7) summarizes the squared output of all neurons. The network to evaluate it can be implemented by a fundamental neuronal model. Figure 2 shows the network, where U denotes the sum-of-squares denominator in (7).

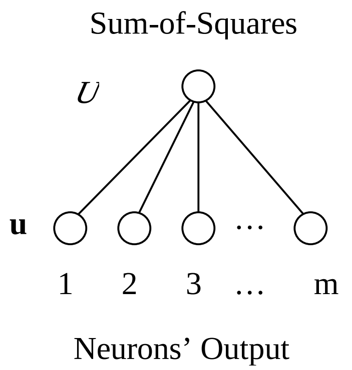

Fig. 2. Evaluation of the overall learning effectiveness in the network.

D. The Learning Rules

Using the definition of the status vector, the learning rules can be easily derived. Differentiating the objective function E with respect to the synaptic weight vectors yields the gradient

$$\frac{\partial E}{\partial w_{ij}} = 4 y_i x_j - \frac{2 E u_i x_j}{\|\mathbf{u}\|^2}. \quad (8)$$

After simplification, the synaptic updates in (5) can be expressed as

$$\Delta \mathbf{w}_i \propto 2 r_i u_i \mathbf{x} - \|\mathbf{r}\|^2 u_i \mathbf{x}. \quad (9)$$

Note that the derived learning rule in (9) have the form in accordance with the Hebbian learning. Each neuron's learning status to overall effectiveness takes part in the synaptic updates to control its adaptation. The larger the value of one's status is, the more the synaptic weights are updated, and vice versa. The self-regulation appears to realize the lateral inhibition among neurons, and the arbitration process is not needed in the learning process.

IV. SUBSPACE DECOMPOSITION

In this Section, we apply the self-regulation learning model to solve the subspace decomposition problem for feature analysis and demonstrate the simulation results in next Section. There are three main processes involved in the application of this model, including feedforward process, learning status evaluation, and synaptic adaptation. The algorithm to solve the subspace decomposition problem is listed as follows:

1. Initialization of **W**.
2. Sampling of **x** from the input space.
3. Calculating the output vectors, **y** and **u**.
4. Evaluating the learning status vector **r**.
5. Adjusting the synaptic weight vectors $\{\mathbf{w}_1, \mathbf{w}_2, \ldots \mathbf{w}_m\}$ according to the learning rule (9).
6. Continuation with the step 2 until no noticeable changes are observed.

V. EXPERIMENTAL RESULTS

We present two experimental results to demonstrate the proposed efficiency of the learning model and verify the practicability of the concept of neuron's self-regulation for learning control.

Firstly, a set of 400 two-dimensional input data is tested. The input is chosen from one of two groups of normally distributed random data with the same mean (5,20) and with the same variances (1,1/6). In Figure 3, the data are depicted as an illustration. We apply the self-regulation model to solve the eigen-decomposition problem, and compare the results with those by the principal component analysis. The experimental results are shown in Fig. 9(a) and 9(b), respectively.

From the results, we can observe that the neuronal self-regulation model compute the effect feature vectors associated with the data, however, in comparisons, the principal component analysis computes a vector that has the largest variance. Furthermore, the two eigenvectors obtained by the principal component analysis hold different significance for the input data.

Secondly, the IRIS data set [17][18] are used to test the proposed model. There are four-dimensional data from three classes. Figure 4 shows the projection results of the data onto the feature vectors by the self-regulation learning. The sum-of-squares-error for the learning is 16.4121 (c.f. that by the principal component analysis, 15.2046) These simulations have verified the effectiveness and efficiency of the proposed learning model.

VI. CONCLUSIONS

A new learning paradigm of neural networks is proposed in this paper. We apply it to solve the subspace decomposition problem effectively. By introducing the learning status evaluation for each neuron, we accomplish the cooperative model which learns the environment through neuron's self-regulation not by global arbitration. The model provides a network with fault tolerant capability for feature analysis. Future works will focus on the simplification of its learning rules and the proof of its effectiveness.

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REFERENCES

[1] D.O. Hebb, *The Organization of Behavior*. New York : John Wiley, 1949.

[2] C. von der Malsburg, "Self-organization of orientation sensitive cells in the striate cortex," *Kybernetik*, vol. 14, pp. 85-100, 1973.

[3] S. Grossberg, "Adaptive pattern classification and universal recoding: Part I. Parallel development and coding of neural feature detectors," *Biological Cybernetics*, vol. 23, pp. 121-134, 1976.

[4] K. Fukushima, "Cognitron: A self-organizing multi-layered neural network," *Biological Cybernetics*, vol. 20, pp. 121-136, 1975.

[5] D.J. Willshaw and C. von der Malsburg, "How patterned neural connections can be set up by self-organization," *Proceedings of the Royal Society of London Series*, B, vol. 194, pp. 431-445, 1976.

[6] T. Kohonen, "Self-organized formation of topologically correct feature maps," *Biological Cybernetics*, vol. 43, pp. 59-69, 1982.

[7] W.T. Powers, *Behavior: The Control of Perception*. Chicago: Aldine, 1973.

[8] W. Glasser, *Stations of the Mind: New Directions for Reality Therapy*. Cambridge: Harper and Row, 1981.

[9] C.S. Carver and M.F. Scheier, *Attention and Self-Regulation: A Control-Theory Approach to Human Behavior*. New York: Springer Verlag, 1981.

[10] E. Oja, "Principal components, minor components, and linear neural networks," *Neural Networks*, vol. 5, pp. 927-935, 1992.

[11] E. Oja and J. Karhunen, "On stochastic approximation of the eigenvectors and eigenvalues of the expectation of a random matrix," *J. Math. Anal. Appl.* vol. 106, pp. 69-84, 1985.

[12] T.D. Sanger, "Optimal unsupervised learning in a single-layer linear feedforward neural network," *Neural Networks*, vol. 2, pp. 459-473, 1989.

[13] J. Rubner, and P. Tavan, "A self-organizing network for principal component analysis," *Europhys. Lett.*, vol. 10, no. 7, pp. 693-698, 1989.

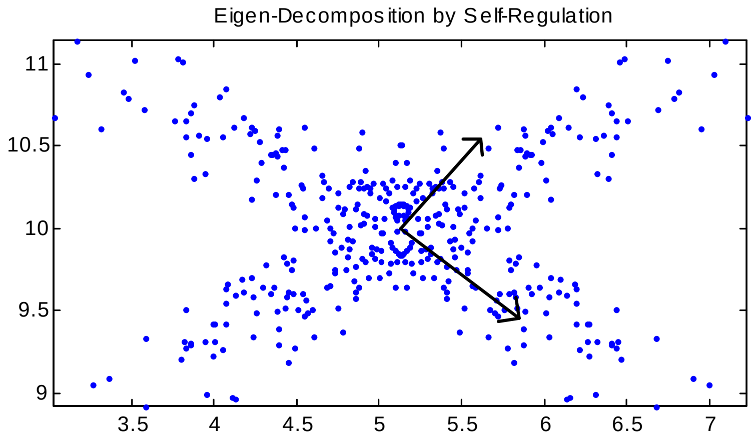
[14] S.Y. Kung and K.I. Diamantaras, "A neural network learning algorithm for adaptive principal component extraction," *IEEE Int. Conf. On Acoustic, Speech, and Signal Processing*, Albuquerque, vol. 2, pp. 861-864, 1990.

[15] N. Kambhatla and T.K. Leen, "Dimension Reduction by Local Principal Component Analysis," *Neural Computation*, vol. 9, pp. 1493-1516, 1997.

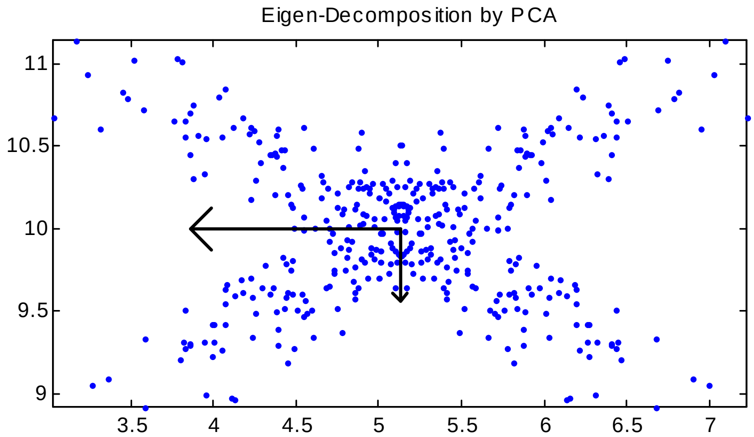
[16] C. Chatterjee, P. Roychowdhury, J. Ramos, and M.D. Zoltowski, "Slf-organizing algorithms for generalized eigen-decomposition," *IEEE Trans. Neural Networks*, vol. 8, no. 6, pp. 1518-,1530 1997.

[17] R.A. Fisher, "The use of multiple measurements in taxonomic problems," *Ann. Eugen.*, vol. 7, pp. 179-188, 1936.

[18] Y.T. Chien, *Interactive Pattern Recognition*. New York: Dekker, 1978.



(a)



(b)

Fig. 3. The experimental results by (a) the self-regulative neural networks, and by (b) the principal component analysis.

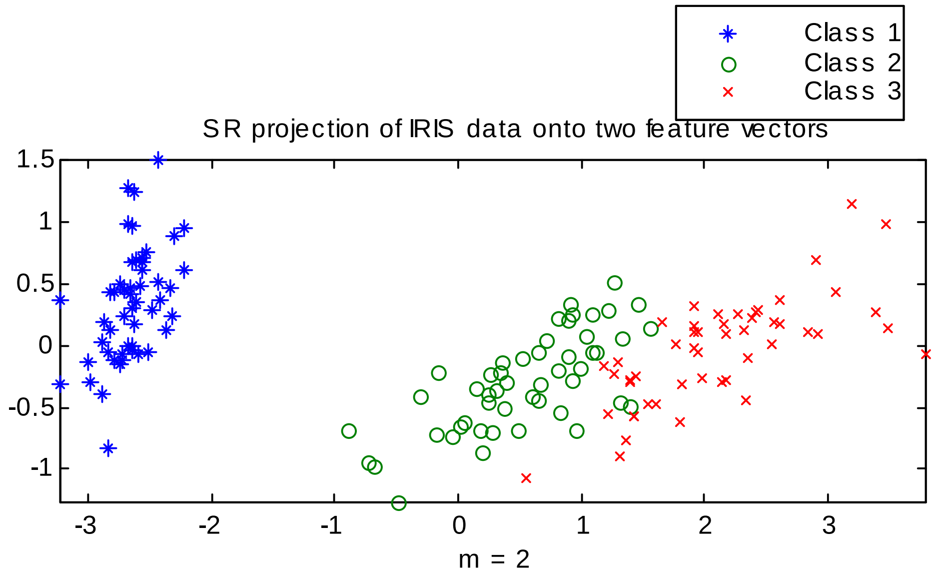


Fig. 4. The experimental results by the self-regulative neural networks.