Pattern Analysis on Core Competency Model for Subcontractors of Construction Companies Using Fuzzy TAM Network

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Abstract- **TAM(Topographic Attentive Mapping) network is a biologically-motivated neural network. It is composed of input layer, category layer, and output layer. The TAM network with three pruning rules for reducing links and nodes at the layer is called fuzzy TAM network. In this paper, we apply fuzzy TAM network to pattern analysis on core competency model for subcontractors of construction companies and show its usefulness.**

Key words - Pattern Analysis, Subcontractors of Construction Companies, Fuzzy TAM Network

I. Introduction

In order to increase the competitiveness of the 21st Century construction industry, subcontractors of construction companies are strongly required to have higher specialties. Thus, the eminent subcontractors must be qualified and managed, and an evaluation system for the subcontractors is strongly needed.

Currently, research on improvement of the evaluation model is rational and objective. However, there is a few research related to pattern analysis of evaluating and rating subcontractors[1]. In the evaluation method for the subcontractors currently in use, a person who has a responsibility in a company assesses subcontractors based on the subcontractors' own appraisals and then adds up all the results. Finally, the level of the subcontractors is decided based on this summation. This method, however, has a problem in objectives and proprieties of the evaluation methodology, so it could not only be just perfunctory but also have different results due to the individual prejudices.

The propriety of the estimated evaluation level for the new subcontractors can be confirmed by forming a fuzzy rule which standardizes the grouping made by the fuzzy TAM network[2-7]. The fuzzy TAM network decides evaluation level made by an expert who is in charge of the evaluation on the core competency model of the subcontractors. Accordingly, this study made the core competency model to analyse systematically the core competency of the subcontractors. This study was based on our goal of providing decision criterion to select an excellent subcontractors by using the fuzzy TAM network to initiate pattern analysis.

Ⅱ. Core Competency Model for Subcontractors of Construction Companies

This study selected 69 items in 10 departments which are administration, finance, technology, degree of company contribution, execution ability, quality management, safety management, environmental management, execution management, and on-site management. These were assessed as the core competency model by document, interview, and opinion research. The core competency model for subcontractors of construction companies is shown Table 1.

Table 1 Core competency model for subcontractors of construction companies

Department	Number of Item
Administration	10
Finance	4
Technology	3
Degree of Company Contribution	4
Execution Ability	3
Quality Management	10
Safety Management	10
Environmental Management	8
Execution Management	10
On-site Management	7
Total	69

The evaluation of core competency model for subcontractors of construction companies is divided into two parts which are head office and on-site. The evaluation departments of head office include administration, finance, degree of company contribution, technology, execution ability. Also, the evaluation departments of on-site include quality management, safety management, environmental management, execution management, and on-site management.

Ⅲ. Fuzzy TAM Network

The structure of the fuzzy TAM network is shown in Fig. 1. The fuzzy TAM network is composed of three layers, namely, input layer, category layer, and output layer. The input layer imitates the retina. The category layer imitates the lateral geniculate nucleus. And, in the output layer, the output is given by the name of object grouping.

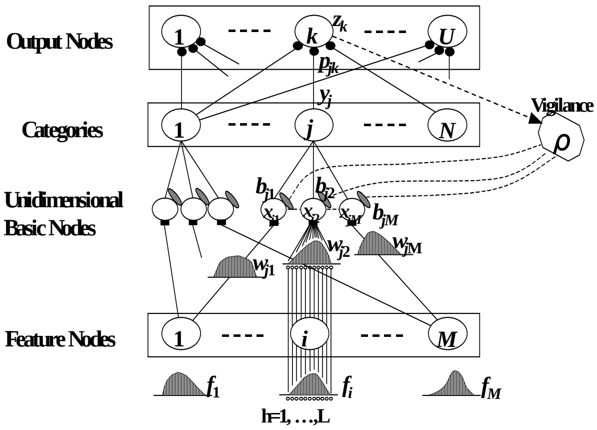

Fig. 1 The structure of the fuzzy TAM network

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 x_{ji} are activities, ρ represents the vigilance parameter, and b_{ji} 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.

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

The learning parameters, w_{jih}, P_{jk}, and 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 $I^* = \{i^*\}$.

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

[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.

Ⅳ. Test and Results

The number of data is 697. They were obtained from 30 construction companies in Busan, Ulsan, and Gyeongnam areas. Number of subcontractors, which are categorized by types of business, is shown Table 2.

Table 2 Number of Subcontractors by Types of Business

Types of Business	Number of Subcontractors	Percent
Steel Structure Installation Work	43	6.17
Metal Structure·Windows and Doors Installation Work	144	20.66
Painting Work	43	6.17
Plaster·Waterproofing·Masonry Work	104	14.92
Stone Work	39	5.60
Elevator Installation Work	67	9.61
Interior Construction Work	97	13.92
Steel Reinforcement · Concrete Work	97	13.92
Civil Engineering Work	63	9.04
Total	697	100.0

For the core competency model, the evaluation experts can evaluate 697 subcontractors in types of business using evaluation contents and level of subcontractors which is shown Table 3.

Table 3 Evaluation Contents and Level of Subcontractors

Evaluation Contents	Evaluation Level
very bad	1
bad	2
poor	3
below average	4
average	5
above average	6
good	7
excellence	8
very excellence	9
super excellence	10

The data, which were obtained from 697 subcontractors, are divided into the training and checking data by types of business. Using these data, we apply fuzzy TAM network to pattern analysis on core competency model for subcontractors of construction companies.

The results of pattern analysis is shown Table 4. In Table 4, we show correct rate of 3 methods - Fuzzy c-Means algorithm[8], IAFC neural network 3[9] and fuzzy TAM network - by types of business. These results show that the fuzzy TAM network is better than the fuzzy c-Means algorithm and the IAFC neural network 3.

From the results, we know that the fuzzy TAM network is a very effective tool for pattern analysis.

Table 4 Results of Pattern Analysis

Methodology	Unsupervised	Supervised			
Tool	Fuzzy c-Means	IAFC Neural Network 3		Fuzzy TAM Network	
Correct Rate of Data / Types of Business	All Data	Training Data	Checking Data	Training Data	Checking Data
Steel Structure Installation Work	61%	78%	80%	100%	100%
Metal Structure·Windows and Doors Installation Work	53%	75%	61%	92%	89%
Painting Work	58%	100%	100%	100%	100%
Plaster·Waterproofing·Masonry Work	58%	76%	76%	88%	62%
Stone Work	57%	80%	78%	100%	100%
Elevator Installation Work	61%	94%	87%	88%	71%
Interior Construction Work	50%	85%	79%	96%	96%
Steel Reinforcement · Concrete Work	62%	89%	91%	90%	75%
Civil Engineering Work	52%	84%	77%	100%	90%

The information entropy, H(i), which means weight of input data is shown Table 5.

Table 5 The Information Entropy

Department \ Types of Business	1	2	3	4	5	6	7	8	9
Administration	0.70	0.51	0.72	0.53	0.75	0.54	0.61	0.81	0.76
Finance	0.68	0.54	0.73	0.43	0.69	1.05	0.63	0.74	0.67
Technology	0.68	0.48	0.72	0.41	0.67	1.13	0.60	0.70	0.73
Degree of Company Contribution	0.71	0.55	0.67	0.59	0.66	1.08	0.65	0.84	0.75
Execution Ability	0.65	0.49	0.62	0.45	0.71	0.58	0.64	0.83	0.75
Quality Management	0.72	0.58	0.74	0.64	0.68	0.94	0.47	0.78	0.77
Safety Management	0.69	0.57	0.71	0.69	0.67	0.82	0.49	0.84	0.76
Environmental Management	0.72	0.57	0.71	0.68	0.65	1.13	0.45	0.82	0.71
Execution Management	0.61	0.46	0.65	0.45	0.67	0.64	0.52	0.01	0.78
On-site Management	0.68	0.44	0.70	0.48	0.64	0.71	0.56	0.77	0.77

1 : Steel Structure Installation Work
2 : Metal Structure·Windows and Doors Installation Work
3 : Painting Work
4 : Plaster·Waterproofing·Masonry Work
5 : Stone Work
6 : Elevator Installation Work
7 : Interior Construction Work
8 : Steel Reinforcement·Concrete Work
9 : Civil Engineering Work

Here, in particular, it can be said that quality management is a very important department from the fact that it has 4 best value among 9 types of business.

Table 6 shows the number of nodes for three layers - input layer, category layer and output layer - by types of business. This value is obtained from the results of pruning.

Table 6 Number of Nodes for Each Layer by Types of Business

Types of Business \ Number of Layer	Input Layer	Category Layer	Output Layer
Steel Structure Installation Work	10	9	4
Metal Structure·Windows and Doors Installation Work	10	52	5
Painting Work	10	14	4
Plaster·Waterproofing·Masonry Work	10	48	5
Stone Work	10	6	4
Elevator Installation Work	10	58	7
Interior Construction Work	10	74	5
Steel Reinforcement · Concrete Work	10	32	6
Civil Engineering Work	10	13	5

Ⅴ. Conclusions

The outcome of this study is as follows:

1. The core competency model which is composed 69 items in 10 departments - administration, finance, degree of company contribution, technology, execution ability, execution management, quality management, safety management, environmental management, and on-site management - is established by document, interview, and opinion research to evaluate the subcontractors of construction companies.

2. This study showed the fuzzy TAM network which is appropriate for pattern analysis tool compared with the Fuzzy c-Means algorithm and the IAFC neural network.

3. The results of this study are expected to assist the unexperienced evaluator to evaluate the subcontractors of construction companies by utilizing the results of the fuzzy TAM network which is trained using expert knowledge.

References

[1] S.E. Kim and S.G. Hwang, “Pattern Analysis of Core Competency Model for Subcontractors of Construction Companies Using Fuzzy TAM Network”, Journal of Korea Fuzzy Logic and Intelligent Systems Society, Vol. 16, No. 1, pp. 86-93, 2006.

[2] I. Hayashi, “A Consideration on Aperture Problems Using TAM Network”, Proc. of the 17th Fuzzy System Symposium, pp. 81-82, 2001.

[3] I. Hayashi and J.R. Williamson, “Acquisition of Fuzzy Knowledge from Topographic Mixture Networks with Attentional Feedback", The International Joint Conference on Neural Networks(IJCNN '01), pp.1386-1391, 2001.

[4] J. R. Williamson, “Self-Organization of Topographic Mixture Networks Using Attentional Feedback", Neural Computation, Vol. 13, pp. 563-593, 2001.

[5] I. Hayashi and H. Maeda,"A Formulation of Fuzzy TAM Network with Gabor Type Receptive Fields", International Symposium on Advanced Intelligent Systems, pp. 620-623, 2003.

[6] I. Hayashi and J. R. Williamson,"A Proposal of Pruning Method for TAM Network", Transactions of the Institute of Systems, Control and Information Engineers, pp. 81-88, 2004.

[7] S.Y. Jung, S.G. Hwang, Y.M. Park, K.P. Park and I. Hayashi,"Pattern Analysis of Dishonor Enterprise Using Fuzzy TAM Network", International Symposium on Advanced Intelligent Systems, pp. 1185-1189, 2003.

[8] Richard O. Duda, Peter E. Hart, David G. Stork, Pattern Classification, Second Edition, 2001.

[9] Y.S. Kim, “Fuzzy Neural Network Model Using Asymmetric Fuzzy Learning Rates”, Journal of Korea Fuzzy Logic and Intelligent Systems Society, Vol. 15, No. 7, pp. 800-804, 2005.