Elicitation of Collective Intelligence by Fuzzy Relational Methodology

Youngdo Joo
Department of Computer and Media Engineering,
College of Engineering, Kangnam University
(ydjoo@kangnam.ac.kr)

The collective intelligence is a common-based production by the collaboration and competition of many peer individuals. In other words, it is the aggregation of individual intelligence to lead the wisdom of crowd. Recently, the utilization of the collective intelligence has become one of the emerging research areas, since it has been adopted as an important principle of web 2.0 to aim openness, sharing and participation. This paper introduces an approach to seek the collective intelligence by cognition of the relation and interaction among individual participants. It describes a methodology well-suited to evaluate individual intelligence in information retrieval and classification as an application field. The research investigates how to derive and represent such cognitive intelligence from individuals through the application of fuzzy relational theory to personal construct theory and knowledge grid technique. Crucial to this research is to implement formally and process interpretatively the cognitive knowledge of participants who makes the mutual relation and social interaction. What is needed is a technique to analyze cognitive intelligence structure in the form of Hasse diagram, which is an instantiation of this perceptive intelligence of human beings. The search for the collective intelligence requires a theory of similarity to deal with underlying problems; clustering of social subgroups of individuals through identification of individual intelligence and commonality among intelligence and then elicitation of collective intelligence to aggregate the congruence or sharing of all the participants of the entire group. Unlike standard approaches to similarity based on statistical techniques, the method presented employs a theory of fuzzy relational products with the related computational procedures to cover issues of similarity and dissimilarity.

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1. Introduction

Recently, the utilization of collective intelligence has been one of fundamental principles of web 2.0 (O'Reilly, 2005) whose philosophy consists of openness, sharing, participation and collaboration. Collective Intelligence is an intelligence that emerges from the collaboration and competition of many individuals, an intelligence that seemingly has a mind of its own. The collective intelligence is an aggregated intelligence to achieve a common purpose by the participation of individuals. Such derived collective intelligence works like an independent entity. As O'Reilly suggested, the collective intelligence may be expressed as a common-base peer production. Frequently, the collective intelligence has greater impact than the simple summation of individual intelligences. The most extreme and successful instance of the collective intelligence is Wikipedia, the on-line encyclopedia.

The essential point is how effectively elicits the collective intelligence to maximize the network economy of participants. The collective intelligence will be a core issue in the next generation web including semantic web (Hendler and Lassila, 2006; Shadbolt et al., 2007) as most of applications deal with the relations, interactions and communication among people, in the form of the social web (Owyang, 2009). The recent research on the social network put the focus on the basics that human being makes the mutual relation and the identity by the interaction and influence (Wasserman and Faust, 1994; Watts and Dodds, 2007). The diverse and significant characteristics of constituent individuals of the social networks may be identified through the extraction of the collective intelligence. This challenge obviously requires a good method for aggregating opinion, in other words, a system to develop *the wisdom of crowd* (Surowiecki, 2005) to lead to the valuable collective intelligence.

This paper will introduce a methodology well-suited to derive a collective intelligence from individual intelligences through collaboration and competition. Individual intelligences are evaluated by human cognition to deal with the high-level mental capability of human beings (Kim and Joo, 1998). Intelligence is described in aspatial terms characterized by the social values, or emotions of each individual. Research efforts start with establishing three main sets : *target objects*, *intelligence constructs* and *participants*. Target objects are the physical or functional description of spatial entities existing in the given environment. Intelligence constructs are the aspatial aspects assigned to target objects. In other words, the intelligence constructs are verbal formulations of the participant's psychological response to target objects. Finally, participants are the set of individual respondents who contribute relational interaction between the spatial and aspatial sets.

All the work is based on the concept of intelligence structure evinced as a cognitive arrangement of target objects and intelligence constructs. Here, the term *structure* is used in a sense which is mathematically well-defined. Structure is one or more sets which have at least one operation or relation (Bandler and Kohout, 1986B). These relations produce aspatial (construct to construct) structures to reflect individual intelligence and aggregate eventually the proposed collective intelligence.

Essential to the systems is the reasonable derivation of the intelligence structures to represent knowledge of individual participants. The work presented herein is mainly concerned with the assessment of the degree of congruence (Mancini and Bandler, 1980) among individual intelligence. Eventually, it aims to seek collective intelligence shared by like-minded groups of individuals beyond individual intelligence. I analyze the overlap of intelligence between individualities and aggregate commonality among them and then quantify their resemblance by employing a fuzzy relational theory as an effective criterion for similarity measurement.

2. Representation of Individual Intelligence

Individual Intelligence from the participants uses a knowledge elicitation technique based on the *personal construct theory* (Kelly, 1965). A construct is a bipolar dimension, consisting of primary (or positive) and contrasting(or negative) poles (Bannister and Fransella, 1986). In this paper, the intelligence construct is defined as the associated keywords for the information retrieval and information grouping. For example, it may be a set of words for tagging (Xu et al., 2006) which is a widely-used techniques in the web to assign the appropriate terms to a given information entity. The tagging is a representative system of the folksonomy (Gordon-Murnane, 2006; Kroski, 2005) which is an information classification system generated by general web users. Folksonomy is sometimes called the wisdom of crowds to revolve the collective intelligence.

It is a *repertory grid technique* (Beail, 1985) that allows for practical usage of personal construct theory. The repertory grid provides a proper way in which the psychological cognition can be organized and studied. In this research, a full repertory grid contains three components : target objects, intelligence constructs and linking values.

An individual participant is presented with a list of target objects and labels of intelligence constructs in a grid-like form. Target objects may correspond to information such as the web resources including an article, an image, a video and a bookmark. Linking values means the degree to which each target object is applied on each intelligence construct. A rating scale with a range of values from 1 to 7 is used to relate intelligence to information object. The points on the rating scale can be interpreted in terms of such semantic hedges as “very”, “slightly”, and “quite” as used in the *semantic differential technique* (Osgood et al., 1967). If neither pole is preferred to a given information object, a rating of 4 is assigned as the neutral point. A ‘not-applicable’ description is denoted by ‘n.’ The ‘n’ indicates that a particular object is not applicable or is not of concern to a participant.

The individual intelligence for the repertory grid is acquired by the tagging from the participants. Unlike the traditional tagging, the individual knowledge of participants is represented with the degree of uncertainty to interpret semantics and context of the knowledge in the repertory grid. Information objects may be chosen from those that are common to the web resources and thus were *a priori* likely to be significant. The intelligence constructs may be selected from a set of key words which is closely related with applied information. This domain-specific work throughout my paper is based on the experiment data which is virtually gathered from 12 participants with respect to 16 intelligence constructs and 18 information objects in order to induce individual intelligence. Each cell of the repertory grid represents the rating values which to relate intelligence constructs to information objects.

If the values represented in the repertory grid are converted to fuzzy values between 0 and 1, inclusive, the repertory grid technique can be an ideal application area for Zadeh's *fuzzy set theory* (Zadeh 1965; Zadeh, 1975), since a fuzzy set is one to which elements may belong in various degrees ranging from 0 to 1 by set membership. The fuzzification is based on an even distribution with exception of the neutral point, i.e by the mapping of 4 to 0.5. The fuzzified grid is instantiation of a fuzzy binary relation between two sets, having intelligence constructs and information objects as rows and columns in matrix form. The *fuzzy relational theory* (Bandler and Kohout, 1986A; Bandler and Kohout, 1986B; Bandler and Kohout, 1988) provides a means of analyzing repertory grid matrices as the proper mathematical implement to be used for structural analysis of intelligence. <Table 1> shows the

<Table 1> Knowledge Grid

		INFORMATION OBJECTS																	
		O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	O12	O13	O14	O15	O16	O17	O18
INTEL-LIGENCE CON-STRUCTS	C1	0.8	1.0	1.0	0.8	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.8	0.8	1.0	n	0.8	0.6
	C2	1.0	0.0	0.8	0.6	0.2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	n	0.6	0.2
	C3	1.0	0.8	1.0	0.8	0.2	1.0	1.0	1.0	0.6	0.8	1.0	1.0	1.0	1.0	0.8	n	0.8	0.5
	C4	1.0	0.8	0.6	0.5	0.2	1.0	1.0	1.0	0.8	0.8	1.0	1.0	0.6	0.8	0.8	n	0.8	0.2
	C5	1.0	1.0	0.5	0.5	0.0	1.0	1.0	1.0	1.0	0.8	1.0	1.0	0.8	0.8	0.5	n	0.5	0.5
	C6	1.0	1.0	0.5	0.5	0.0	1.0	1.0	0.8	0.8	0.8	0.8	1.0	0.8	0.8	0.5	n	0.6	0.5
	C7	1.0	0.8	0.8	0.5	0.4	1.0	1.0	0.8	0.6	0.8	0.5	1.0	1.0	1.0	0.5	n	0.6	0.5
	C8	1.0	0.6	0.6	0.5	0.0	1.0	1.0	1.0	0.6	0.6	0.5	1.0	0.8	0.8	0.5	n	0.5	0.5
	C9	1.0	0.5	1.0	0.5	0.0	1.0	1.0	1.0	0.8	0.8	0.8	1.0	1.0	1.0	0.8	n	0.6	0.5
	C10	1.0	0.8	0.6	0.4	0.0	0.8	0.6	0.8	0.8	0.6	0.6	0.8	0.8	0.6	0.5	n	0.6	0.0
	C11	1.0	0.8	0.8	0.5	0.5	1.0	0.8	1.0	0.8	0.6	1.0	1.0	0.8	0.6	0.5	n	0.8	0.8
	C12	1.0	0.8	0.6	0.5	0.5	1.0	0.8	1.0	0.8	0.6	0.8	0.8	0.8	0.6	0.5	n	0.8	0.5
	C13	1.0	0.8	0.8	0.5	0.5	1.0	0.8	1.0	1.0	0.8	0.8	0.8	0.8	0.6	0.5	n	0.8	0.5
	C14	1.0	0.8	0.8	0.5	0.8	1.0	0.5	0.8	0.8	0.5	0.6	1.0	0.6	1.0	0.5	n	0.8	0.0
	C15	1.0	0.5	0.8	0.5	0.2	1.0	1.0	1.0	0.8	0.5	0.5	1.0	1.0	1.0	0.5	n	0.8	0.5
	C16	0.8	0.8	0.6	0.5	0.5	0.8	0.5	0.8	0.8	0.5	0.6	0.8	0.6	0.8	0.5	n	0.6	0.0

output grid from a specific participant. I call it knowledge grid as it contains the basic knowledge to extract collective intelligence. The fuzzy relational theory, as an extension of Zadeh's fuzzy set theory helps locate and formalize meaningful structures implicit in real-world data (Joo and Noe, 1998; Stiller et al., 1990). Practically, the theory was established by means of fuzzy relational products and the related computational procedures (Bandler and Kohout, 1988).

The following contains a brief review of the main idea. Let R be the relation from intelligence constructs to information objects as in the knowledge grid. Let X be the set of intelligence constructs and Y be the set of information objects, xRy denotes the relation from X to Y where $x \in X$ and $y \in Y$. Rx_iy_j is the degree to which the participants attributes construct x_i to object y_j. In matrix notation, that is the value at i^{th} row and j^{th} column, simply written as R_{ij}.

As Bandler and Kohout introduced, *fuzzy relational products* are composed of two triangle products and one square product with two relations: R and S.

Definition :

Triangle Subproduct, $\lhd$:

$$(R \lhd S)_{ik} = \min_j(R_{ij} \rightarrow S_{jk}) \tag{1}$$

Triangle Superproduct, $\rhd$:

$$(R \rhd S)_{ik} = \min_j(R_{ij} \leftarrow S_{jk}) = (S^{-1} \lhd R^{-1})^{-1}{}_{ik} \tag{2}$$

Square product, $\square$:

$$(R \square S)_{ik} = \min_j(R_{ij} \leftrightarrow S_{jk}) \tag{3}$$

where $\rightarrow$ is the fuzzy implication operator.

The research efforts start with the *triangle subproduct* as it gives the degree to which whenever the participant applies construct x_i, he also applies construct x_j. The formula for the subproduct translates as the degree to which x_i relating to y_j (R_{ij}) implies y_j relating to z_k(S_{jk}) for the two relations R and S where $x \in X$, $y \in Y$ and $z \in Z$. The desired finding is the degree to which construct x_i implies construct x_j based on how a participant applied both of intelligence constructs to information objects. Formally, it is the degree to which a given x_i relates to y in R, x_j relates to y in R for all y. So, Let X and Z be the same set and R and S be the same relation. Using the inverse relation of R, we can make a formula of the triangle subproduct on the single relation desired.

$$(R \lhd R^{-1})_{ij} = \min_k(R_{ik} \rightarrow R_{kj}) \tag{4}$$

This formula eventually gives the degree to which the use of construct x_i implies the use of construct x_j. The degree may be interpreted as a certainty value in the statement, "whenever the participant attributes intelligence construct x_i to an information object, s/he also attributes intelligence construct x_j". The formula above is regarded as a *harsh version* since it takes the minimum of all those values. As the mean value has been more suitable to many applications (Joo and Noe, 1998; Kim and Joo, 1998), I adopt a *mean version* by replacing $\min_j$ by $\frac{1}{N_j}\sum_j$ to express the mean value.

For the triangle subproduct of a single relation, an equivalent definition is produced (Willmott, 1981).

<Table 2> Definition of Fuzzy Implication Operators

Name	Definition
Standard Shape(S#)	$a \rightarrow_1 b = \begin{cases} 1 \text{ if } a \neq 1 \text{ or } b = 1 \\ 0 \ \ otherwise \end{cases}$
Standard Strict(S)	$a \rightarrow_2 b = \begin{cases} 1 \text{ if } a \leq b \\ 0 \ \ otherwise \end{cases}$
Standard Star(S*)	$a \rightarrow_3 b = \begin{cases} 1 \text{ if } a \leq b \\ b \ \ otherwise \end{cases}$
Gaines 43(G43)	$a \rightarrow_4 b = \min(1, \frac{b}{a})$
Modified Gaines 43 (G43′)	$a \rightarrow_{4'} b = \min(1, \frac{b}{a}, \frac{1-a}{a-b})$
Lukasiewicz(L)	$a \rightarrow_5 b = \min(1, 1-a+b)$
Kleene-Dienes-Lukasiewicz(KDL)	$a \rightarrow_{5.5} b = 1-a+a \times b$
Kleene-Dienes(KD)	$a \rightarrow_6 b = \max(1-a, b)$
Early Zadeh(EZ)	$a \rightarrow_7 b = \max(\min(a, b), 1-a)$
Willmott(W)	$a \rightarrow_8 b = \min(\max(\min(a, b), 1-a), \max(b, 1-b))$

$$(R \lhd R^{-1})_{ij} = \frac{1}{N_k} \sum_k (R_{ik} \rightarrow R_{kj}) \qquad (5)$$

The implication operators allow change to occur in the computational process of the triangle subproduct. Many definitions (Bandler and Kohout, 1980; Willmott, 1980) exist for the fuzzy implication operator, →. <Table 2> shows the name and definition for each of them. <Table 3> shows the computational result of the triangle subproduct of the relation from the knowledge grid of <Table 1>. The implication operator used in this paper is Lukasiewicz ($\rightarrow_5$).

As a preliminary stage of the representation of individual intelligence, the triangle product contains a cognitive view of the participant

<Table 3> Knowledge Grid for Triangle Subproduct

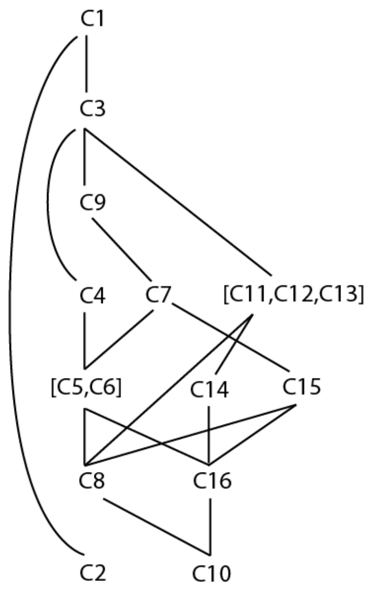
		INTELLIGENCE CONSTRUCTS															
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
INTEL-LIGENCE CONSRUCTS	C1	1.0	.85	.90	.84	.84	.81	.81	.76	.84	.69	.85	.81	.85	.78	.80	.71
	C2	.96	1.0	.95	.91	.89	.86	.89	.84	.94	.77	.88	.85	.88	.82	.89	.76
	C3	.96	.90	1.0	.91	.88	.86	.90	.84	.93	.75	.89	.86	.88	.82	.89	.75
	C4	.99	.94	.99	1.0	.95	.93	.92	.89	.95	.84	.95	.92	.94	.89	.92	.84
	C5	.99	.92	.96	.95	1.0	.96	.92	.91	.95	.84	.94	.92	.94	.85	.91	.82
	C6	.99	.92	.98	.96	.99	1.0	.96	.93	.97	.87	.95	.94	.95	.89	.94	.85
	C7	.96	.92	.99	.92	.93	.94	1.0	.91	.96	.84	.94	.92	.94	.90	.95	.84
	C8	.99	.95	1.0	.97	.99	.98	.99	1.0	.99	.89	.98	.96	.96	.91	.99	.88
	C9	.96	.94	.99	.92	.92	.92	.93	.89	1.0	.81	.91	.89	.91	.85	.94	.79
	C10	.99	.95	.99	.99	.99	.99	.98	.96	.98	1.0	1.0	1.0	1.0	.98	.97	.96
	C11	.98	.89	.95	.92	.92	.90	.91	.87	.91	.82	1.0	.95	.96	.88	.91	.82
	C12	.99	.91	.97	.95	.95	.94	.94	.91	.94	.88	1.0	1.0	1.0	.91	.94	.88
	C13	.99	.91	.96	.93	.94	.92	.93	.88	.93	.84	.98	.96	1.0	.89	.94	.84
	C14	.98	.91	.95	.94	.91	.91	.95	.88	.92	.88	.96	.94	.95	1.0	.94	.91
	C15	.96	.94	.99	.94	.93	.92	.96	.92	.98	.84	.95	.93	.94	.91	1.0	.84
	C16	1.0	.94	.97	.98	.96	.96	.98	.94	.95	.95	.99	.99	.99	1.0	.96	1.0

implicitly. The result of the triangle subproduct is a unary relation from constructs to constructs that one view as a fuzzy matrix having intelligence constructs only as rows and columns. The main concern is to transform the matrix into a graphical representation illustrating the order-like links among constructs. This will be done through the use of *a transitive closure* of the original relation and the *technique of α-cuts*.

Fuzzy relations require a method for realistic study in which complexity existing in such a representation can be eased for better utility. The technique of α-cuts makes it possible to examine a fuzzy relation in crisp perspective. The *α-cut* or *α-level* of the fuzzy relation is the crisp relation R_α, defined by

$$(R_\alpha)_{ij} = \begin{cases} 1 & if\ R_{ij} \geq \alpha \\ 0 & otherwise \end{cases} \tag{6}$$

An order is a relation R from a set of elements X, to itself, that has the properties of reflexivity, transitivity, and antisymmetry. These properties permit the partitioning of the elements of X into n exclusive subsets. The partition of structurally equivalent elements is called *an equivalence class* which is easily obtained from R_α. The resulting structure is a one-way hierarchical order. The graphical representation of the order relationships of intelligence constructs on the crisp matrix like R_α, is called a Hasse diagram. <Figure 1> shows a Hasse diagram at a specific α-cut value; 0.96. The notation, [ ] indicates an equivalence class reduced as a single partition.



<Figure 1> Intelligence Structure

The hierarchy of intelligence constructs offers insight into cognition of an individual participant's intellectual view about information objects given to him. A Hasse diagram can be viewed as a cognitive intelligence structure through the dependencies of constructs specific to the participant's thought about the particular set of the information objects. The following can be spelled out as in the intelligence structure, <Figure 1>. Whenever the participant feels that he want to assign the intelligence construct C4 to a particular information objects he finds it is given by C3, and when he finds the information object is marked by C3, he finds it is done by C1. By the transitivity, if the participant feels it to be C4 then he also feels it to be C1. The intelligence structure has two equivalence classes : one consisting of C5 and C6 and the other consisting of

C11, C12, and C13. These intelligence constructs imply each other and share the same implication link(s) to intelligence constructs outside the class.

One immediately wonders how much the dependencies are specific to the individual participant's intelligence about the particular set of information objects. All the participants usually give different opinions or knowledge on the given information objects and consequently each participant's intelligence structures are vastly different. In some cases, two participants show an extreme difference between two structures to characterize respective intelligences whose participants have exactly opposite placement by the top and bottom intelligence constructs. Empirically, the majority of participants in the data set for my experiment is neither fully agreed nor disagreed, but very often overlapped in their arrangement of intelligence. Thus, *collective intelligence structure* by groups of individuals beyond individual intelligence exists. I try to seek the collective intelligence that characterizes "like-mindedness" of groups by devising effective criteria. To begin this task, I analyze the overlap between intelligence structures, and aggregate their resemblance through a method of similarity.

3. Comparison of Individual Intelligence

Two individual intelligences can be compared by examining how two individuals share meaning- the measurement of understanding and agreement between two individuals. Two participants have an area of common intellectuality (Shaw, 1994) in their own knowledge grid. Two knowledge grids can be compared with respect to the similar or different use of intelligence constructs by examining the difference in the patterning at each grid.

The fuzzy relational theory provides a valuable method to measure similarity between two grids. I utilize the mean version of the square product as mentioned earlier as follows :

$$(R \square S)_{ik} = \frac{1}{N_j} \sum_j (R_{ij} \leftrightarrow S_{jk}) \tag{7}$$

Using the inverse relation of R, instead of S, we can have the following formula of the square product on a single relation.

$$(R \square R^{-1})_{ik} = \frac{1}{N_k} \sum_k (R_{ik} \leftrightarrow S_{kj}) \tag{8}$$

As proven in the development of theory (Bandler and Kohout, 1986A),

$$\begin{aligned}(R \square R^{-1}) &= (R \lhd R^{-1}) \cap (R \rhd R^{-1}) \\ &\quad (R \lhd R^{-1}) \cap (R \lhd R^{-1})^{-1}\end{aligned} \tag{9}$$

The intersection, ∩ between two relations reflects semantically the logical connectives, AND usually given by

$$(R \cap S)_{ij} = \min(R_{ij}, S_{ij}) \tag{10}$$

Finally,

$$(R \square R^{-1}) = \min\left\{(R \lhd R^{-1})_{ij}, (R \lhd R^{-1})^{-1}_{ij}\right\} \tag{11}$$

The square product can be calculated by taking minimum values between the subproduct and inverse of the subproduct. $(R \square R^{-1})_{ij}$ gives the degree to which a participant attributes intelligence construct x_i to exactly the same information object to which s/he attributes intelligence construct x_j. In other words, it is the degree to which the participant applies intelligence construct x_i and x_j, interchangeably, or synonymously. Based on the square product of two relations extended easily from one on a single relation, the fuzzy relational theory provides a method to measure similarity between two grids. Let two relations R_1 and R_2 be the relation of R from two different participants.

The square product of R_1 and R_2 is given by

$$(R_1 \square R_2^{-1}) = (R_1 \triangleleft R_2^{-1}) \cap (R_1 \triangleright R_2^{-1})$$
$$(R_1 \triangleleft R_2^{-1}) \cap (R_2 \triangleleft R_1^{-1})^{-1} \quad (12)$$

So,

$$(R_1 \square R_2^{-1}) = \min\{(R_1 \triangleleft R_2^{-1})_{ij}, (R_2 \triangleleft R_1^{-1})_{ij}^{-1}\} \quad (13)$$

The formula gives the degree to which one participant assigns intelligence construct x_i to the same information object that the other participant assigns intelligence construct x_j. My focal point is just $(R_1 \square R_2^{-1})_{ij}$, occurring when i = j, as it may represent similar or different uses of each intelligence construct from two people. All the values of $(R_1 \square R_2^{-1})_{ii}$ make up the main diagonal of the square product matrix.

In other words, $(R_1 \square R_2^{-1})_{ii}$ gives the degree to which two participants attribute each intelligence construct, x_i to the objects mutually. This leads to *a mutual implication value* of x_i happening between two participants. An average value of those values resulting from each intelligence construct is taken as a measure of similarity between two participants. Specifically, the similarity measure is regarded as a mutual implication or mutuality between two people in that they understand and empathize with each other in the context of each construct's mutual assignment. <Table 4> shows the scores for the mutual sharing of each intelligence construct and the measure of similarity between the individual intelligences of two participants.

This similarity by the matching algorithm with respect to the given intelligence constructs described above does not necessarily reflect the totality of intelligence from two participants. Thus, analysis of the commonality to uncover the shared understanding and agreement between two people is an indispensable part of the comparison

<Table 4> Similarity between Two Individual Intelligences

Intelligence Constructs	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	Similarity Measure(%)
Mutual Sharing	94	94	93	83	91	91	93	89	87	86	89	85	86	86	93	93	89.56

of two intelligence structures. Given two intelligence structures, it is possible to see which intelligence constructs are used relatively identically or somewhat differently. It gives useful idea to identify *core intelligence constructs* acting as pivots around which these similarities or discrepancies revolve. If one can locate those core constructs, he may extract the closer commonality of two individual intelligences. For this purpose, a simple procedure may be applied in order to make a successive deletion of constructs based on mutual sharing of each intelligence construct. The procedure deletes the intelligence construct with least mutual sharing and ascertains whether two reduced intelligence structures without it produce a common structure with a high degree of similarity. The procedure will be repeated by deletion of the construct with the next lowest value until this criterion is satisfied. This gives users more flexibility to discover core intelligence constructs because they can terminate this iteration, at any time as needed, rather than by an arbitrary cut-off point. From <Table 4>, I may identify the core intelligence constructs for two participants as follows; intelligence construct C1, C2, C3, C5, C6, C7, C15 and C16 as each one of intelligence structures with these cores satisfies the requirements given in the procedure. As a matter of facts, intelligence structures of two participants demonstrates an almost identical structure with the core constructs. Thus, one can also locate where discrepancies between two people occur, by them. Intelligence structures created by the core intelligence constructs exhibit a meaningful commonality extracted from two individuals intelligence.

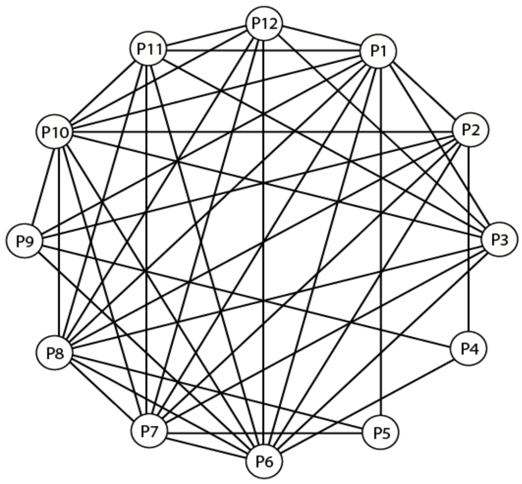
4. Elicitation of Collective Intelligence

The knowledge grid is an effective technique whereby individual participants share their ideas with a group of participants while keeping individual opinions unchanged, by extracting a group representative. The mapping of pairs of intelligence structures identifies subgroups of commonality, groups of "like-minded" individuals, and finally may place these in the perspective of the entire group. Obviously, the relational square product offers new potential for investigating the closeness of understanding between two people through the mutual application of intelligence constructs as discussed previously. This technique can be used to explore commonality in the group. Now every pair of grids in the group is tried by the square product, thereby each pairing yields a measure of similarity for the intelligence of two corresponding members of the group. The output resulting from the exhaustive pairing process is useful for determining subgroups to exhibit similarity and eventually, for extracting a collective intelligence structure shared by all members. <Table 5> indicates scores of intelligence similarity among 12 participating members of the group. Just a half of the matrix is really needed, as it is symmetrical about its leading diagonal. For example, participant P2 shows 86.13% of similarity to P1, 88.31% of similarity to P3, and 85.56% of similarity to P4, and so on.

<Table 5> Intelligence Similarity among Participants

		PARTICIPANTS											
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
PARTICI-PANTS	P1		86.13	79.81	85.75	78.25	82.38	82.56	87.75	85.75	78.50	85.63	86.81
	P2			88.31	85.56	83.69	85.06	87.56	89.38	87.50	86.06	89.69	85.88
	P3				84.94	89.50	83.31	89.75	86.56	86.25	90.69	90.75	81.56
	P4					79.31	84.94	86.25	88.25	91.69	82.19	89.38	88.00
	P5						78.25	86.69	81.31	79.75	90.81	84.56	76.31
	P6							84.25	87.38	86.44	81.69	84.31	86.19
	P7								88.06	88.25	89.44	89.13	85.50
	P8									91.13	84.63	88.25	89.13
	P9										83.38	88.75	89.56
	P10											86.50	80.38
	P11												85.31
	P12												

The measure of similarity in <Table 5> possesses great potential interest to build up a social network to show the relation among the group members. The pair with the highest similarity is chosen as an initial subgroup to express the intelligence commonality, followed by another subgroup with second highest and followed by other subgroups in the order of the similarity values. During the development of such social network, significant subgroups may be identified and some remarkable interactions among the participants may be discovered. For example, one can find a participant to have connection to all the members, in other words a node with highest value based on the degree which means the number of adjacent nodes. The participant should be an influential (Wasserman and Faust, 1994; Watts and Dodds, 2007) to have the greatest effect on the entire group.



<Figure 2> Social Network

The incremental construction of the social network is similar to conventional clustering technique based on the geometrical relationships among members. Obviously, the tightly-coupled subgroup of the social network consists of individuals with more-likely commonality in terms of intelligence. If one employ a proper procedure and a specific threshold value for the grouping, interesting findings would be possible according to his own research purpose. <Figure 2> depicts a social network to take all the intelligence similarity higher than a threshold value of 85% from <Table 5>.

The goal of the research is to seek a collective intelligence to represent individual intelligences of all the participants of the group. Each of individual intelligences may represent a participant's intellectual thoughts and feelings. If some of his ideas are shared by other members of the group, they may benefit all the members. My concern is to extract normative intelligent constructs which integrate individuals' ideas beneficially for the entire group. Remember that the square product for an individual and every other participant produces mutual sharing for every intelligence construct between each pairing. If one takes an average of those mutuality values over all such pairings, he can derive the degree to which the individual and others in the group apply each intelligence construct, mutually. In turn, every other participant is considered to find this value.

<Table 6> shows those values obtained for each member where participants and intelligence constructs represent the columns and the rows of the matrix, respectively. Specifically, an entry at row i and column j indicates how interchangeably j^{th} participant, Pj and every other 11 partic-

<Table 6> Mutual Sharing of Intelligence Constructs

		PARTICIPANTS											
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
INTELLIGENCE CONSTRUCTS	C1	88.09	91.91	92.05	82.55	90.27	91.18	91.55	91.55	90.00	91.73	***92.09***	89.91
	C2	93.64	90.55	92.09	91.73	91.55	93.45	93.27	93.73	93.91	***94.09***	93.55	90.64
	C3	91.00	87.73	89.27	89.73	86.91	75.64	91.00	89.55	***91.36***	90.27	90.73	89.73
	C4	81.91	83.64	85.00	83.36	79.82	83.00	84.91	***85.27***	84.27	84.36	83.82	78.45
	C5	81.55	86.09	***86.36***	84.64	76.45	85.00	85.64	85.45	85.18	83.18	86.18	83.00
	C6	80.18	83.18	84.55	83.82	81.27	86.64	86.18	84.45	84.36	81.55	***86.91***	84.91
	C7	81.91	87.55	87.18	83.55	86.09	85.55	87.00	87.27	***89.00***	83.64	88.45	88.45
	C8	85.55	87.82	84.36	86.91	78.36	87.36	87.55	85.64	86.82	84.45	***87.91***	85.45
	C9	83.64	89.91	88.82	90.09	84.09	85.36	89.55	89.27	***90.45***	89.73	90.09	88.45
	C10	82.45	86.55	***86.73***	85.09	83.00	86.09	85.82	86.09	82.18	82.09	85.55	84.73
	C11	85.73	88.45	86.36	86.18	84.27	76.55	86.64	88.55	87.82	83.73	***89.09***	84.27
	C12	83.27	84.55	79.45	83.36	81.09	74.73	82.73	***85.64***	79.64	76.36	85.00	76.18
	C13	82.09	81.91	83.64	85.91	74.27	83.18	85.45	84.27	***86.45***	85.18	84.64	79.36
	C14	77.09	***86.82***	84.55	84.82	80.73	77.91	82.00	86.45	86.36	83.55	82.91	83.18
	C15	75.91	87.00	89.55	86.91	85.36	87.55	88.36	88.18	***89.64***	85.27	86.55	88.64
	C16	83.19	85.18	83.91	***87.73***	77.82	85.09	85.00	87.64	86.64	79.73	86.18	84.09

ipants in the group use intelligence construct Ci with respect to the given information objects.

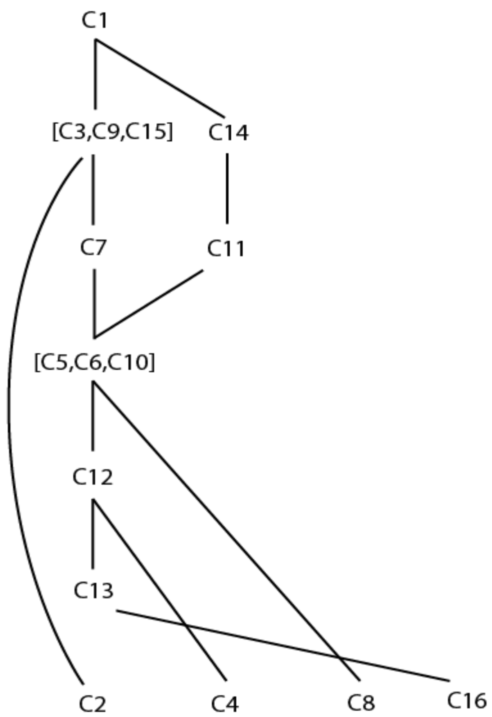
For each intelligence construct, the participant with maximum value is considered as a person who has the strongest sharing of the rest of the group in terms of the corresponding intelligence construct. Reasonably, the participant is a representative enough to donate his own intelligence construct. By the same manner, all the contributors of remaining intelligence constructs can be determined and the gathered constructs lead to the completion of normative intelligence constructs. Those maximum values are marked in bold from <Table 6>. For example, the giver of intelligence construct C1 is P11 and C3 located at the 3rd row is donated from P9.

Finally, these intelligence constructs make up *a normative knowledge grid*, as illustrated in <Table 7>. The normative knowledge grid is not a consensus which discovers the mean of the individual intelligences of the group, but it is believed that this normative grid reflects the aggregation of intelligences of individuals within the group, adequately.

Eventually, the collective intelligence can be instantiated in the form of a collective intelligence structure from the normative knowledge grid. <Figure 3> shows a collective intelligence derived from the norm grid as indicated in <Table 7>.

<Table 7> Normative Knowledge Grid for Collective Intelligence

		INFORMATION OBJECTS																	
		O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	O12	O13	O14	O15	O16	O17	O18
INTELLIGENCE CONSTRUCTS	C1	0.8	1.0	1.0	0.8	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.8	0.8	1.0	n	0.8	0.6
	C2	1.0	0.6	1.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	n	0.6	0.0
	C3	1.0	0.8	1.0	0.8	0.0	1.0	1.0	1.0	0.8	0.8	1.0	1.0	1.0	1.0	0.8	0.5	0.0	0.6
	C4	1.0	0.2	0.6	0.4	0.0	1.0	0.8	1.0	1.0	0.6	1.0	0.8	0.8	0.5	0.0	n	0.2	0.6
	C5	1.0	1.0	0.8	0.6	0.0	1.0	1.0	1.0	1.0	0.8	1.0	0.8	1.0	0.5	0.5	n	0.5	0.5
	C6	1.0	1.0	0.5	0.5	0.0	1.0	1.0	0.8	0.8	0.8	0.8	1.0	0.8	0.8	0.5	n	0.6	0.5
	C7	1.0	0.8	0.6	0.8	0.0	1.0	1.0	0.8	0.8	0.6	1.0	1.0	1.0	0.8	0.8	0.5	0.5	0.6
	C8	1.0	0.6	0.6	0.5	0.0	1.0	1.0	1.0	0.6	0.6	0.5	1.0	0.8	0.8	0.5	n	0.5	0.5
	C9	1.0	0.8	1.0	0.6	0.0	1.0	1.0	1.0	0.8	0.8	1.0	1.0	1.0	1.0	0.8	0.5	0.6	0.5
	C10	1.0	1.0	0.6	0.5	0.2	1.0	1.0	0.8	1.0	0.8	1.0	0.8	1.0	0.5	0.5	n	0.5	0.5
	C11	1.0	0.8	0.8	0.5	0.5	1.0	0.8	1.0	0.8	0.6	1.0	1.0	0.8	0.6	0.5	n	0.8	0.8
	C12	1.0	0.5	0.6	0.5	0.5	1.0	0.6	0.8	1.0	0.5	0.8	0.6	0.8	0.5	0.5	n	0.5	0.8
	C13	1.0	0.8	0.2	0.5	0.5	0.8	0.6	1.0	0.8	0.5	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.8
	C14	1.0	1.0	1.0	0.5	0.5	1.0	0.5	1.0	0.8	0.5	0.8	1.0	0.8	1.0	0.5	n	1.0	0.8
	C15	1.0	0.5	1.0	0.6	0.0	1.0	1.0	1.0	0.8	0.8	1.0	1.0	1.0	0.8	1.0	0.5	0.8	0.6
	C16	0.8	0.8	0.5	0.5	0.5	0.6	0.5	0.6	0.8	0.4	0.6	n	0.5	0.6	0.5	0.5	0.5	0.5



<Figure 3> Collective Intelligence

The collective intelligence may lead, hopefully, to ideals incorporating the overall intellectuality of participants of the group to greatest extent. In other words, this representative intelligence may involve overlapping and congruence among individual intelligence when it is interpreted for investigation of group sharing. Sometimes, collective intelligence may be called normative in that it ought to be according to the ideals for the end. It is attractive that the collective intelligence can be compared with each of individual intelligences of all the participants in similar way in the previous chapter, in order to investigate the degree of closeness or dissimilarity if necessary for further interest.

5. Conclusions

In this paper, I proposed a fuzzy relational methodology to elicit the collective intelligence from the individual intelligences. From the viewpoint of social engineering, the collective intelligence involves the feature of cognition, as well as collaboration and coordination. This research starts with the evaluation of human cognition in order to represent an individual intelligence. The application of intelligence constructs to an information object in conjunction with the intellectual attributes of the participants when expressed as a fuzzy relation, represents a powerful knowledge presentation scheme for human cognition.

Obviously, the fuzzy relational theory to the cognitive intelligence structure presented, provides a new view to evaluate cognition in a way that differ from the standard approach which is based on statistical techniques as it may analyze personal intelligence directly by means of meaningful logic. Specifically, the square product from fuzzy relational theory yields good measure of similarity in individual intelligence by the mutual implication. In my work, the algorithm to find mutual sharing yields desirable results as an effective criterion for the similarity theory. It is appropriately applied to search for the collective intelligence to aggregate individual intelligences of a group including extracting a social network to characterize close commonality or like-mindedness.

It is believed the applicability of these techniques from my research to other web-based information retrieval and classification area including the emerging web science (Berners-Lee et al., 2006) is high. This study may suggest a valuable similarity technique for the influential ranking (Watts and Dodds, 2007) to identify the influential people from the given social network although this subject was not discussed here.

With the success of the proposed model, the substantiation of collective intelligence may contribute to the development of more advanced human decision-making system and advisory system in artificial intelligence area. Also, this study gives an informative idea for the evolution of next generation web to understand the meaning, the semantics and the context of knowledge in that the integration of knowledge should demand the manipulation of the uncertainty and imprecision in a smart way like the fuzzy theory presented.

The limitation of this paper is that the proposed theory was not applied to the realistic data associated with a kind of service to seek the collective intelligence. Thus this study needs the strong empirical validation to analyze the theory based on the application of practical case and the comparison with the similar techniques. My future studies including the influential ranking in marketing areas aim to enhance the validity and reliability of the theoretical approach. In addition, several technical problems await enlightenment. Due to the conversion of the fuzzy closure by alpha-cutting, there exists a set of Hasse diagrams indexed by α-cut values. As the α-cut value is lowered, new implications are added, increasing the complexity of a graph. This causes semantic addition to an intelligence structure. Thus, further research entails the task of choosing α-cut values with the right amount of information to account for 'best' representative intelligence. Fuzzy relational products are based on several fuzzy implication operators and mean/harsh functions. All of these affect the semantics of intelligence structure and consequentially the analysis of the individual intelligences and the elicited collective intelligence. How to choose which operator to use in processing the data are matters left to the empirical judgment and investigative purpose of the researchers. Choosing between mean and harsh cases for the computation of fuzzy relational products also depends on the individual's agenda in a given research area even if a mean version produces a more plausible output in some applications.

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Abstract

퍼지관계 이론에 의한 집단지성의 도출

주영도*

집단지성은 개인들의 협업과 경쟁을 통한 공통이해에 기반한 생산으로서 대중의 지혜를 창출하는 개별 지성들의 통합체라고 할 수 있다. 집단지성의 활용은 공개와 공유 그리고 참여의 기본 철학을 갖고 있는 웹 2.0의 주요한 설계원칙으로 자리잡은 후로, 이와 관련된 연구가 다양하게 진행되고 있다. 이 논문은 개인들간의 관계와 상호작용에 대한 인식을 기반으로 집단지성을 밝혀보려는 방법론을 제안한다. 응용대상은 정보검색과 분류 분야이며, 개인지성의 표현과 도출을 위해 개인 컨스트럭트 이론과 지식 그리드 기법에 퍼지관계이론을 적용한다. 개인의 개별적인 지성은 헤세 다이어그램의 형태로 구현된 지성구조로 표현하여 내재된 지식적인 의미를 분석한다. 논문의 목적인 집단지성의 도출은 개인지성들의 비교를 통해 상호간 공유와 일치를 찾아낼 수 있는 유사성 이론의 도입에 의해 이루어진다. 제안하는 방법론은 퍼지관계 이론 및 퍼지 매칭 알고리즘을 기반으로 실험 데이터로부터 유사성을 측정하고, 개인지성들을 대표할 수 있는 최적의 집단지성을 이끌어내고자 한다.

Keywords : 지식 그리드, 지성구조, 퍼지관계 이론, 소셜 네트워크, 집단지성

* 강남대학교 공과대학 컴퓨터미디어 공학부

저 자 소 개

주영도
현재 강남대학교 공과대학 컴퓨터미디어 공학부 부교수 겸 아태국제학 연구소장으로 재직 중이다. 한양대학교 전자통신공학과를 졸업한 후, University of South Florida에서 컴퓨터 공학 석사, Florida State University에서 전산학 박사를 취득하였다. 주요 관심분야는 인공지능 및 지능형 시스템, 퍼지이론, 지식기반 시스템, 전문가 시스템, 사회관계망 분석 등이다.