Fuzzy Inference Mechanism Based on Fuzzy Cognitive Map for B2B Negotiation

Kun Chang Lee* and Byung Uk Kang**

*Professor of MIS
School of Business Administration
Sung Kyun Kwan University
Seoul 110-745, Korea
leekc@skku.ac.kr

**School of Business Administration
Sung Kyun Kwan University
Seoul 110-745, Korea

Abstract

This paper is aimed at proposing a fuzzy inference mechanism to enhancing the quality of cognitive map-based inference. Its main virtue lies in the two mechanisms: (1) a mechanism for avoiding a synchronization problem which is often observed during inference process with traditional cognitive map, and (2) a mechanism for fuzzifying decision maker's subjective judgment. Our proposed fuzzy inference mechanism (FIM) is basically based on the cognitive map stratification algorithm which can stratify a cognitive map into number of strata and then overcome the synchronization problem successfully. Besides, the proposed FIM depends on fuzzy membership function which is administered by decision maker. With an illustrative B2B negotiation problem, we applied the proposed FIM, deducing theoretical and practical implications. Implementation was conducted by Matlab language.

Keywords: *Cognitive map, Fuzzy inference mechanism, Synchronization problem, Stratification algorithm, Membership function*

1. Introduction

The purpose of this paper is to suggest a fuzzy inference mechanism (FIM) to secure more flexible and natural inference. For this purpose, cognitive map is used to represent decision maker's cognitive structure. Besides, fuzzy membership function is utilized to incorporate decision maker's subjective judgment about some factors involved in a specific decision making problem.

Taber (1991) has used cognitive map to model gastric-appetite behavior and popular political developments. The use of cognitive map has been found in various application domains such as analysis of electrical circuits (Styblinski & Meyer 1988), analysis and extension of graph-theoretic behavior (Zhang & Chen 1988), and plant control modelling (Gotoh et al. 1989). Refer to Kosko (1986, 1992) for an excellent reference on cognitive map. However, cognitive map has some drawbacks for it to be effectively applied to a lot of decision-making problems. Among them, we will tackle the synchronization problem in which all the values of input nodes need to be specified before a final value of an output node can be obtained. If this problem can be overcome, then we can apply cognitive maps to a wider variety of decision-making problems. For the sake of resolving this kind of synchronization problem and enabling cognitive maps to be used in more various decision-making problems, we will suggest the stratification algorithm, and apply to a real-world problem. Another point of this paper is to introduce FIM where a stratified cognitive map is integrated with fuzzy membership function.

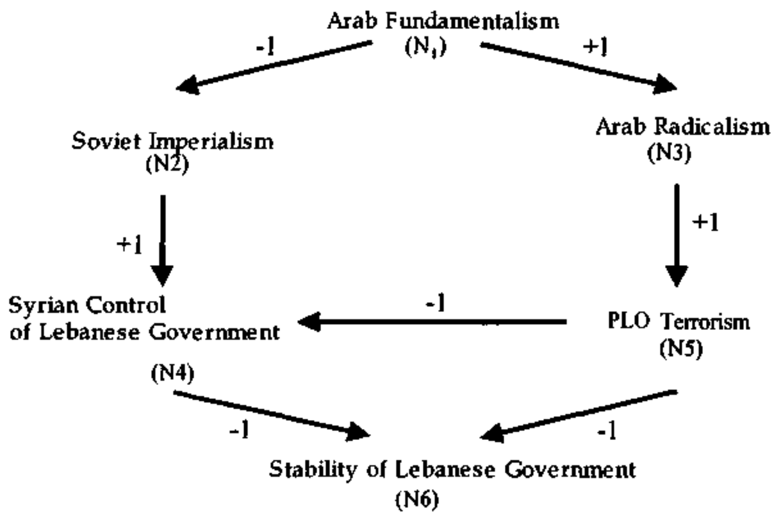
This paper is organized as follows. Section 2 addresses the synchronization problem we often encounter when trying to use cognitive maps in decision-making problems. The stratification algorithm is alternatively proposed in section 3. Based on this stratification algorithm, FIM is proposed in section 4. This paper is ended with some concluding remarks in section 5.

2. Synchronization Problem

Cognitive map proposed by Axelrod (1976) is a signed digraph designed to capture the causal assertions of a person (Asher 1983) with respect to a certain domain and then use them in order to analyze the effects of alternative upon certain goals. Cognitive map has only two basic types of elements: concepts and causal beliefs. Concepts are represented as variables or nodes and causal beliefs as relationships among variables. Concepts of cognitive map can take either continuous, ordinal, or dichotomous variables, while causal beliefs link variables to each other and they can be either positive or negative. Variables that cause a change are called cause variables while those that undergo the effect of the change in the cause variable are called effect variables. If the causal relationship is positive, an increase or decrease in a cause variable causes the effect variable to change in the same direction. If the relationship is negative, then the change which the effect variable undergoes is in the opposite direction. Therefore, cognitive map is a graphical representation of variables as nodes and causal relationships as directed arrows between variables, thus constructing a signed digraph.

Fuzzy cognitive map introduced by Kosko (1986) can allow the sign assigned to each causal relationships to be replaced with fuzzy weights which show not only the direction, but also the magnitude of the change. Fuzzy cognitive maps are more specific and information rich than the cognitive maps. Also it is argued that cognitive map eliminate the *indeterminacy* problem of the total effect where it is not possible to determine the total effect which is the result of negative and positive effects (Kardaras & Karakostas 1999). This property of fuzzy cognitive map has enlarged its applicability to a wide variety of decision-making problems such as simulation (Fu 1991), organizational strategies modelling (Paradice 1992), support for strategic problem formulation and decision analysis (Warren 1995; Heintz & Acar 1992; Diffenbach 1982; Fiol 1992; Eden & Ackerman 1993; Lee 1993), knowledge bases construction (Taber 1991; Nakamura et al. 1982), social and psychological processes modelling (Craiger & Coovert 1994), virtual worlds behavior modelling (Dickerson & Kosko 1994), requirements analysis in information systems (Montazemi & Conrath 1986), coordination of distributed cooperative agents (Zhang et al 1992), integration of marketing decisions and differential game (Lee et al 1998), and stock market analysis (Lee & Kim 1997).

However, despite the successful applications of cognitive map[1] above, there exist still a synchronization problem where all the values of concept nodes connecting to a specific concept node under consideration should be known a priori before a final inference is made with respect to that node. Otherwise, the inference process fails, and decision makers cannot obtain inference results about that node. Let us consider a cognitive map depicted in Figure 1 so that we can fully understand traditional inference process with cognitive map which is described later in two steps. The cognitive map in Figure 1 is based on a former US diplomat Henry Kissinger's article about the Middle East Peace Policy appeared in Los Angeles Times (1982).



<Figure 1> Exemplar cognitive map

$$N_1 \ N_2 \ N_3 \ N_4 \ N_5 \ N_6$$

[1] In this paper, we use a term *cognitive map* to stand for both cognitive map and fuzzy cognitive map.

$$
E=\begin{array}{c}\begin{pmatrix}0 & -1 & 1 & 0 & 0 & 0\\ 0 & 0 & 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 0 & 0 & -1\\ 0 & 0 & 0 & -1 & 0 & -1\\ 0 & 0 & 0 & 0 & 0 & 0\end{pmatrix}\end{array}\begin{array}{l}N_1\\ N_2\\ N_3\\ N_4\\ N_5\\ N_6\end{array}
$$

<Figure 2> Cause-Effect Matrix for the cognitive map in Figure 1

Traditional inference with cognitive map is based on cause-effect matrix like E shown in Figure 2. Types of nodes in cognitive map can be classified into the following three ones; Input node, Output node, and Intermediate node. Input node is one with only outcoming arrows or arcs, and therefore used usually for controllable and measurable facts. Output node is used usually for final decision variable(s) with only incoming arrows or arcs. Meanwhile, intermediate node is for concept variable with both incoming and outcoming arrows and arcs, therefore linking input nodes to output nodes. Based on the notion so far, inference with traditional cognitive map can be summarized in the following two steps.

Step 1: Input value calculation

Suppose that $I(N_i)$and $O(N_i)$denote respectively input value and output value of a certain concept node N_i. Also suppose that $N_j^i, j=i^1,\ldots,i^k$ represent a set of cause nodes for node N_i. Then $I(N_i)$ can be calculated as a weighted sum of all the cause nodes for node N_i as follows:

$$I(N_i)=\sum_{j=i^1}^{i^k} e_{ji}\cdot O(N_j^i) \qquad \text{(Eq. 1)}$$

where e_{ji} : a fuzzy membership value (or causal beliefs value) of causal relationship $N_j^i \rightarrow N_i$

$O(N_j^i)$: output value (or certainty) for node N_j^i

Step 2: Output value calculation

With $I(N_i)$ determined by (Eq. 1), $O(N_i)$ representing a certainty value for node N_i is computed as follows.

$$O(N_i)=I(N_i) \qquad \text{(Eq. 2)}$$

However, critical trouble with this kind of inference with traditional cognitive map is that if all the cause nodes for a target node are not known beforehand, decision makers cannot obtain exact output value for the target node. We herein define this *synchronization* problem. To solve this problem, we will suggest a *stratification* algorithm in which a cognitive map is stratified so that all the values of cause nodes do not need to be known beforehand for making inference about a target node.

3. Stratification Algorithm

The cognitive map stratification is to stratify a given cognitive map into a properly stratified one in which cognitive map can be analyzed more easily and clearly. Especially, the stratified cognitive map can resolve the synchronization problem, yielding more exact and natural inference results than traditional cognitive map. For the sake of convenience of explaining the proposed stratification algorithm, let us describe the following four definitions.

[Definition 1] Let $L(N_i)$ denote a stratum to which node N_i belongs. Then $L(N_i)$ is defined as follows:

□ If N_i is an input node, then $L(N_i)$ = 0.

□ Otherwise, $L(N_i) = MAX_{j=i^1}^{i^k} L(N_j^i) + 1$,

where $N_j^i, j = i^1, \ldots, i^k$ is a set of cause nodes affecting N_i

[Definition 2] Suppose that *n* is the number of nodes in a certain cognitive map. Then n by n a*djacency matrix* A is defined as follows:

$$A_{ij} = \begin{cases} 1, & if\ N_i \rightarrow N_j \\ 0, & otherwise \end{cases} \qquad i, j = 1, 2, \ldots, n.$$

If a cause-effect matrix E is given, the adjacency matrix A can be alternatively obtained as follows.

$$A_{ij} = \begin{cases} 1, & if\ e_{ij} \neq 0 \\ 0, & otherwise \end{cases} \qquad i, j = 1, 2, \ldots, n.$$

The adjacency matrix for cognitive map shown in Figure 1 is as follows in Figure 3.

$$N_1\ N_2\ N_3\ N_4\ N_5\ N_6$$

$$E=\begin{array}{c} \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{l} N_1 \\ N_2 \\ N_3 \\ N_4 \\ N_5 \\ N_6 \end{array}$$

<Figure 3> Adjacency matrix for cognitive map shown in Figure 1

[Definition 3] Let $F^I(N_i)$ denote the number of "fan-in" for node N_i, implying the number of cause nodes affecting N_i. Therefore, with n x n adjacency matrix A given, $F^I(N_i)$ is computed as follows:

$$F^I(N_i)=\sum_{j=1}^{n} A_{ji}$$

For example, a fan-in vector F^I for cognitive map shown in Figure 1 is

$$F^I=\left[\quad F^I(N_1),\ldots\ldots,F^I(N_6)\quad\right]=\left[\,0,1,1,2,1,2\,\right]$$

[Definition 4] If the number of nodes of a certain cognitive map is *n*, then *r*-order 1 by n synchronization vector S^r, r = 0,1,2,... is defined as follows:

$$S^0 : S_i^0=\begin{cases}1, & \textit{if } N_i \textit{ is an input node} \\ 0, & \textit{otherwise}\end{cases}, \quad i=1,2,\ldots,n.$$

$$S^r=Th\left(S^{r-1}\cdot A\right)+S^{r-1}, \quad r\geq 1.$$

Operator Th() above is called a threshold operator indicating either 1 or 0 depending on the value in parenthesis. For example, let $\mathrm{B}=S^{r-1}\cdot\mathrm{A}$ and C = Th(B). Then 1 by n vector *C* is computed as follows:

$$C_i=\begin{cases}1, & \textit{if } B_i=F^I(N_i) \\ 0, & \textit{if } B_i<F^I(N_i)\end{cases}, \quad i=1,2,\ldots,n.$$

Letting $N'_j, j=i^1,\ldots,i^k$ denote cause nodes for node N_i, then *r*-order 1 by n synchronization vector S^r, r = 1,2,... is computed as follows:

$$S_i^r = \begin{cases} 1, & if\ MAX_{j=i'}^{i^*}\left[L\left(N_j'\right)\right] < r \\ 0, & otherwise \end{cases} \quad , \quad i = 1, \ldots, n.$$

This equation means that the synchronization vector S_i^r becomes 1 if the stratum of cause nodes for N_i is less than *r*, and otherwise becomes 0. Considering definition 1 as well as the property of synchronization vector above, $L(N_i)$ the stratum of node N_i is newly derived as follows:

$$L(N_i) = Min\left\{ r \,\middle|\, S_i^r = 1 \right.$$

On the basis of explanation so far, the proposed stratification algorithm for a certain cognitive map is listed in Table 1 as follows;

<Table 1> Stratification Algorithm for cognitive map

Step 1 : Obtain 0-order synchronization vector S^0
Step 2 : Let r = 1 and
    C = set of all the intermediate nodes and output nodes
Step 3 : Compute r-order synchronization vector S^r like
    $S^r = Th\left(S^{r-1} \cdot A\right) + S^{r-1}$
Step 4 : Repeat the following process for all $N_i \in C$
    IF $S_i^r == 1$
        THEN {
            $L(N_i) = r$;
            $C = C - N_i$;}
    ELSE $L(N_i)$ = unknown.
Step 5 : Check whether the stratum of all the nodes is decided.
    IF C == Ø THEN Stop.
    ELSE r = r + 1 and goto Step 3.

Applying the stratum algorithm to the cognitive map shown in Figure 1,

S^0 = [□, 0, 0, 0, 0, 0] ==> $L(N_1) = 0$.

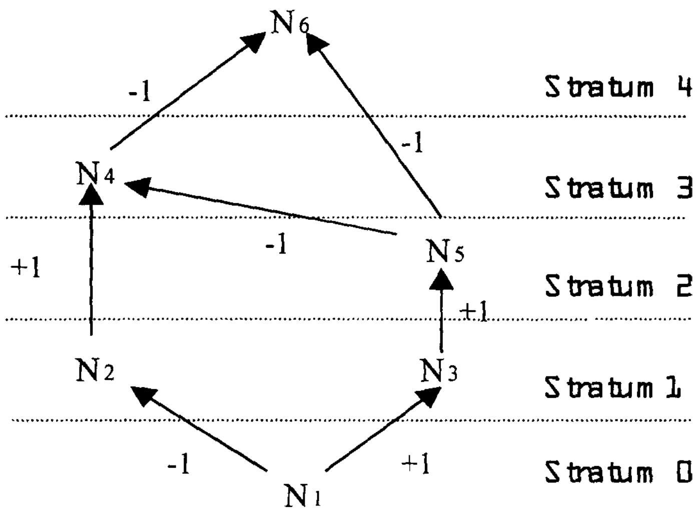
S^1 = [1, □, □, 0, 0, 0] ==> $L(N_2) = 1$, $L(N_3) = 1$

S^2 = [1, 1, 1, 0, □, 0] ==> $L(N_5) = 2$

S^3 = [1, 1, 1, □, 1, 0] ==> $L(N_4) = 3$

S^4 = [1, 1, 1, 1, 1, □] ==> $L(N_6) = 4$

In other words, it is decided that node N_1 belongs to stratum 0, N_2 and N_3 stratum 1, N_5 stratum 2, N_4 stratum 3, and N_6 stratum 4. Using this information, the cognitive map in Figure 1 can de stratified as depicted in Figure 4.



<Figure 4> Stratified cognitive map

From the stratified cognitive map shown in Figure 4, it can be concluded generally that input node belongs to stratum 0, and the stratum of output node is greater than the strata of cause nodes affecting the output node.

4. Proposed FIM

4.1 Basic Inference Process with Stratified Cognitive Map

Before elaboration on the proposed FIM, we suggest a basic inference process with a stratified cognitive map. Let us suppose that *hyperbolic tangent* function is used for generating output value of a node N_i In other words, Eq. 2 is converted into the following Eq. 3.

$O(N_i) = \tanh [\, I(N_i) \,]$ (Eq. 3)

The reason of using hyperbolic tangent function for computing output value of a node like Eq. 3 is that (1) output value of a node implies a certainty value ranging between 1 and -1 which hyperbolic tangent function can yield, (2) output value becomes 0 when input values from cause nodes are null, and (3) hyperbolic tangent function is suitable for conservative decision-making with a sort of uncertainty existing in concept nodes and causal relationships. With the stratified cognitive map, a synchronization problem can be avoided in the way that output value computation is made step by step from lower stratum to higher one. First, the input value computation for nodes in stratum r is made by Eq. 4 as follows:

$$\mathbf{I}_r = \mathbf{E}_r \cdot \mathbf{O}^r \qquad \text{(Eq. 4)}$$

where $\mathbf{I}_r$: vector representing input values for nodes in stratum r,
$\mathbf{O}^r$: vector representing output values for all the cause nodes with respect to nodes in $\mathbf{I}_r$,
$\mathbf{E}_r$: matrix consisting of fuzzy membership values for causal relationships between nodes in $\mathbf{O}^r$ and $\mathbf{I}_r$.

Especially, $\mathbf{O}^r$ is computed via the following Eq. 5

$$\mathbf{O}_r = \tanh(\mathbf{I}_r) \qquad \text{(Eq. 5)}$$

$\mathbf{E}_r$ shown in Eq. 4 can be obtained alternatively by eliminating all the rows from cause-effect matrix E except those rows corresponding to nodes in $\mathbf{I}_r$, and then additionally deleting columns made up of only zeros. Also nodes belonging to $\mathbf{O}_r$ correspond to those belonging to columns of $\mathbf{E}_r$. For illustration, suppose that certainty value about a concept node "Arab Fundamentalism" (N_1) which belongs to stratum 1 is 1. Then, based on the stratified cognitive map shown in Figure 4, computational processes using Eq. 4 and 5 are as follows.

$$\mathbf{O}^1 = [\,O(N_1)\,] = [\,1\,]$$
$$\mathbf{I}_1 = [\,I(N_2), I(N_3)\,]' = \mathbf{E}_1 \cdot \mathbf{O}^1 = [\,-1, 1\,]' \cdot [\,1\,] = [\,-1, 1\,]'$$
$$\mathbf{O}_1 = [\,O(N_2), O(N_3)\,]' = [\,\tanh(-1), \tanh(1)\,]' = [\,-0.76, 0.76\,]'$$
$$\mathbf{I}_2 = [\,I(N_5)\,] = \mathbf{E}_2 \cdot \mathbf{O}^2 = [\,1\,] \cdot [\,0.76\,] = [\,0.76\,]$$
$$\mathbf{O}_2 = [\,O(N_5)\,] = [\,\tanh(0.76)\,] = [\,0.64\,]$$
$$\mathbf{I}_3 = [\,I(N_4)\,] = \mathbf{E}_3 \cdot \mathbf{O}^3 = [\,1, -1\,] \cdot [\,-0.76, 0.64\,]' = [\,-1.4\,]$$
$$\mathbf{O}_3 = [\,O(N_4)\,] = [\,\tanh(-1.4)\,] = [\,-0.89\,]$$
$$\mathbf{I}_4 = [\,I(N_6)\,] = \mathbf{E}_4 \cdot \mathbf{O}^4 = [\,-1, -1\,] \cdot [\,-0.89, 0.64\,]' = [\,0.25\,]$$
$$\mathbf{O}_4 = [\,O(N_6)\,] = [\,\tanh(0.25)\,] = [\,0.24\,]$$

==> Final inference result:

$$[\ O(N_1),\ O(N_2),\ O(N_3),\ O(N_4),\ O(N_5),\ O(N_6)\ ]$$

= [1, -0.76, 0.76, -0.89, 0.64, 0.24]

Therefore, given the situation that Arab Fundamentalism is strong with certainty value 1, inference with the stratified cognitive map shown in Figure 4 results in output node 'Stability of Lebanese Government' (N_6) with certainty value .24 showing a rather weak affirmation. Note that a concept node 'Stability of Lebanese Government' (N_6) belongs to stratum 4, implying that it is an output node.

This is comparable with inference with traditional cognitive map shown in Figure 1. Suppose that a concept node vector $\underline{\mathbf{N}}$ = (N_1, N_2, N_3, N_4, N_5, N_6). Similar to the inference with stratified cognitive map, we assume that Arab Fundamentalism is strong with certainty value 1. Therefore,

$\underline{\mathbf{N}}_1$ = (1 0 0 0 0 0).

Then, applying a threshold criterion of 1/2 suggested by Kosko (1992), inference processes with traditional cognitive map in Figure 1 are as follows.

$\underline{\mathbf{N}}_1 \times \underline{\mathbf{E}}$ = (0 -1 1 0 0 0) -----> (1 0 1 0 0 0) = $\underline{\mathbf{N}}_2$

where arrow indicates applying 1/2 threshold criterion.

$\underline{\mathbf{N}}_2 \times \underline{\mathbf{E}}$ = (0 -1 1 0 1 0) -----> (1 0 1 0 1 0) = $\underline{\mathbf{N}}_3$
$\underline{\mathbf{N}}_3 \times \underline{\mathbf{E}}$ = (0 -1 1 -1 1 -1) -----> (1 0 1 0 1 0) = $\underline{\mathbf{N}}_3$

It is noted that $\underline{\mathbf{N}}_3$ reaches an equilibrium state. However, this kind of inference result with traditional cognitive map is aggregating information too much, failing to show the subtle change of related concept nodes. Meanwhile, inference result with the stratified cognitive map, (1, -0.76, 0.76, -0.89, 0.64, 0.24) is revealing the delicateness of changes among concept nodes including output node.

4.2 FIM with an illustrative example

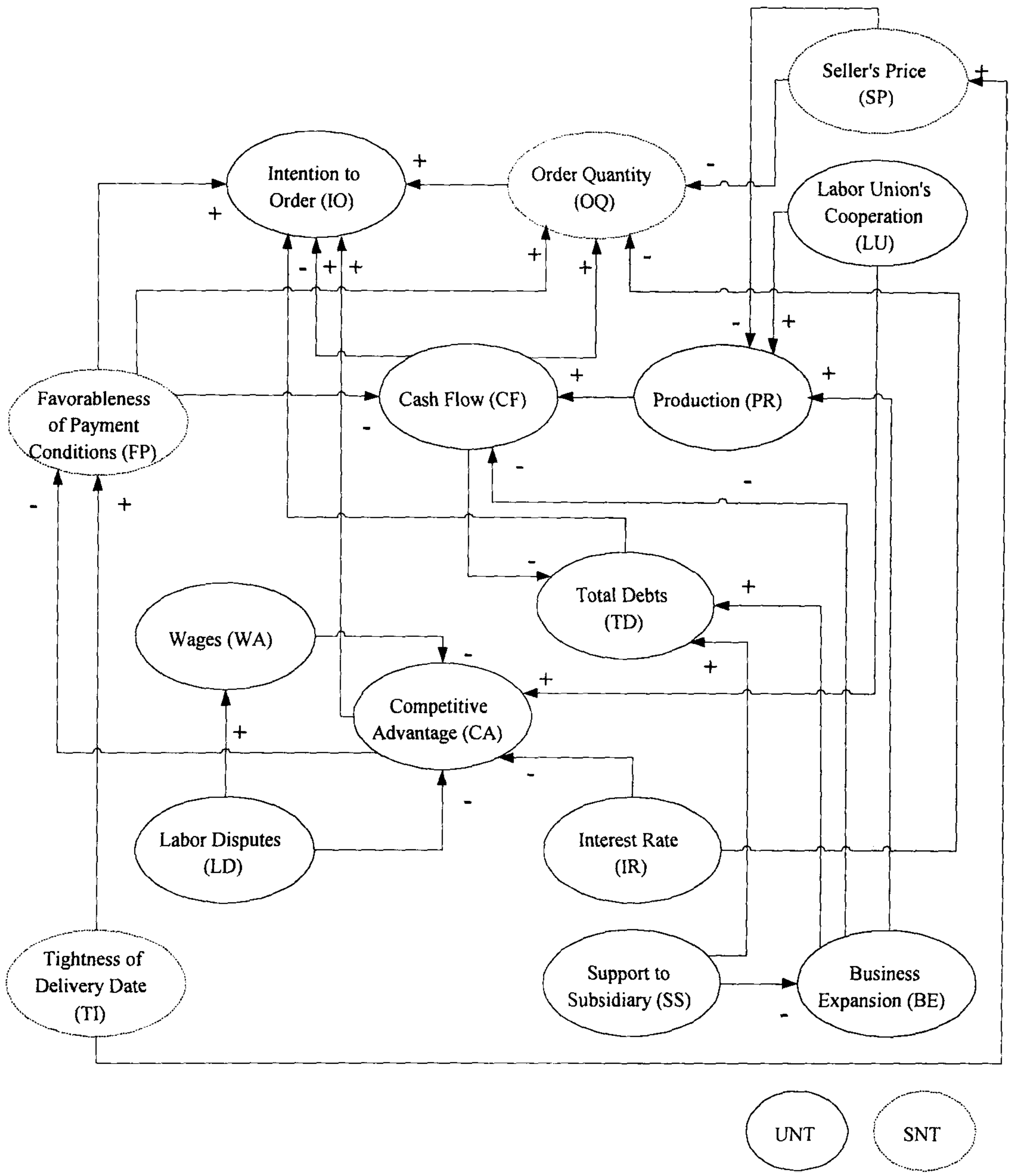
First of all, it is necessary to introduce a concept of membership function at this moment. If *X* is a collection of objects denoted generically by x, then a fuzzy set *A* in *X* is defined as a set of ordered pairs:

$$A = \{(x, \mu_A(x)) \mid x \in X\}$$

where $\mu_A(x)$ is called the membership function (or MF for short) for the fuzzy set *A*. The MF maps each element of X to a membership grade (or membership value) between 0 and 1. Based on the concept of MF like this, let us consider an illustrative example which is related to B2B negotiation problem. A B2B negotiation problem always occurs whenever an organization attempts to procure raw materials. Note that this study focuses on a manufacturing company (or buyer) which is trying to purchase raw materials from a seller through the B2B transaction on the Internet. The B2B negotiation problem requires a great deal of know-how or tacit knowledge. For instance, the procurement department of the buyer company has to make a procurement decision under the potential risk of high cost and poor quality. To avoid such kind of procurement risk, the buyer company should rely on its procurement know-how or tacit knowledge which has been accumulated in the company through a lot of B2B transactions. The most valuable know-how related with the B2B transaction is the capability to perform high-quality B2B negotiations, analyzing appropriately the intent of other B2B players and making appropriate counter-offers to derive the most favorable negotiation term. In B2B electronic commerce, a final deal is reached after an array of non-face-to-face negotiation among involved entities. During the negotiation, a lot of trading terms are addressed and discussed such as price, quantity, payment conditions, delivery time, refund, discount rate, resource availability, labor union's cooperation, etc. Those terms are classified into two kinds- structured ones and unstructured ones. Structured negotiation terms (SNTs) include crucial negotiation terms such as price, quantity, quality, payment conditions, delivery time, etc, while unstructured negotiation terms (UNTs) encompass resource availability, labor union's cooperation, and corporate culture, etc. It is noted that SNTs are target terms to be negotiated between B2B partners, and should be fully negotiated before reaching a final deal. Meanwhile, UNTs encompass such non-negotiable and firms-specific inside conditions as labor union's cooperation, bargaining power in the negotiation with raw materials dealers, CEO's leadership style, morale level of employees, etc. Both SNTs and UNTs should be first agreed upon between B2B partners before taking more concrete actions.

However, this paper argues that SNTs are not the only term to be considered in B2B negotiation. Our research premise is therefore that B2B partners should also contemplate UNTs as well as SNTs to investigate their influence to the final agreement from collective viewpoints. It is observed that mulling both UNTs and SNTs simultaneously in negotiation is better than taking either UNTs or SNTs. For example, a manufacturing company engaging in B2B negotiation is likely to offer a buyer company who intends to purchase a relatively large number of products within rather a short period under a good payment condition. The manufacturing company may therefore want to pay employees to work extra shifts in order to meet a tight delivery schedule. However, whether the employees of the manufacturing company would accept such extra shifts or not depends on the level of cooperation of company's labor union, which is one of UNTs. Therefore, although an UNT such as labor union's cooperation cannot be dealt with explicitly in the course of B2B negotiation, it is clear that B2B negotiation performance would be enhanced significantly if both UNTs and SNTs are considered with balance. The related cognitive map is obtained as shown in Figure 5, with the consultation with five B2B experts working in KTNet and EC Plaza.

<Figure 5> Cognitive map for an illustrative B2B negotiation problem



To perform what-if analysis with the final cognitive map, adjacency matrix $\underline{E}$ is first organized as follows based on Figure 5.

$$
\underline{E} = \begin{array}{c} FP \\ TI \\ OQ \\ SP \\ IO \\ CF \\ PR \\ LU \\ WA \\ LD \\ CA \\ TD \\ IR \\ SS \\ BE \end{array}
\begin{pmatrix}
0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & -1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 \\
0 & 0 & 0 & 0 & 0 & -1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0
\end{pmatrix}
$$

<Figure 6> Adjacency matrix for the cognitive map in Figure 5

For the sake of brevity, we use acronyms to represent original names of nodes. After stratification of cognitive map in Figure 5, we obtained 7 strata where nodes located in 1st stratum include one SNT such as TI(Tightness of Delivery Date), and four UNTs such as LU(Labor Union's Cooperation), LD(Labor Disputes), IR(Interest Rate), SS(Support to Subsidiary). Target node is IO(Intention to Order). Scenario for proving the validity of our proposed FIM is as follows;

SNTs: TI = 3 days after order placement (0.8)
UNTs: LU = labor union's cooperation (0.7), LD = labor disputes (0.4), IR = interest rate (0.3), SS = support to subsidiary (0.8)

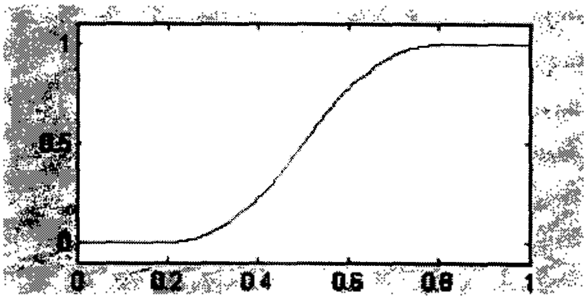
Based on this scenario information, inference results without using FIM is shown in Table 1, where target node inference value is -0.9978.

	FP	TI	OQ	SP	IO	CF	PR	LU	WA	LD	CA	TD	IR	SS	BE
S 0	0	0.8	0	0	0	0	0	0.7	0	0.4	0	0	0.3	0.8	0
S 1	0	0.8	0	0.664	0	0	0	0.7	0.3799	0.4	0	0	0.3	0.8	0
S 2	0	0.8	0	0.664	0	0	0	0.7	0.3799	0.4	-0.3627	0	0.3	0.8	-0.664
S 3	-0.8219	0.8	0	0.664	0	0	-0.5567	0.7	0.3799	0.4	-0.3627	0	0.3	0.8	-0.664
S 4	-0.8219	0.8	0	0.664	0	-0.6135	-0.5567	0.7	0.3799	0.4	-0.3627	0	0.3	0.8	-0.664
S 5	-0.8219	0.8	-0.9837	0.664	0	-0.6135	-0.5567	0.7	0.3799	0.4	-0.3627	-0.3627	0.3	0.8	-0.664

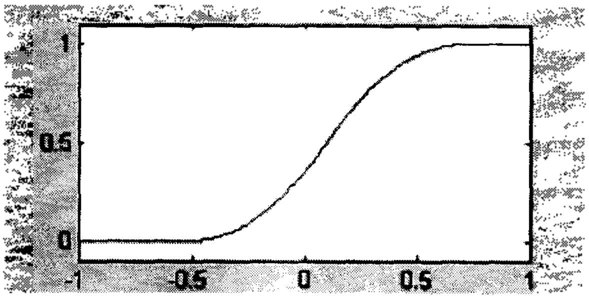
S 6	-0.8219	0.8	-0.9837	0.664	-0.9978	-0.6135	-0.5567	0.7	0.3799	0.4	-0.3627	-0.3627	0.3	0.8	-0.664

[Table 1] Inference results without using FIM

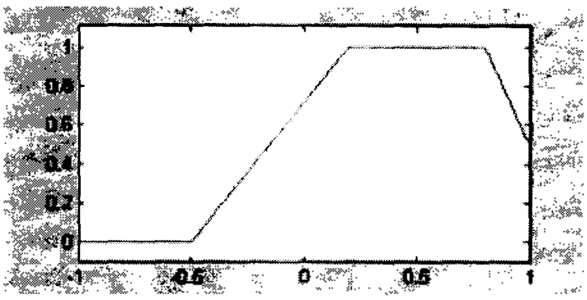
However, after incorporating decision maker's judgment about some negotiation terms such as LU, LD, FP, and OQ, and applying the proposed FIM, we obtained inference results as shown in Table 2. Decision maker's judgment about LU. LD, FP, and OQ is represented in MFs. For example, with the aid of MATLAB, S-shaped MF in Figure 7 (a) was used to represent decision maker's judgment about both LU and LD. Similarly, another form of S-shaped MF was applied to FP (Figure 7 (b)), while trapezoidal MF to OQ (Figure 7 (c)).



(a) S-Shaped MF for LU and LD (smf(x,[0.2 0.8]))



(b) S-Shaped MF for FP (smf(x,[-0.5 0.7]))



(c) Trapezoidal MF for OQ (trapmf(x,[-0.5 0.2 0.8 1.2]))

Figure 7. MFs for LU, LD, FP, OQ

	FP	TI	OQ	SP	IO	CF	PR	LU	WA	LD	CA	TD	IR	SS	BE
S 0	0	0.8	0	0	0	0	0	0.7	0	0.4	0	0	0.3	0.8	0

S 1	0	0.8	0	0.664	0	0	0	0.9444	0.2186	0.2222	0	0	0.3	0.8	0
S 2	0	0.8	0	0.664	0	0	0	0.9444	0.2186	0.2222	0.2008	0	0.3	0.8	-0.664
S 3	-0.5365	0.8	0	0.664	0	0	-0.3659	0.9444	0.2186	0.2222	0.2008	0	0.3	0.8	-0.664
S 4	0	0.8	0	0.664	0	0.2896	-0.3659	0.9444	0.2186	0.2222	0.2008	0	0.3	0.8	-0.664
S 5	0	0.8	-0.9396	0.664	0	-0.2339	-0.3659	0.9444	0.2186	0.2222	0.2008	-0.1525	0.3	0.8	-0.664
S 6	0	0.8	0	0.664	[redacted]	-0.2339	-0.3659	0.9444	0.2186	0.2222	0.2008	-0.1525	0.3	0.8	-0.664

[Table 2] Inference results with FIM

Inference value for target node changed into -0.3944, which is sharply different from -0.9978 in Table 1. Therefore, the proposed FIM can be used effectively to represent decision maker's judgment in the course of inference.

5. Concluding Remarks

Traditional cognitive map is often suffering from a synchronization problem during inference with it, which places hindrance to more useful and robust use of cognitive map in various decision-making problems. Also, traditional cognitive map suffered from lack of technique for representing decision maker's subjective judgment. To overcome this pitfalls, we proposed a new FIM where stratification algorithm to avoid a synchronization problem of cognitive map was suggested, and MF is developed and incorporated in the course of inference.

By using an illustrative B2B example, comparative results were analyzed, revealing that inference results with the proposed FIM is more practical in terms of information richness and robustness. We are now developing more refined version of FIM.

Acknowledgment

This paper was supported by Korea Research Foundation Grant (KRF-2001-005-C20010).

References

Asher, H., *Causal Modelling*, 2, Sage, Beverly Hills, CA, 1983.

Axelrod, R., *Structure of Decision : The Cognitive Maps of Political Elites*, Princeton University Press, Princeton, New Jersey, 1976.

Craiger, P. and Coovert, M.D., "Modelling Dynamic Social and Psychological Processes with Fuzzy Cognitive Maps", *3rd IEEE COnference on Fuzzy Systems, IEEE World Congress on Computational Intelligence*, June 1994.

Dickerson, J.A. and Kosko, B., "Adaptive Cognitive Maps in Virtual Worlds", International Neural Network Society, *Annual Meeting World Congress Neural Networks*, June 1994.

Diffenbach, J., "Influence Diagrams for Complex Strategic Issues", *Strategic Management Journal*, 3, 1982.

Fiol, M.C., "Maps for Managers: Where are We ? Where do We Go from Here ?", *Journal of Management Science*, 29 (3), 1992.

Fu, L., "CAUSIM: A Rule-Based Causal Simulation System", *Simulation*, 56 (4), 1991.

Gotoh, K., Murakami, J., Yamaguchi, T., and Yamanaka, Y., "Application of Fuzzy Cognitive Maps to Supporting for Plant Control", (in Japanese) *SICE Joint Symposium of 15th Syst. Sym. and 10th Knowledge Engineering Symposium*, 1989, pp. 99-104.

Heintz, T.J. and Acar, W., "Toward Computerising a Causal Modelling Approach to Strategic Problem Framing", *Decision Sciences*, 23 (5), 1992, pp.1220-1230.

Kardaras, D. and Karakostas, B., "The Use of Fuzzy Cognitive Maps to Simulate the Information Systems Strategic Planning Process", *Information and Software Technology*, 41, 1999, 197-210.

Kosko, B., "Fuzzy Cognitive Maps", *International Journal of Man-Machine Studies*, 24, 1986, 65-75.

Kosko, B., *Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence*, Prentice Hall, Englewood Cliffs, NJ, 1992.

Lee, K.C., "A Cognitive Map Knowledge-Based Strategic Planning Simulation", *Proceedings of 26th Hawaii International Conference on Systems Sciences*, Wailea (Hawaii), Vol. III, January 1993, 249-267.

________, and Kim, H.S., "A Fuzzy Cognitive Map-Based Bi-Directional Inference Mechanism: An Application to Stock Investment Analysis", *International Journal of Intelligent Systems in Accounting and Management*, 6 (1), 1997, 41-57.

Montazemi, A.R. and Conrath, D.W., "The Use of Cognitive Mapping for Information Requirements Anslysis", *MIS Quarterly*, 1986, pp. 45-56.

Nakamura, K., Iwai, S., and Sawaragi, T., "Decision Support Using Causation Knowledge Base", *IEEE Transactions on Systems, Man, and Cybernetics*, 12 (6), 1982, pp. 765-777.

Paradice, D., "SIMON: An Object-Oriented Information System for Coordinating Strategies and Operation", *IEEE Transactions on Systems, Man and Cybernetics*, 22 (3), 1992, pp.513-525.

Styblinski, M.A. and Meyer, B.D., "Fuzzy Cognitive Maps, Signal Flow Graphs, and Qualitative Circuit Analysis", *Proceedings of the 2nd IEEE International Conference on Neural Networks (ICNN-87)*, vol. II, 1988, pp. 549-556.

Taber, W.R., "Knowledge Processing with Fuzzy Cognitive Maps", *Expert Systems with Applications*, 2 (1), 1991, 83-87.

Warren, K., "Exploring Competitive Futures Using Cognitive Mapping", *Long Range Planning*, 28 (5), 1995.

Zhang, W., Chen, S.S. Wang, W. and King, R., "A Cognitive Map-Based Approach to the Coordination of Distributed Cooperative Agents", IEEE Transactions on Systems, Man, and Cybernetics, 22 (1), 1992.

Zhang, W. and Chen, S.S., "A Logical Architecture for Cognitive Maps", *Proceedings of the 2nd IEEE Conference on Neural Networks (ICNN-88)*, vol. I, 1988, pp. 231-238.