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Fuzzy TAM Network Model with SOM

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***Abstract*--The fuzzy TAM (Topographical Attentive Mapping) network is a supervised method of pattern analysis which is composed of an input layer, a category layer, and an output layer. But if we don't know the target value of the pattern, the network can not be trained. In this case, the target value can be replaced by a result induced by using an unsupervised neural network as the SOM (Self-organizing Map). There was a result of research how target values which are classified by the SOM can effect to the results of analyzing patterns using the fuzzy TAM network. Therefore, In this paper, we apply the results of the SOM to the fuzzy TAM network and show its usefulness through the case study.**

I. INTRODUCTION

The TAM network based on nervous systems motivated by a biological model is especially an efficient model for pattern analysis[1]. This structure is consist of an input layer, a category layer and an output layer. And when input data is inputted as the form of distribution in the input layer, the number of node in category layer are produced, which related with the number of node in output layer. And as much as the number of node in category layer, fuzzy rules are produced [2-5]. These would be standards to classify patterns that come under the number of nodes in the output layer. The fuzzy rules about data of input and output are obtained in the TAM network. We call the TAM network which is using three kinds of prunning rule to reduce links and nodes in each layer as the fuzzy TAM network [6]. The fuzzy TAM network is basically same the TAM network. Because the processing procedure of TAM network is same as fuzzy inference, we can obtain the number of properties, classes and rules which are adjusted. Difference is the fuzzy network has a function that can delete the connections between links and nodes in each layer of TAM network.

To use this fuzzy TAM network algorithm, we need target values of the output layer because the fuzzy TAM network is a kind of supervised neural network [7]. If we don't know the target values, the values could be gotten and replaced by SOM [8, 9] which is a kind of unsupervised neural network. We also have a research that target values classified by the SOM can give certain effect to result of pattern analysis using Fuzzy TAM network [10].

Therefore, we classify groups by clustering using the SOM which is a kind of unsupervised neural network and by using them we will analyze patterns as target values of the output layer of the fuzzy TAM network which is a kind of supervised neural network in this paper. For this case study, we analyze nine patterns of job satisfactions [11] and Enneagram [12] of employees who are working on a same service in four factories which belongs to a same car company. Here, we don't have the existing classified criteria about job satisfaction, we will use SOM to get the target value.

II. SOM and FUZZY TAM NETWORK ALGORITHMS

A. SOM

The human's brain cortex has functions of thinking, talking, listening and judging. And each function performs at the different section. We call this characteristic as the ordered feature map. The SOM is nervous network, which imitates this feature of brain's cortex, and it learns without an unsupervisor through competitive study. The SOM is consist of an input layer and an output layer, and it's structure is same as Fig. 1. [13-15].

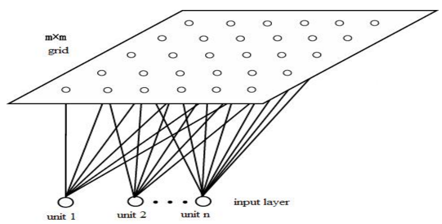

Fig. 1. Structure of SOM

The learning algorithm of SOM is as follows.

[Step 1] The synaptic weights between N inputs and M output neurons are assigned to as some small values. Neighborhood radius is big enough to include all the neurons at first and get smaller step by step.

[Step 2] A new input vector is presented.

[Step 3] Distances between input vector and all the neurons are calculated. The following equation is how to calculate distance between an input vector and all the neuron.

$$d_j = \sum_{i=0}^{N-1} (x_{i(t)-w_{ij}}(t))^2$$

where $x_i(t)$ is ith input vector at time t, $w_{ij}(t)$ is a synaptic weight between ith input vector and jth output neuron at time t.

[Step 4] Select the output neuron j^* that is the minimum distance, d_j.

[Step 5] Readjust the synaptic weights between neuron j* and its neighborhood by the following equation.

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(x_i(t) - w_{ij}(t))$$

where j is neuron that is a neighborhood of j*, and i is a integer number between 0 to N-1. α is a gain term which has a value between 0 and 1, and it become smaller as time goes.

[Step 6] go back to step 2 and repeat.

B. Fuzzy TAM Network

The structure of the TAM network is shown in Fig. 2. The TAM network is composed of three layers where feature layer imitates the retina, category layer imitates the lateral geniculate nucleus and in the class layer, the output is given by the name of object grouping.

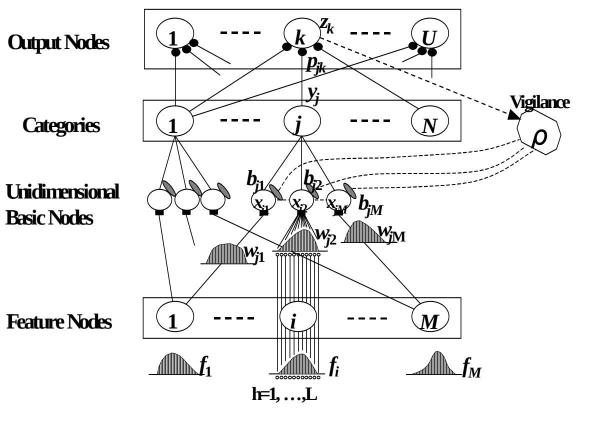

Fig. 2 The structure of the TAM network

When feature maps, f_{ih}, are calculated, the output signal to the category layer, y_j, are calculated using the node's weights, w_{jih}.

$$\begin{aligned} y_j &= \prod_{i=1}^{M} x_{ji} \\ &= \prod_{i=1}^{M} \frac{\sum_{h=1}^{L} f_{ih} w_{jih}}{1+\rho^2 b_{ji}} \end{aligned}$$

where xji are activities, ρ represents the vigilance parameter and bji are inhibitory weights.

The output prediction, K, is calculated as follows:

$$\begin{aligned} K &= \{k \mid \max_k z_k\} \\ &= \{k \mid \max_k \sum_{j=1}^{N} y_j p_{jk}\} \end{aligned}$$

where, z_k are the output at each node of output layer and p_{jk} are weighted connections.

Let K^* denote the index of the "correct" supervised output class. If the network's output prediction K is not similar enough to K^*, we do $\rho = \rho + \rho^{(step)}$ until either $z_{k^*}/z_k \geq OC$ or $\rho \geq \rho_{(max)}$, where OC is the maximal vigilance level. Once the subject of $z_{k^*}/z_k \geq OC$ is satisfied, the feedback signal y^*_j is calculated for the learning step.

$$\begin{aligned} y^*_j &= \frac{\prod_{i=1}^{M} x_{ji} \times \sum_{k=1}^{U} z^*_k p_{jk}}{\sum_{j'=1}^{N} \prod_{i=1}^{M} x_{j'i} \times \sum_{k=1}^{U} z^*_k p_{j'k}} \\ z^*_k &= 1 \text{ if } k = K^*; \quad z^*_k = 0 \text{ otherwise} \end{aligned}$$

The learning parameters, w_{jih}, P_{jk}, b_{ji}, are obtained as follows:

$$\begin{aligned} \triangle w_{jih} &= \frac{\alpha y^*_j (1-\lambda^{1/M})(f_{ih} - w_{jih})}{(\alpha-1)\lambda^{1/M} + n_j}, \lambda \in (0,1) \\ \triangle p_{jk} &= \frac{\alpha y^*_j (z^*_k - p_{jk})}{\alpha + n_j} \\ \triangle b_{ji} &= b_j^{(rate)} y^*_j (x_{ji} - b_{ji}) \\ \triangle n_j &= \alpha y^*_j (1 - n_j) \end{aligned}$$

where, α, λ and $b_j^{(rate)}$ are parameters.

The algorithm of the TAM network including learning steps and pruning steps is represented as follows:

[Step 1] The output prediction, K, is calculated.

[Step 2] If K is not similar enough to K^*, we do $\rho = \rho + \rho^{(step)}$. When ρ reachs the maximal level, one node is added to categories.

[Step 3] If $z_{k^*}/z_k \geq OC$, the learning step starts. Parameters, w_{jih}, P_{jk}, and b_{ji} are updated.

[Step 4] Until $z_{k^*}/z_k \geq OC$, let the algorithm repeat from step 1 to step 3.

[Step 5] After learning, the pruning step starts. The data set in which f_{si}, s=1,2,⋯,R is divided into learning data and checking data. The information entropy, H(i), is calculated using the learning data for feature selections, where ψ_k is a set of the data of the class k.

$$
\begin{aligned}
H(i) &= -\sum_{j=1}^{N} g_j \sum_{k=1}^{U} G_{jk} \log_2 G_{jk} \\
g_j &= \frac{\sum_{s=1}^{R} x_{jis}}{\sum_{j=1}^{N}\sum_{s=1}^{R} x_{jis}} \\
G_{jk} &= \frac{\sum_{s\in\psi_k} \gamma_{js} \times p_{jk}}{\sum_{s=1}^{R} \gamma_{js} \times p_{jk}} \\
\gamma_{js} &= \prod_{i\in I^*} x_{jis} \times x_{jis}
\end{aligned}
$$

[Step 6] The following feature i^* is extracted as an important feature and we set $I^* = \{i^*\}$.

$$i^* = \{i \mid \max_i H(i)\}$$

[Step 7] If the following condition is satisfied for checking data at a category j, the link connections between j and outputs k', k' = 1, 2, ⋯, U, k' ≠ k, are removed. Simultaneously, the connections between j and features $i' \notin I^*$, are removed, where Θ is a threshold.

$$G_{jk} \geq \eta$$

[Step 8] If the following condition is satisfied for checking data at the category j, the link connections between j and I, and $i' \notin I^*$ are removed, where Θ is a threshold.

$$\frac{1}{R}\sum_{s=1}^{R} \gamma_{js} < \theta$$

[Step 9] If the following condition is satisfied for checking data at K, the link connections between K and categories, j', j' = 1, 2, ⋯, N, j' ≠ j, are removed, where ξ is a threshold.

$$\varphi_{jK} = \frac{\sum_{s\in\Gamma_K} \gamma_{js} \times p_{jK}}{\sum_{j=1}^{N}\sum_{s\in\Gamma_K} \gamma_{js} \times p_{jK}} \geq \xi$$

[Step 10] When a category has lost connections to all outputs or features, the category is removed. Any output and feature which has been disconnected from all categories is also removed.

[Step 11] Until all features are selected at step 6, let the algorithm repeat from step 5 to step 10.

From the above, step 7,8,9 are pruning rules. When the algorithm is terminated, the neural network whose needless connections and nodes are pruned is obtained. We should notice that the algorithm is a kind of fuzzy tuning methods since the data procedure is the same as that of fuzzy logic. Thus, we can acquire fuzzy rules from the TAM network as a knowledge representation.

Ⅲ. CASE STUDY

For this case study, we got the data from 63 employees who are working on the same service in four factories and who belong to the same car company. We analyzed job satisfactions and nine types of Enneagram which is classifying people's personality into nine types by using the fuzzy TAM network.

Enneagram sheets were distributed to 63 employees and all of them were returned. 57 data of them were used for this paper except six sheets which were not suitable for our research.

Table 1 is input data for classifying job satisfaction to use the SOM. Table 2 shows the result of sum of distances between centers of cluster, and sum of distances between data which belong to each cluster and the center of the each clusters when the SOM was studied for 2000 epochs while the number of cluster is changed from 3 to 5. Here each data were normalized.

Table 1 Data for SOM to Cluster Types of Job Satisfaction

subjects	A	B	C	D	E
1	24	24	29	8	14
2	24	16	22	7	13
3	22	22	27	7	13
4	31	23	27	8	13
5	28	25	28	8	15
6	29	26	24	8	14
7	31	25	31	8	13
8	24	20	23	6	10
9	36	26	35	9	17
10	24	24	26	6	13
11	32	23	29	9	18
12	30	25	26	8	16
13	32	28	30	8	16
14	32	28	32	8	16
15	26	23	25	8	14
16	23	12	23	5	12
17	22	23	21	6	15
18	24	17	24	5	12
19	22	15	24	6	13
20	23	17	26	7	11
21	30	20	23	9	16
22	27	23	25	8	13
23	25	20	23	6	12
24	28	21	30	9	12
25	33	25	33	9	16
26	33	26	33	9	16
27	21	19	23	7	14
28	37	30	28	8	12
29	24	18	23	8	12
30	32	24	27	8	15
31	32	28	32	8	16
32	28	28	28	8	16
33	25	20	24	6	9
34	33	25	30	6	15
35	24	23	25	7	12
36	21	20	25	6	13
37	19	25	23	8	10
38	27	22	23	7	15
39	17	20	23	7	14
40	28	27	28	9	15
41	32	21	30	8	15
42	30	26	26	6	13
43	28	22	25	8	14
44	32	29	32	8	17
45	22	18	23	7	12
46	30	22	30	7	13
47	25	21	28	8	14
48	24	22	25	7	11
49	27	21	27	6	13
50	32	26	28	7	13
51	24	21	24	6	12
52	32	28	29	8	15
53	29	27	27	8	14
54	26	22	22	6	12
55	29	26	26	8	15
56	29	25	32	5	15
57	26	18	25	8	15

Table 2 Clustering Results of SOM for Types of Job Satisfaction

Items \ # of class	3	4	5
average distance between cluster center	0.20858	0.28626	0.36920
epochs	2000	2000	2000
total sum of distance	1.75276	1.57830	1.42653

Table 3 Data of Personality Types of the Enneagram and Types of Personal Job Satisfaction

	Wh	Lo	Su	Un	Om	Fa	Bl	Po	Pe	유형
1	32	31	27	30	27	33	26	28	29	3
2	31	37	33	35	29	40	28	31	29	2
3	32	30	31	31	33	34	29	31	28	3
4	29	28	36	32	27	34	26	28	27	3
5	35	36	26	29	32	37	31	29	37	3
6	34	37	35	33	30	28	27	32	30	3
7	37	35	34	34	31	37	30	30	34	1
8	32	31	30	37	34	37	36	33	32	2
9	28	28	31	33	25	31	27	30	29	1
10	28	32	31	27	29	29	33	32	31	2
11	40	40	35	18	31	38	32	31	29	1
12	31	34	40	27	31	30	33	32	33	1
13	32	35	32	30	27	33	27	25	34	1
14	32	31	32	25	27	25	28	31	30	1
15	28	31	24	21	33	32	35	28	33	3
16	38	30	34	35	35	35	28	30	36	2
17	37	33	35	31	28	35	27	35	31	2
18	31	27	27	27	29	27	21	26	26	2
19	32	34	35	33	34	31	33	35	32	2
20	31	33	32	22	28	28	24	25	27	2
21	28	33	31	36	25	33	29	24	35	1
22	33	30	36	33	28	32	24	31	25	3
23	30	28	26	27	28	33	23	27	28	2
24	31	36	38	32	28	30	35	28	28	3
25	30	37	34	20	27	32	33	29	29	1
26	31	38	34	23	27	33	33	30	30	1
27	35	34	36	31	28	35	24	34	31	2
28	35	35	33	26	27	35	27	29	25	1
29	28	29	24	29	25	33	27	25	29	2
30	29	31	33	28	26	27	32	28	32	1
31	31	35	32	24	25	31	24	25	23	1
32	28	28	35	31	34	32	29	29	26	1
33	34	36	29	34	28	31	31	32	27	2
34	31	30	29	30	28	27	28	28	29	1
35	27	30	26	28	29	30	29	24	31	3
36	31	26	28	24	26	30	25	31	28	2
37	34	33	32	30	28	34	28	31	29	2
38	29	29	30	26	29	33	25	28	27	3
39	32	29	31	30	30	30	26	32	26	2
40	29	33	31	31	26	33	30	29	32	1
41	30	30	34	24	31	32	32	27	33	1
42	33	35	34	34	31	29	31	34	29	3
43	35	35	32	25	26	31	28	31	28	3
44	34	38	33	31	30	35	33	32	33	1
45	31	35	32	34	23	36	33	32	33	2
46	28	34	27	28	33	34	33	31	36	3
47	37	34	27	39	31	37	34	32	30	3
48	31	31	31	27	23	29	29	27	28	2
49	35	27	30	27	26	32	25	33	28	2
50	31	33	32	28	30	34	26	32	30	3
51	28	31	29	22	30	28	24	32	26	2
52	33	35	32	34	31	35	30	31	35	1
53	27	32	30	25	23	32	27	28	26	3
54	30	28	28	25	28	31	27	28	24	2
55	29	35	29	26	24	31	25	27	24	3
56	30	27	23	25	28	33	28	25	31	1
57	30	26	27	30	25	28	25	26	28	3

Table 3 shows data of personality types of Enneagram and job satisfaction for the pattern analysis. In table 3, we clustered job satisfaction using scores of nine types which was obtained by Enneagram sheets on the assumption that there isn't target values of job satisfaction.

To apply table 3 to the fuzzy TAM network algorithm, we used even numbers for training data and odd numbers for checking data. Table 4 shows the results.

Table 4 Results of Fuzzy TAM for Personal Job Satisfaction

Items	Personal Job Satisfaction
pruning feature switch	2
pruning class switch	1
a percentage of correct answers of training data	81%
a percentage of correct answers of checking data	59%

Table 4 shows a percentage of correct answers of training data was 81% and a percentage of correct answers of checking data was 59%.

Table 5 Pruning Results for Personal Job Satisfaction

Job Satisfaction	
pruning features	the number of features
1,2,4,5,6,7,8,9	9 ⇒ 1
pruning classes	the number of classes
nothing	3 ⇒ 3
pruning category	the number of categories after pruning
nothing	52 ⇒ 52

Table 5 shows prunning result. Prunning was happened and the number of node in the input layer was 1, the number of node in the output layer was 3 and the number of node in the category layer was 52.

In table 5, The fuzzy rule is standards of classifying patterns equivalent to the number of node in output layer and produce as much as the number of node in category layer and is the same as following.

r_1: if f_1 is w_{11} then $C_1=p_{11},\cdots,C_3=p_{13}$
r_2: if f_1 is w_{21} then $C_1=p_{21},\cdots,C_3=p_{23}$
r_3: if f_1 is w_{31} then $C_1=p_{31},\cdots,C_3=p_{33}$
⋮ ⋮ ⋮
r_{50}: if f_1 is w_{501} then $C_1=p_{501},\cdots,C_3=p_{503}$
r_{51}: if f_1 is w_{511} then $C_1=p_{511},\cdots,C_3=p_{513}$
r_{52}: if f_1 is w_{521} then $C_1=p_{521},\cdots,C_3=p_{523}$

where, f_i, i=1 ; node of input layer,
w_{ji}, j=1,2,⋯,52, i=1 ; membership functions in fuzzy set,
C_k, k=1,2,3 ; output class,
P_{jk}, j=1,2, ⋯, 52, k=1,2,3 is weight about output pattern in node of category layer.
r_j, j=1,2, ⋯, 52 is representing number of Fuzzy rule.

Table 6 shows the amount of information about personal job satisfaction. Using training data, we can know the rank of amount of information which is representing importance of a input that is equal to each attribute of input layer

Table 6 Information Entopy for Personal Job Satisfaction

Features		Persona Job Satisfaction	
		H(i) order	H(i)
1	Om	7	0.491
2	Fa	8	0.478
3	Bl	1	0.559
4	Un	9	0.459
5	Su	3	0.541
6	Lo	6	0.513
7	Wh	2	0.552
8	Pe	4	0.535
9	Po	5	0.515

Ⅳ. CONCLUSIONS

In this paper, when we have no output data or not certain output data among input and output data, while we are doing analysis of patterns using the fuzzy TAM network, we tried to solve the absent or vague problem of output values by giving value of object that can be substituted using the SOM that is a neural network of unsupervised learning.

In the case study, the output data was job satisfaction which is felt by employees who works the same service in a car company and the input data was nine types of Enneagram's personality. And when we want to analyze patterns related to classes of job satisfaction by using those data as the input and output even though we don’t know classes of job satisfaction, we got the target value using the SOM and analyzed the patterns by using them as the output data of the fuzzy TAM network.

A percentage of correct answers of training data was 81% and a percentage of correct answers of checking data was 59%. We could grasp the importance of Enneagram’s personality patterns by calculating amount of information, and obtain the fuzzy rules that classify thee patterns of job satisfaction using the fuzzy TAM network through the prunning.

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