GENCOM: An Expert System Mechanism of Genetic Algorithm based Cognitive Map Generator

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Abstract

Cognitive map (CM) has long been used as an effective way of constructing the human thinking process. In literature regarding CM, a number of successful researches were reported, where CM based what-if analysis could enhance firm's performance. However, there exit very few researches investigating the CM generation method. Therefore this study proposes a GENCOM (Genetic Algorithm based Cognitive Map Generator). In this model combined with CM and GA, GA will find the optimal weight and input vector so that the CM generation. To empirically prove the effectiveness of GENCOM, we collected valid questionnaires from expert in S/W sales cases. Empirical results showed that GENCOM could contribute to effective CM simulation and very useful method to extracting the tacit knowledge of sales experts.

Keywords:

Cognitive Map, Genetic Algorithm, Expert System, Simulation, Sales Strategy,

Introduction

Expert system (ES) is a branch of AI that makes extensive use of specialized knowledge to solve problems at the level of a human expert (Joseph & Gray 1998). This knowledge is then stored in the computer and users call upon the computer for specific advice as needed. The computer can make inferences and arrive at a specific conclusion. Then like a human consultant, it gives advices and explains, if necessary, the logic behind the advice (Turban & Aronson, 2001). ES provide powerful and flexible means for obtaining solutions to a variety of problems that often cannot be dealt with by other, more traditional and orthodox methods. Thus, their use is proliferating to many sectors of our social and technological life, where their applications are proving to be critical in the process of decision support and problem solving (Liao, 2005). To build ES several key tasks such as knowledge definition, knowledge design, coding, knowledge verification, system evaluation (Joseph & Gray 1998) need to be done. Each of tasks is time consuming and needs utmost effort. There have been many researches on ES and each specific tasks in building ES. However, cognitive map (CM) is a very useful tool to extracting the tacit knowledge. Although CM is very useful and effective way to dealt with tacit knowledge, but it is really difficult to find the CM connected weight. Many study suggest the variety way to find the connected weight such as questionnaire, LISREL etc., it is not effective way to find the CM connected weight. Therefore, this study developed a new ES mechanism by using genetic algorithm based cognitive map generator (GENCOM). The search function of Genetic Algorithm (GA) is support the usage of CM. To test the feasibility of proposed methodology and application, experiment on enterprise S/W selection is done with real world data that is from the consulting division in global IT company. The enterprise S/W selection ES that is build using GENCOM show statistically meaningful result.

Background

Cognitive Map

The CM is a representation of the causal relationships among the elements of a given object and/or problem. It describes the experts' perceptions about a subjective world rather than an objective reality. CM is composed of (1) concept nodes that represent the factors describing a target problem, (2) arrows that indicate causal relationships between two concept nodes, and finally (3) causality factors on each arrow indicating a positive (or negative) strength with which a node affects another node. Although it is difficult to quantify causality coefficients objectively, the CM allows a set of identified causality coefficients to be organized in an adjacency matrix, yielding a simulation based on it. Such CM-based simulation enables designers to identify the most relevant design factors for enhancing outcome variables. Therefore, more objective method is required to quantify the causality coefficients and help organize an adjacency matrix in order to perform a CM simulation. This paper proposes to use a CM to define knowledge and it's inference. Tacit knowledge is often elicited by means of figurative language and symbolism to express the inexpressible (Numata et al. ,1997). Using CMs is well known as a highly promising technique for capturing tacit knowledge. Lee et al. (1992) have also suggested a CM as a means for constructing organizational memory, and claimed that a CM is superior to common knowledge representation schemes such as rule and frame. Therefore, CMs can be used effectively for making tacit knowledge. CMs have been found especially useful in solving unstructured problems dealing with many variables and their causal relationships. For example, in the field of administrative sciences (Eden et al. 1979), where many decision variables and uncontrollable variables are causally interrelated with each other (Eden & Ackermann, 1989). CMs have been used for distributed decision process modeling on the network (Zhang et al. 1994), geographical information systems (Liu & Satur, 1996; Liu & Satur, 1999), the design of electronic commerce web sites (Lee & Lee, 2003). knowledge management (Noh et al., 2000), bosphorus crossing problems (Ulengin et al. 2001), wayfinding processes (Chen & Stanney,1999), decision analysis (Zhang et al, 1989), business process redesign (Kwahk & Kim, 1999), complex war games (Klein & Cooper,1982), strategic planning problems (Ramaprasad & Poon ,1985), information retrieval (Johnson & Briggs ,1994), and distributed decision process modeling (Zhang et al., 1994). The primary concern of a CM is to see whether the state of one element is perceived to have an influence on the state of the other. In addition, several researchers proved that CM is a technically and methodologically mature technique to solve a wide variety of unstructured decision problems.(Liu & Satur, 1999; Park & Kim, 1995; Wellman,1994; Zhang & Chen,1989; Zhang et al., 1994).. Therefore, a CM can represent experts' beliefs and cognition about ill-structured social relationships (Huff, 1990). A CM is composed of concept nodes (or nodes) of a target problem, signed directed arrows, and causality value between the nodes. Concept nodes represent concepts consisting of a given target problem, signed directed arrows, and causal relations between two concept nodes. Causality value means '+' and '−'. The causality coefficient can be fuzzified into a real value between −1 and +1 (Lee et al, 1992). Axelrod (1976) stated that the simple CM with a causality coefficient '+' and '−' is sufficient for replicating human cognition because decision-makers typically do not use a more complicated set of relationships.

Expert System

ES is "a computer program that has built into it the knowledge and capability that will allow it to operate an expert level" (Feigenbaum and McCorduck 1983). The definition of ES is simple. But, A successful ES development needs a well-planned course of activities. There have been many researches on methodologies and applications for ES. Since the mid 1980s, considerable research attention has been devoted to understanding the process of ESs implementation (Gill, 1996). Recently, Liao (2005) has surveys and classifies ES methodologies using eleven categories. rule-based systems (Valenzuela et al, 2004), knowledge-based systems (Sen at al., 2004 ; Saunders at al., 2003; Cohen & Shoshany, 2002), neural networks (Liau et al, 2004; Li et al, 2004, Wang et al, 2004), fuzzy Ess (Frantti & Kallio, 2004; Lee et al, 1998; Boegl et al, 2004), Object-oriented methodology (Depradine,2003; Lau et al, 1998), case-based reasoning (CBR) (Fu & Shen,2004; Gardan & Gardan, 2003, Montani & Bellazzi, 2002, Takahashi et al, 1995), System architecture development (Chau & Albermani,2004; Shaalan et al, 2004) intelligent a gent (IA) systems (Shaalan et al, 2004; Thomson & Willoughby,2004), modeling (Shaalan et al, 2004; Cheung et al, 2004; Abacoumkin & Ballis,2004), ontology (Ruiz-Sanchez et al, 2003; Takaoka & Mizoguchi, 1996), database methodology (Yan et al., 2004; Filis et al.,2003). ES methodologies are tending to develop towards expertise orientation and that ES applications development is a problem-oriented domain. It is suggested that different social science methodologies, such as psychology, cognitive science, and human behavior could implement ES as another kind of methodology. Integration of qualitative, quantitative and scientific methods and integration of ES methodologies studies may broaden our horizon on this subject (Liao, 2005). But, there are ES development procedures and components generally known. To build ES several key tasks such as knowledge definition (Knowledge Acquisition), knowledge design, coding, knowledge verification, system evaluation are required (Joseph & Gray 1998). In this paper, we tried to develop not problem-oriented but generic methodological framework that can be applied to various problems. ES consists of three main components, which include the knowledge base, the inference engine and the user interface (Metaxiotis & Psarras, 2003). The knowledge base is the hart of system and contains the knowledge needed for solving a specific problem. The knowledge may be in the form of facts, heuristics (e.g. experience, opinions, judgments, predictions, algorithms) and relationships usually gleaned from the mind of expert. Knowledge can be represented using a variety of representation techniques (e.g. semantic nets, frames, predicate logic) but the most commonly used technique is "if-then" rules, also known as production rules. The inference engine is employed during a consultation session, examines the status of the knowledge base and determines the order in which inference are made. It may use various inference methods for reasoning in the presence of uncertainty. The user interface part enables interaction of the system with the user. It mainly includes screen displays, a consultation/advice dialogue and an explanation component. In addition, ESs provide interface for communication with external programs including database and spreadsheets.

Genetic Algorithm

Genetic Algorithm (GA) were first introduced by John Holland in the 1970s as an overcome of investigations into the possibility of computer programs undergoing evolution in the Darwinian sense (Khan et al., 2004). GA maintains and manipulates a population of solutions in their search for better solutions. GA is based on a randomized search and adopt a random choice as a means to guide a highly explosive search through a coding of a parameter space (Lee, 2000). GA have been used to solve linear and nonlinear problems by searching all regions of the state space and exponentially exploring promising areas through mutation, crossover, and selection operations applied to individuals in populations (Goldberg, 1978). Although GA do not guarantee the best possible solution, GA are applied as heuristic procedures, which like evolution in living organisms, to improve results in each generation as it adapts to environmental conditions. GA attempts to arrive at optimal solutions through a process similar to biological evolutions. This involves following the principles of survival of the fitness, crossbreeding and mutation to generate better solutions from a pool of existing solutions. GA performs optimization process in four stages (Lee, 2000): initialization, selection, crossover, and mutation. The steps in the typical GA for finding a solution to a problem are listed below (Khan et al., 2004):

(1) Create an initial solution population of a certain size randomly.

(2) Evaluate each solution in the current generating and assign it a fitness value.

(3) Select "good" solutions based in fitness value and discard the rest.

(4) If acceptable solutions are found in the current generation, or maximum number of generations is exceeded, then stop.

(5) Alter the solution population using crossover and mutation to create a new generation of solutions.

(6) Go to step 2.

In this study is an attempted to optimize the search for the CM connected weight that will lead to a GENCOM simulation. A Methodology developed for this purpose is describes below.

Methodology

The main idea of proposed methodology in this paper is to build CM that is used as core knowledge representation mechanism and to solve new problem by using GA. Although numerous experimental studies reported the usefulness of CM in tacit knowledge management studies, there is a major drawback in searching connected weight. An advantage of present approach using GENCOM is that it is capable of tacit knowledge management that is easy to understand for user like ES.

This paper proposes 4 steps procedure for GENCOM simulation, which is consisted of 'Gathering partial information', 'Preparing CM', 'GENCOM simulation', 'Problem solving'. The first phase is the procedure that collects partial knowledge of expert. In this step, tacit knowledge is gathered by expert survey. Also rough relationships between factors are gathered by asking to experts. The second phase is the procedure for preparing data that will be used in phase 3. Phase 2 is the procedure to sophisticating knowledge models based on uncertain information that is gathered in phase 1. To sophisticate knowledge model, we introduced 'learning by example' approach. And this phase 2 is the procedure that is preparing examples from real data. Traditional CM construction algorithm didn't suggest procedural finding method of CM connecting weight, but GENCOM easily find the optimal CM connecting weight by using GA. Therefore phase 2 finding feasible CM models that meet prepared examples. Each set of relation between factors (nodes or concepts) in CM can be found by GA searching space. GENCOM that is combined with CM and GA will find the best model that fit to example data. Phase 3 is the simuation using GENCOM. Traditional CM simulation can only what-if analysis, but in this study GENCOM can play goal-seeking analysis by using GA search function. Finally, phase 4 solves problem using CM.

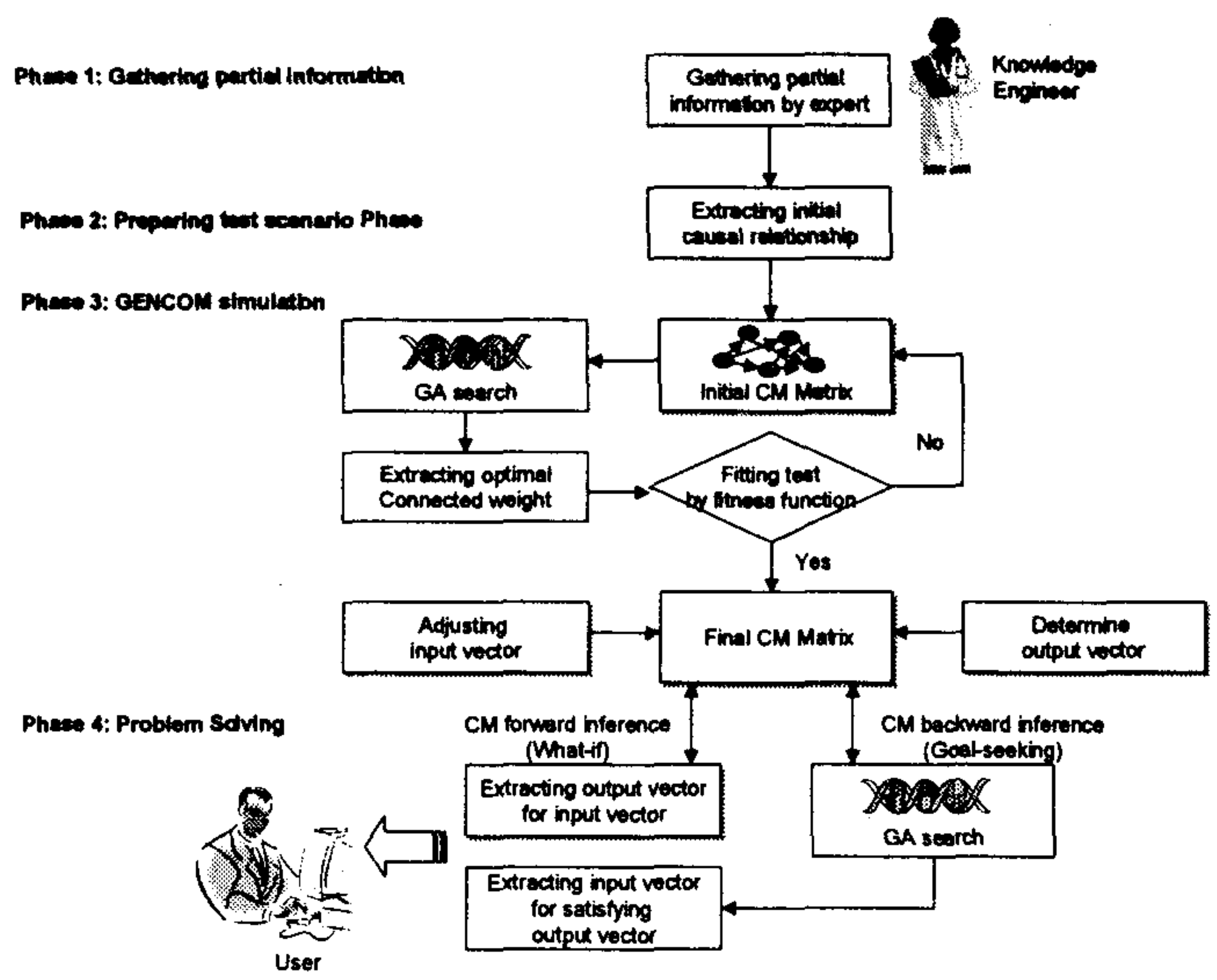

Figure 1. Step 4 procedures for GENCOM simulation

Gathering Partial Information Phase

We could not know complete knowledge model that is represented by CM at the starting point. The first phase of constructing GENCOM is gathering partial information (tacit knowledge). Knowledge acquisition from multiple experts was proposed to avoid some pitfalls of replying on a single expert. In this study, gathering partial information from expert is interview and survey method. And then we elicit the draft relationship between partial information. Experts are asked to draw arrows between partial information and mark '+' or '-' sign depends on positive or negative relation. Finally, we combined all the partial information using fuzzy operation method.

Preparing Test Scenario Phase

After gathering raw information for causal knowledge (attribute and it's relations), supervised learning is adopted to sophisticating CM. First of all, this phase is to preparing test data to train CM. Before preparing test data, fuzzy conversion table needs to be prepared for real attributes values. By using this conversion table we can convert real attribute values are quantitative and qualitative, into fuzzy value which are between -1 and 1 and can be used in CM simulation.

CM simulation Phase

Other sides, there are just few CM learning algorithm (Kosko, 1986; Papageorgiou et al., 2004) and they are mostly based on ideas coming from the field of artificial neural networks training. Therefore, in this study GA was used for searching connected weight of each causal relationship between node and node. Using this method, GENCOM that is combined with CM and GA will find the optimal CM among possible CMs that fit to example data.

Problem Solving Phase

Final phase is to solve the problem by using GENCOM. After the CM was constructed we can easily simulation by using GENCOM. Traditional CM only can play a what-if analysis by using CM forward inference. But, GENCOM can goal-seeking analysis by using GA search function. In this study, we called this method as CM backward inference. Using this two inference mechanism, decision maker can decision making more effective way. Also, fuzzy conversion table (made by phase 2) is also needed in this phase.

Experiment Using Enterprise S/W Sales Case

Dramatic development of information technology requires new type of sales strategy to enterprise S/W dealers. That is, one should thoroughly consider diversified types of enterprise S/W and more elaborated consumer needs to establish successful sales strategy. However, various factors that should be considered in establishing enterprise S/W sales strategy are different according to types of enterprise S/W and hard to be managed systematically which led to the current situation where they have not been discussed enough. Therefore, this study used an enterprise S/W sales case to empirically test for our GENCOM methodoiogy.

Gathering partial information

As we proposed in section 3.1, 4 steps are applied to gather partial causal information from expert. The first issue with CM is how to gathering the partial causal information among relevant enterprise S/W sales factors. To resolve this issue, we interviewed 5 sales experts who have more than 5 to 10 years sales manager experience of enterprise S/W sales. After interviewed 16 attributes are selected as factors that affected enterprise S/W sales. These attributes are categorized into 'Input attributes (input vector)' and 'Result attributes (output vector)' (See Table 1). Input attribute is the attribute that can get information or data for the attribute before starting project. And result attribute is the attribute that can be known as a result or calculation of input attributes.

Table 1. Sixteen Enterprise S/W sales factors

Node	Factor Name	Definition
C1	Function Fit (FIT)	The functional coverage of user requirement
C2	New Technology (NT)	How the S/W are state of the art technology
C3	Market Share (MS)	Market share of vendor company
C4	Reference (REF)	How many references has the S/W
C5	Consultant (CON)	The experience level of consultant
C6	Proposal (PT)	Proposal presentation
C7	S/W function (SW)	S/W overall functionality (Speed, User Interface etc.)
C8	Ease of use (EOU)	How easily user can use this S/W
C9	Price (PRC)	Price attractiveness
C10	Ease of implementation (IMP)	In terms of implementation project risk, ease of implementation level
C11	Education (EDU)	Education support for this S/W
C12	A/S (AS)	After Service
C13	System Stability (SS)	System stability after go-live
C14	Top management (TOP)	Top management involvement in decision making of vender selection
C15	Relationship (REL)	Relationship with C-level management
C16	Vendor Image (VEN)	Reputation for vendor in market
C17	Vendor Selection (VS)	Vendor selection, whether selected as S/W provider or not

According to the phase 3 in section 3.1 partial causal information are extracted by using form like figure 2. We got 25 semantic information for causal relationships between attributes from experts.

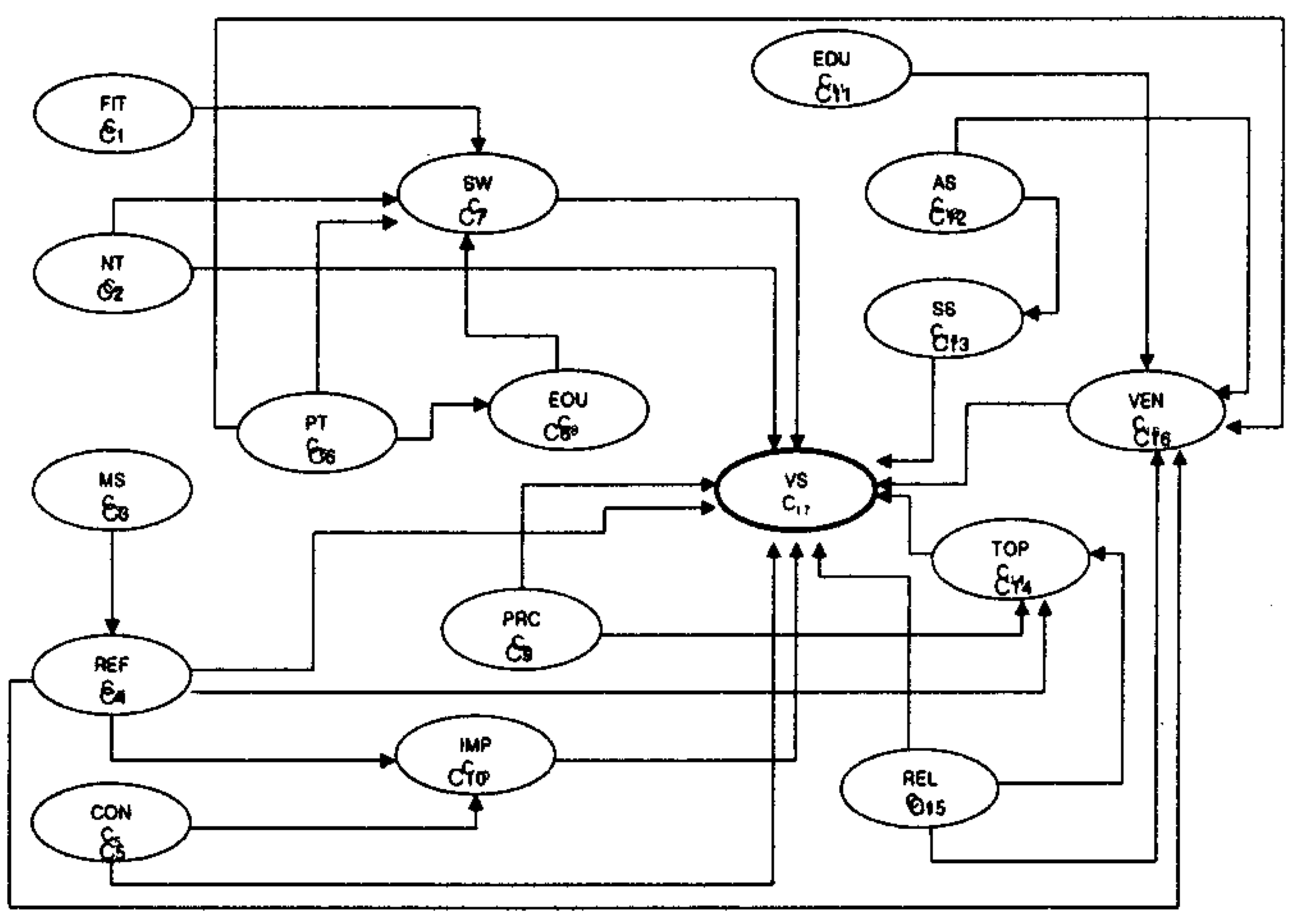

Figure 2. Schematic CM for enterprise S/W sales

These semantic information are provided draft causal relation data for GENCOM.

Preparing Test Scenario Phase

As proposed in section 3.2, this phase is to prepare test data to sophisticating CM based on draft partial causal information that is gathered in previous phase. Fuzzy conversion table needs to be pared. This table is extracted from the FGI (Focus Group Interview) with five experts working as sales manager.

Table 2. Fuzzy conversion table for enterprise S/W sales

Node	Input Range (Fuzzified value)
C1	Mapping Ratio less than 30% : -0.8 Mapping Ratio 30 ~ 50 % : -0.5 Mapping Ratio 50 ~ 70 % : 0.5 Mapping Ratio more than 70% : 0.8
C2	A : State of the art : 1 B : Leading technology : 0.5 C : general technology : 0 D : out of date : -0.5
C3	Market Share No.1 : 1 Market Share 2,3 : 0.5 Market Share 4,5 : - 0.5 Market Share over 6 – less than 10: -1
C4	Reference in peer industry in the same country : 1 Reference in peer industry(not in the same country): 0.5 Reference in other industry : 0.2 No Reference : -1
C5	Average consultant career (more than 10 years) : 1 5 ~ 7 years : 0.5 3 ~ 5 years : 0.2 under 3 years : -0.5
C6	A: Excellent :1 B: Good: 0.5 C: Average :0.1 D: Under expectation : -0.5
C7	A: Very satisfied :1 B: satisfied : 0.5 C: average : 0 D: unsatisfied : -0.5 E: Bad: -1
C8	A: Very satisfied :1 B: satisfied : 0.5 C: average : 0 D: unsatisfied : -0.5 E: Bad: -1
C9	A: under 80% of client budget : 1 B: 90% ~ 100% of client budget : 0.8 C: over budget : -0.2
C10	A: very easy to implement : 1 B: easy to implement : 0.5 C: Average : 0 D: difficult to implement : -0.5 E: Very difficult to implement : -1
C11	A: very good support : 1 B: easy to be supported in the country : 0.5 C: moderate: 0 D: difficult to be supported : -0.5 E: very difficult to be supported : -1
C12	A : 24 hour on-line & on-site support possible in the country : 1 B : No realtime, but no problem in receiving support : 0.7 C: Domestic support system available, but not efficient process: -0.3 D: domestic support is difficult : -0.8
C13	A : No problem in system stability(Stable in other reference) : 1.0 B : Problem occurred in other site : -0.5 C : Problem occurred frequently : -1.0
C14	A: Top management has significant influence in decision making : 1.0 B: more than 50% of influence in decision making : 0.7 C: Working level's influence more important : -0.6 D: Decision making made almost by the working level : -1.0
C15	A: Very strong relationship : 1.0 B: have held informal meetings such as golf, drinks : 0.7 C: have met in a few formal meetings : 0.2 D: No special relationship : 0.0 E: Negative relationship : -0.7
C16	A: Very good image: 1.0 B: good image : 0.5 C: average : 0 D: bad image : -0.5 E: very bad image : -1
C17	selected as S/W provider : 1 not selected : 0

GENCOM Simulation Phase

As proposed in section 3.3, we gathered 25 experts to assess enterprise S/W sales cases. But only 15 cases was used to training data and a remaining cases (10 cases) will be used to evaluate the performance of GENCOM in phase 4. GA training was done by the GA S/W package Evlover™ called from an excel macro, and crossover rate ranges from 0.5 to 0.7 and the mutation rate ranges from 0.06 to 0.12 for our experiments. As stopping condition, we used 5000 trials. And the defining a fitness function is always very important. This study, the objective of the system is to find the CM connected weight matrix (E), which is minimized the RSS (predicting the vendor selection, 1=success, 0= fail).

Table 3. Optimal CM weight matrix by using GENCOM

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	-0.78	-0.97	0.27	0.06	-0.55	-0.46	-0.02	0.43	-0.59	-0.90	0.03	-0.14	0.89	-0.45	-0.06	-0.77	0.07
C2	-0.71	0.50	-0.21	0.67	-0.20	0.13	1.00	0.89	-0.22	0.56	-0.74	-0.31	-0.13	0.44	-0.82	-0.75	1.00
C3	-0.95	0.43	0.09	0.41	0.58	0.71	0.88	-0.93	0.61	0.85	0.49	0.40	0.04	-0.41	0.64	0.75	-0.71
C4	0.11	-0.11	0.98	-0.19	0.04	0.93	-0.26	0.09	0.03	0.71	-0.20	0.37	-0.08	0.99	0.50	0.79	-0.98
C5	0.13	-0.95	0.90	-0.58	0.60	0.12	-0.62	0.60	0.76	-0.87	-0.14	-0.03	-0.70	0.18	-0.25	-0.10	0.07
C6	0.61	-0.48	0.90	0.92	-0.04	-0.69	0.13	0.44	0.90	0.37	-0.38	0.01	0.27	0.78	-0.94	-1.00	0.30
C7	0.48	0.94	0.50	-0.47	-0.75	-0.14	-0.65	0.03	-0.43	0.67	0.80	-0.07	0.86	-0.84	0.70	-0.27	1.00
C8	-0.64	0.48	-0.86	0.18	0.63	-0.47	-0.13	0.30	0.99	-0.67	0.13	-0.81	-0.72	0.38	0.93	0.41	0.80
C9	0.84	-0.56	-0.64	0.25	-0.17	0.28	0.28	-0.67	-0.89	-0.56	-0.69	-0.28	0.54	0.66	0.46	-0.41	0.33
C10	0.95	0.29	0.55	-0.57	0.04	-0.24	-0.74	0.01	0.09	-0.51	-0.07	0.61	0.06	-0.40	0.78	0.97	1.00
C11	-0.66	0.86	0.50	-0.75	-0.86	0.53	-0.35	-0.40	-0.27	-0.74	-0.69	-0.48	-0.07	0.21	-0.56	-1.00	-0.08
C12	-0.25	0.83	-0.21	-0.31	0.56	-0.14	-0.21	-0.37	0.48	-0.47	0.19	-0.32	1.00	-0.87	-0.62	0.21	0.02
C13	-0.67	0.49	0.74	-0.94	0.95	0.88	-0.22	0.48	-0.74	0.52	-0.87	-0.10	0.13	0.13	-0.62	0.28	0.88
C14	-0.54	-0.30	-0.43	0.70	0.75	-0.55	-0.53	0.76	-0.53	-0.65	-0.68	0.62	-0.53	0.68	0.78	0.35	-1.00
C15	-0.65	-0.91	0.31	0.80	0.10	0.96	0.01	-0.02	0.80	-0.06	0.16	0.85	0.60	-0.06	0.51	-1.00	0.83
C16	-0.29	-0.28	0.72	-0.76	0.62	-0.39	0.76	-0.80	0.44	0.08	0.39	-0.91	0.33	0.78	-0.48	0.36	-0.80
C17	0.30	0.31	0.24	0.22	-0.83	0.36	-0.39	-0.25	-0.16	-0.11	-0.17	-0.06	-0.74	-0.23	0.42	0.94	0.44

Problem Solving Phase

Using GENCOM, we have assessed an enterprise S/W sales stage with given information. We conducted an evaluation for our methodology and application to test the accuracy of GENCOM's recommendation.

Table 4. The Performance Comparison

Case No.	Actual Value 1: Success 0: Fail	Predicted Value			
		GENCOM		11 Experts Average	
		Estimation	Cutoff 0.5	Estimation	Cutoff 0.5
Test 1	1	0.90	1	1.00	1
Test 2	1	0.95	1	1.00	1
Test 3	0	0.04	0	0.55	1
Test 4	0	0.18	0	0.09	0
Test 5	1	0.97	1	0.45	0
Test 6	0	0.01	0	0.18	0
Test 7	1	0.40	0	0.82	1
Test 8	1	0.60	1	0.55	1
Test 9	0	-0.41	0	0.73	1
Test 10	0	0.82	1	0.82	1
		Fitting Ratio: 80%		Fitting Ratio :70%	

To test an accuracy we compared 10 actual enterprise S/W sales case between GENCOM and 11 sales experts. The hit ratio calculated from GENCOM simulation and hit ratio of sales experts are summarized in table 4. The GENCOM hit ratio is 80% of 10 case (evaluation data), but sales experts hit the 70%. This means if the enterprise S/W related factors are within the feature range of derived connected weight, the probability of good hit is about 80%. This results mean that GENCOM is a effective method to elicit the tacit knowledge of enterprise S/W sales experts.

Conclusion

This study developed a new ES mechanism by using GENCOM. This paper contributes to (1) the building seamless methodological process from extracting expert's tacit knowledge to constructing knowledge base with CM, (2) the proposing of GENCOM that the construct ES using GA and CM, (3) the addressing of GA approach to sophisticating CM and problem solving, and (4) the proposing GENCOM that is used as core inference engine. With the help of world wide famous IT company's south korea local branch office, we tested GENCOM on developing enterprise S/W sales case. The overall experimental results are very positive. GENCOM showed 80% of accuracy for enterprise S/W sales with real data. And provided very useful functionality that recommends alternatives to reduce vender selection. We believe that the proposed methodology also provides a foundation for other related research in the field of ES and CM. We hope that more studies will be suggested where the proposed framework is tested against cases from various industries and businesses to prove its applicability and extensibility.

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