DOI: 10.3745/KIPSTB.2008.15-B.2.147

인과관계 지식 모델링을 위한 퍼지인식도와 베이지안 신뢰 네트워크의 비교 연구

Wooi Ping Cheah† · 김 경 윤†† · 양 형 정††† · 김 수 형†††† · 김 정 식†††††

요 약

본 논문에서는 인과관계 지식의 표현과 추론에 가장 대표적으로 사용되는 퍼지인식도(FCM, Fuzzy Cognitive Map)와 베이지안 신뢰 네트워크(BBN, Bayesian Belief Network)를 구조적으로 분석한다. 퍼지인식도와 베이지안 신뢰 네트워크는 의사 결정을 지원하는데 중요한 인과관계 지식을 표현하고 추론하는데 사용되는 가장 대표적인 프레임워크이지만 인과관계 지식응용 영역에서 두 프레임워크의 역할에 대한 구조적 비교 연구는 이루어지지 않고 있다. 본 논문에서는 두 프레임워크의 구조적 비교를 통해 퍼지인식도와 베이지안 신뢰 네트워크의 중요한 특징들을 추출하고, 이를 통해 인과 지식 공학에서 어떻게 퍼지 인식도와 베이지안 신뢰 네트워크가 이용되어야 하는지를 보인다. 인과관계 지식의 표현과 추론의 과정을 평가하는데 비교 평가를 위한 항목으로서 본 논문에서는 사용성, 표현력, 추론능력, 정형화와 완결성이 사용되었다.

키워드 : 퍼지인식도, 베이지안 신뢰 네트워크, 인과 추론, 지식공학, 소프트컴퓨팅

Fuzzy Cognitive Map and Bayesian Belief Network for Causal Knowledge Engineering: A Comparative Study

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ABSTRACT

Fuzzy Cognitive Map (FCM) and Bayesian Belief Network (BBN) are two major frameworks for modeling, representing and reasoning about causal knowledge. Despite their extensive use in causal knowledge engineering, there is no reported work which compares their respective roles. This paper aims to fill the gap by providing a qualitative comparison of the two frameworks through a systematic analysis based on some inherent features of the frameworks. We proposed a set of comparison criteria which covers the entire process of causal knowledge engineering, including modeling, representation, and reasoning. These criteria are usability, expressiveness, reasoning capability, formality, and soundness. The results of comparison have revealed some important facts about the characteristics of FCM and BBN, which will help to determine how FCM and BBN should be used, with respect to each other, in causal knowledge engineering.

Key Words : Fuzzy Cognitive Map, Bayesian Belief Network, Causal Reasoning, Knowledge Engineering, Soft Computing

1. Introduction

Causal reasoning seeks to establish the relationship between causes and effects. From the model of such a relationship the causes of some events can be diagnosed and their effects can be predicted. Causal reasoning is useful in decision making for two main reasons: first, it is natural and easy to understand because the ability is inherent in human beings; second, it is convincing as it explains why a particular conclusion is made. However, causality utterances are often used in situations that are plagued with uncertainty. FCM and BBN are two major frameworks for modeling, representing and reasoning about causal knowledge [1,2,3]. Both of them are graphical, and they use nodes for representing domain variables and directed links between nodes for representing cause-and-effect relationships between the variables.

Despite the fact that both FCM and BBN have been used extensively in causal knowledge engineering for decision support systems, there is no reported work

※ 이 논문은 2007년도 정부재원(교육인적자원부 학술연구조성사업비)으로 한국학술진흥재단의 지원을 받아 연구되었음(KRF-2007-331-D00412).
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논문접수 : 2007년 11월 22일, 심사완료 : 2008년 1월 26일

which compares their respective roles. This paper aims to fill up the gap by providing a qualitative comparison of the two frameworks through a systematic analysis based on some inherent features of the frameworks. The results of comparison have revealed some important facts about the characteristics of FCM and BBN which are not found in the literature. These facts will help to determine how FCM and BBN should be used, with respect to each other, in causal knowledge engineering. To be more focused, we confine our scope of study to the comparison from the perspective of knowledge engineering. We consider the following set of criteria: usability in causal modeling [4,5], expressiveness in causal representation [6,7,8,9], adequacy and efficiency in causal reasoning [7,9], formality in semantics, and soundness in inference [7,9, 10,11]. These are commonly used criteria in knowledge engineering for the evaluation of traditional knowledge representation frameworks. In this paper, they have been adapted for the evaluation of FCM and BBN. The selection of these criteria is based on the principle that they collectively cover the entire process of causal knowledge engineering. For each criterion, we formulate a set of specific comparison items, expressible in the form of distinguishing questions, which are sufficient to reveal some important characteristics of the frameworks.

The first criterion is usability in causal modeling, a user's perspective. A framework can be viewed either as a modeling tool for specifying knowledge of the application domain, or as a knowledge elicitation tool for transferring knowledge of a domain expert into a causal model. In either view, a front-end framework is required to be simple and user friendly. The models constructed have to be legible and maintainable. Detailed comparison items under usability include user interface, representation of causal relationship, representation of causal strength, intuitiveness of causal structure, level of specifying causal relationship, and complexity of specifying combination effects. The second criterion is expressiveness in causal representation. This is considered as a back-end machine's perspective as it is only concerned with the automatable representation schemes. Detailed comparison items under expressiveness include tolerance of uncertainty in prior likelihood of variable states, tolerance of unrepresented causes, tolerance of uncertainty in individual causal effects, tolerance of uncertainty in combination formula, representation of causal loops and temporal knowledge. The third criterion is adequacy in causal reasoning, another back-end machine's perspective as it is only concerned with the automated reasoning. Reasoning adequacy determines the reasoning capability (power). Detailed comparison items under reasoning adequacy include the ability of backward chaining, ability of diagnostic reasoning, efficient inference mechanism, availability of powerful commercial reasoning systems, and good records in industry-scaled applications. The fourth criterion is formality in semantics and soundness in inference. Formality is mainly associated to the way how expressions are interpreted in the framework. The accuracy and consistency of the semantic assignment is very often determined by the profoundness of the underlying theory. Formality in turns affects the soundness of inference mechanism which determines the correctness of the knowledge derived from the represented causal model. Detailed comparison items under formality and soundness include well-defined mathematical foundation and provable inference mechanism.

An outline of the remainder of the paper is as follows. In Section 2, we mention some important literature related to the fundamentals and applications of FCM and BBN. We also survey their respective roles in large-scale industry applications. Section 3 is the main section of this paper, in which we compare the roles of FCM and BBN in causal modeling, causal knowledge representation, and causal reasoning. In Section 4, we conclude the results of the comparison and point out some possible future research.

2. Related Work

Axelrod proposed Cognitive Map (CM) in 1976 [12]. It is also called Causal Map because it is used for representing causal relationships between domain variables. It is the predecessor of FCM, and it has a collection of nodes connected by some causal links or edges. The nodes represent concepts or variables of a domain. The edges represent the direction of influence. Edges have a sign, which can be positive (a promoting effect) or negative (an inhibitory effect). An FCM is a "fuzzified" version of CM [13,14]. It allows causal links to have a value in [-1, 1]. It also allows feedback, which adds a temporal aspect to its operation. Carvalho and Tomé argue that FCMs are not fuzzy in the traditional sense, because they do not use any type of fuzzy or membership function [15]. Aguilar provides an introduction and a thorough survey for the recent development of FCM [16]. FCM has shown to be useful in modeling complex dynamic systems. Some reported applications are: stock investment analysis[17], decision support in geographic information systems[18], human relationship management in airline service[19], analysis of the impacts of an eco-industrial park[20], decision support in medicine[21], and assembly design decision making[22]. However, most of the works using FCM are mainly research based and confined to modeling some application domains. To the best of our knowledge, there is no report on any successful implementation of large-scale industry application using FCM that contains practical and powerful automated causal reasoning capability. Moreover, there is also lack of commercially available FCM development tool which incorporates both causal modeling and automated causal reasoning components.

BBN is a well established method for probabilistic causal reasoning. It uses a graphical structure to represent causal relationships and probability calculus to quantify these relationships and update beliefs given new information. Pearl, in 1986[23] and later in 1988[24], introduced the concept of conditional independence for a more tractable and efficient evidence propagation mechanism. Since then, BBN has become a practical tool for reasoning under uncertainty. Charniak described its role in the AI-uncertainty community as comparable to the role of resolution theorem proving in the AI-logic community[25]. BBN has had considerable number of real-world applications, such as MIT's Heart Disease Program for differential therapy of cardiovascular disorders[26], Microsoft's Lumiere Project for inferring the goals and needs of software users[27], Hewlett Packard's SACSO project for automatic customer support operations [28], and change impact analysis in architecture design [29]. There are many commercially available BBN development tools, such as Hugin [30] and Netica [31], which incorporate both causal modeling and reasoning components. Korb and Nicholson provide an introduction to BBN as well as a thorough survey for its applications and development tools [32]. Despite the efficient evidence propagation mechanism and powerful reasoning capability, knowledge elicitation from domain experts has never been easy in BBN, for two main reasons [33]. First, the number of probability values required to populate a Conditional Probability Table (CPT) grows exponentially with the number of parent nodes associated with the table. Second, the elicitation of conditional probability distributions from a domain expert is a very complex task and it requires a systematic approach to handle.

Despite the fact that FCM and BBN are two major frameworks for causal reasoning, for some reason, they did not come across each other until Nadkarni and Shenoy proposed using BBN for making inferences in CM [34], and later, they proposed using CM for constructing the causal structure in BBN [35]. However, the two papers were related to CM and not FCM (the "fuzzified" version), and hence, they were unable to take advantage of the causal values found in FCM. Even so, the idea of integrating the two families of frameworks by complementing each other's strengths is quite obvious. However, the integration will not be effective without a thorough understanding of the mutual strengths and weaknesses of the two frameworks. This work of comparison will provide the required guidelines in this direction.

3. The Comparison

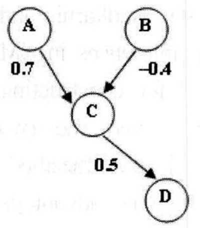
A detailed qualitative comparison of FCM and BBN is done in this section through a systematic analysis under the headings of the following criteria: usability in causal modeling, expressiveness in causal representation, adequacy in causal reasoning, and formality in semantics and soundness in inference.

3.1 Usability in Causal Modeling

Before domain experts perform causal reasoning based on what they know about the domain, they have to first transform their causal knowledge into a causal model using a modeling framework such as FCM or BBN. How good the framework is, in supporting such a transformation, is largely dependent on how easy and straightforward the transformation process can be done using it.

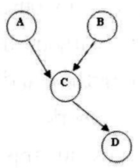
When experts specify causal knowledge using FCM, they only need to work with a visual graphical model. The conversion into a corresponding adjacency matrix is straight forward and the process can be easily automated. For example, in (Fig. 1), an expert first determines the domain variables A, B, C, and D. He/she then determines the causal links, (A→C), (B→C), (C→D), and their respective causal strengths, 0.7, -0.4, 0.5. The whole process is to construct a directed graph visually. The corresponding adjacency matrix to the right of the graph can be obtained through a straight forward conversion process or can be generated automatically.

When BBN is used for specifying causal knowledge, besides drawing the graphical structure, a domain expert's main task is to construct the CPTs. In fact, the graphical structure is, in principle, not required (or redundant) after



	A	B	C	D
A	0	0	0.7	0
B	0	0	-0.4	0
C	0	0	0	0.5
D	0	0	0	0

(Fig. 1) Illustrative FCM and the corresponding adjacency matrix



CPT for A

A	
+	–
0.50	0.50

CPT for B

B	
+	–
0.60	0.40

CPT for C

A	B	C	
		+	–
+	+	0.80	0.20
+	–	0.90	0.10
–	+	0.10	0.90
–	–	0.40	0.60

CPT for D

C	D	
	+	–
+	0.80	0.20
–	0.20	0.80

(Fig. 2) Illustrative BBN graphical structure and the CPTs

the CPTs have been constructed. This is because the graphical structure is implicitly represented in the CPTs, and it can be inferred from them. For example, in (Fig. 2), the expert first draws the graphical structure by specifying the nodes and the links. However, he/she does not attach causal strengths to the links, as was done in the case of FCM. Instead, his/her main task is the subsequent construction of the CPTs, one for each node, and the assignment of the probability value for each entry in the CPTs. There are two such values in the CPTs for A and B, eight in the CPT for C, and four in the CPT for D (Fig. 2). It can be inferred from the CPTs for A and B that they have no parent; from the CPT for C that it has two parents (i.e., A and B); from the CPT for D that it has a parent (i.e., C). From these inferences, the graphical structure can be made available.

The visual graphical interface provided by FCM is more intuitive and user friendly than the tabular interface provided by the CPTs of BBN because the dependency structure of the domain variables in FCM is more explicit and easy to understand [36]. This will in turn facilitates the process of domain modeling or knowledge elicitation.

Domain experts specify causal relationships between domain variables in FCM, but they specify probabilistic relationships between the possible states of these variables in BBN. For example, in the FCM of (Fig. 1), a domain expert specifies a causal relationship between the domain variables C and D. On the other hand, in the BBN of (Fig. 2), he/she specifies, in CPT for D, the probabilistic relationships between the '+' and '-' states of C and those of D. Obviously, the expert works at a higher level of abstraction with FCM than with BBN. On the other hand, he/she works at a more detailed level with BBN than with FCM. Higher level of abstraction is generally recognized as more appropriate for the earlier phases of knowledge engineering, such as during the phase of domain modeling or knowledge acquisition.

In FCM, domain experts quantify a causal relationship by attaching a single value, representing causal strength, directly to the causal link itself. For example, in (Fig. 1), the causal strengths 0.7, -0.4, and 0.5 are attached to the causal links (A→C), (B→C), and (C→D) respectively. In BBN a causal relationship is not represented as a single value attached directly to the causal link. Instead, it is represented indirectly as multiple probabilistic values in a CPT attached to the effect (child) node of the link. For example, in (Fig. 2), the causal strength of the link (C→D) is represented in the CPT for D, as conditional probability values for the '+' and '-' states of D given '+' and '-' states of C. Obviously, it is more intuitive for an expert to specify the causal strength, as a single value, directly attached to the causal link itself. In contrary, it is less intuitive for the expert to perceive the causal strength as multiple probabilistic values in a CPT attached to the effect node. The latter requires a paradigm shift of the way how we normally perceive the strength of a causal effect.

Domain experts use, in FCM, the same number of values as the number of cause (parent) nodes, or the number of causal links, to quantify the combination causal effect to a particular effect node. For example, in (Fig. 1), only one value (i.e., 0.5) is used to quantify the causal effect to D, because there is only one cause node (i.e., C). Two values are used to quantify the combination causal effect to C, because there are two cause nodes (i.e., A and B). In BBN, domain experts use the number of values equivalent to the product of the number of possible states of individual cause and effect nodes, to quantify the combinational causal effect to the effect node. For example, in (Fig. 2), an expert uses four (=2×2) values to quantify the combination causal effect to D, because both cause node (i.e., C) and effect node (i.e., D) have two possible states each. He/she uses eight (=2×2×2) values to quantify the combinational causal effect to C, because both cause nodes (i.e., A and B) and effect node (i.e., C) have two possible states each. Obviously, it is a more complex task for the expert to quantify combinational causal effect in BBN than in FCM because more values are normally required to specify the same causal effect.

3.2 Expressiveness in Causal Representation

FCM and BBN can be considered as two different frameworks for the representation of causal knowledge. One main consideration for the choice of knowledge representation framework is its expressiveness. The expressiveness of knowledge representation framework is a measure of what can be specified by an expert, and more importantly, what can be left unspecified, when the framework is used [6].

In BBN, domain experts are allowed to assign different prior probabilities to different states of a variable. For example, in (Fig. 2), an expert may assign the same prior probability (i.e., 0.5) to both '+' and '-' states of variable A. Having the same prior probability for both states indicates that the variable has the same chance to increase and to decrease, before any evidence is found. The expert may assign different prior probabilities (i.e., 0.6 and 0.4 respectively) to the '+' and '-' states of variable B. Having different prior probabilities for the states indicates that the variable has a higher chance to increase than to decrease. In FCM, all the possible states of a variable (i.e., increase and decrease) are determined to be equally probable, before any evidence is found. A domain expert has no control over the assignment of likelihood to the initial states of a variable. The disparity between the frameworks is due to their different basic underlying assumptions. FCM assumes a close cause-and-effect system, in which all the possible causes of an effect must be captured and represented in the causal model. Therefore, as long as there is no trigger from the causes which disturbs the balance, the equal likelihood of all the possible states of a variable remains unchanged. BBN, on the other hand, assumes an open cause-and-effect system which allows hidden or unrepresented causes. The absent of these causes may be due to the ignorance of the domain expert or the complexity of the causal relationships. Therefore, when some states have higher initial probability then the others, it simply implies that there are some unrepresented causes which should be responsible for it. BBN is clearly more expressive than FCM in this sense, because it allows the experts to leave some causes unrepresented when they are ignorant about the causes or when they are uncertain about their relationships due to complexity.

Domain experts, in BBN, specify the combination causal effect of multiple causes to a variable, not their individual effects. This is very useful because very often the expert is uncertain or even ignorant of the strength of individual effects or how they are combined. For example, in (Fig. 2), an expert may have specified that when both A and B increase, their combination effect to C is an increase with a probability of 0.8, and a decrease with a probability of 0.2. However, the expert may not know how much is the individual influences of A and B, or how the individual influences are combined. From the CPT for C, the sum of the '+' and '-' columns are 2.2 and 1.8 respectively, and the normalized ratio is 0.55 to 0.45. Therefore, we say that the combination effect of A and B causes C to increase with a probability of 0.55 and causes it to decrease with a probability of 0.45. However, we do not know which one (A or B) has a stronger influence to C, what is the ratio of their respective influences to C, and how these individual influences are combined. In this respect, the expressiveness of BBN makes it flexible enough to tolerate such an uncertainty or ignorance of the individual influences and the formula for combining them, by allowing them to be left unspecified. In FCM, domain experts specify individual causal effects, not the combination. The combinational effect is computed during the reasoning process. Therefore, it is a requirement for the domain experts to specify the causal strength of individual causal effects and the ignorance or uncertainty in this respect is not allowed. For example, in (Fig. 1), an expert has to assign a causal strength to each causal link without an exception. It is clearly specified that A has a stronger influence to C as compared to B, in terms of the magnitude (i.e., 0.7 as compared to 0.4).

FCM is a dynamic knowledge representation framework which allows feedback. If the change in a node affects one or more other nodes through causal links directed from it to these other nodes, the resulting change in these other nodes can affect the node initiating these changes. The presence of feedback adds a temporal aspect to the operation of the FCM and enables the observation of progressive changes in a scenario as events unfold. BBN, on the other hand, is a static knowledge representation framework which does not allow circular relations or causal loops. It is characterized by a hierarchical (or acyclic) graph structure. Circular relations or causal loops immediately violate the acyclic graphical structure required in a BBN. Because of this cyclic prohibition nature, BBN does not represent dynamic relations between variables across multiple time frames. For example, in (Fig. 1), we can add a causal link (D→B) to the FCM, to denote a causal effect happening on a different time frame from the other causal effects: (A→C), (B→C), and (C→D). However, the same link (D→B) can not be added to the BBN in (Fig. 2). In this sense, FCM is more expressive than BBN.

3.3 Adequacy in Causal Reasoning

Adequacy in reasoning about the represented knowledge refers to the reasoning power of a particular framework. It is the capability which determines what kind and how much of implicit knowledge can be inferred from the knowledge represented explicitly.

When causal knowledge is represented using BBN, two basic forms of reasoning can be done: forward predictive reasoning and backward diagnostic reasoning[32]. The purpose of forward predictive reasoning is to predict the impacts of a change happening on a particular variable. The backward diagnostic reasoning is to diagnose the possible causes of the change. In the reality, however, it is rarely to have only predictive or diagnostic reasoning. Normally, when there is a change on a variable, we want to trace its consequences as well as to investigate the possible sources - hybrid reasoning. For example, in (Fig. 2), when there is a concrete evidence that A has increased (i.e., A is +1), we want to predict the impacts of this change. When there is a concrete evidence that C has increased (i.e., C is +1), besides predicting the impacts of the change, we also want to diagnose the causes of the change. <Table 1> summarizes the results of simulation using a typical BBN tool, such as Hugin Expert [30] or Netica [31]. From the table, when there is evidence that A has increased, the probability that C will increase is 0.84, higher than the prior probability, 0.527, when the evidence is not found. The probability that D will increase is 0.704, also higher than the prior probability, 0.516. However, variable B will not be affected at all by the increase of A. Now suppose there is evidence that C has increased, the probability that D will increase is 0.8, higher than the prior probability, 0.516. Also, it is noticeable that the probabilities that A and B will increase are 0.797 and 0.507 respectively, higher than their respective prior probabilities, 0.5 and 0.6. This is an indication that the increase in C is most likely caused by the increase in A and B - a diagnostic reasoning.

The de facto standard inference mechanism for FCM is the iterative vector-matrix multiplication followed by threshold [37,15]. When this mechanism is used, only forward predictive reasoning can be carried out [38]. Iterative vector-matrix multiplication does not support backward diagnostic reasoning. Therefore, FCM can only answer what-if questions, and it can not answer why questions. For example, in (Fig. 1), when there is evidence that A has increased, the information can be represented as an input vector [1, 0, 0, 0]. Multiplying it with the adjacency matrix in the figure, called M, we obtain an output vector [0, 0, 0.7, 0]. The output vector is then adjusted by holding A = 1, which yields [1, 0, 0.7, 0]. The adjusted vector is then taken as an input vector for the next step. The process is repeated, as shown below, until we get an output vector which has occurred before.

〈Table 1〉 Simulation Results of BBN Reasoning

	A	B	C	D
No Evidence	(+) 0.500	(+) 0.600	(+) 0.527	(+) 0.516
	(–) 0.500	(–) 0.400	(–) 0.473	(–) 0.484
Evidence: A = +1	(+) 1.000	(+) 0.600	(+) 0.840	(+) 0.704
	(–) 0.000	(–) 0.400	(–) 0.160	(–) 0.296
Evidence: C = +1	(+) 0.797	(+) 0.507	(+) 1.000	(+) 0.800
	(–) 0.203	(–) 0.493	(–) 0.000	(–) 0.200

[1, 0, 0, 0] × M = [0, 0, 0.7, 0] → [1, 0, 0.7, 0]
[1, 0, 0.7, 0] × M = [0, 0, 0.7, 0.35] → [1, 0, 0.7, 0.35]
[1, 0, 0.7, 0.35] × M = [0, 0, 0.7, 0.35] → [1, 0, 0.7, 0.35]

The final result [1, 0, 0.7, 0.35] can be interpreted as: when A increases by 1, C increases by 0.7, D increases by 0.35, and there is no increase for B. When there is evidence that C has increased, the information can be represented as an input vector [0, 0, 1, 0]. Multiplying it with the adjacency matrix M, we obtain an output vector [0, 0, 0, 0.5]. The output vector is then adjusted by holding A = 1, which yields [0, 0, 1, 0.5]. The adjusted vector is then taken as an input vector for the next step. The process is repeated, as shown below.

[0, 0, 1, 0] × M = [0, 0, 0, 0.5] → [0, 0, 1, 0.5]
[0, 0, 1, 0.5] × M = [0, 0, 0, 0.5] → [0, 0, 1, 0.5]

The final result [0, 0, 1, 0.5] can be interpreted as: when C increases by 1, D increases by 0.5. The increase in D is due to the impact of the increase in C, in the forward direction. However, the increase in C does not affect A and B, even though they are causes of C. This is because the reasoning mechanism using the iterative vector-matrix multiplication is unable to diagnose the possible causes for the increase in C. How can C change without a change in its causes, A or B? The only reasonable explanation is that the stimulation comes from external variable(s).

In FCM, causal effects to an effect variable are assumed to be mutually independent. It means the presence of one effect does not change the strength of the other effects before its presence. This basic assumption simplifies the process of combining causal effects to the algebraic sum of the individual causal strengths. The summation process can be built into the mechanism of vector-matrix multiplication. For example, in (Fig. 1), when there is evidence that both A and B have increased, the information can be represented as an input vector [1, 1, 0, 0]. Multiplying it with the adjacency matrix M, we obtain an output vector [0, 0, 0.3, 0]. The result shows an increase in the effect variable C by 0.3, which is the algebraic sum of the causal effect from A (0.7) and the causal effect from B (-0.4). In BBN, the combination causal effect of a set of cause variables to an effect variable, is interpreted as the conditional probability distributions of the effect variable given joint events of the cause variables. The individual events are, in general, not mutually independent. It means the occurrence of one event may change the probability of the occurrence of the others. Moreover, the dependency between the events is complex, and very often is unknown to the expert. Therefore, in most cases the expert estimates, rather than compute, the conditional probability distributions. For example, in (Fig. 2), the probability that C will increase given the evidence that A and B have increased may be different when both of them are separately considered, and when both of them are collectively considered. If the expert does not know how A and B are related and dependent on each other, the best he/she can do is to estimate the probability for the increase in C. Often, it is a difficult task for the expert to give an accurate estimation. Therefore, BBN provides the flexibility (due to its expressiveness) for the ignorance or uncertainty of the formula for combining causal effects by over burdening the expert with the responsibility for estimating the conditional probability distributions. FCM, on the other hand, frees the expert from the responsibility of calculating the combination causal effect (it is done automatically during the vector-matrix multiplication) by rigidly requiring him to specify individual causal effects, and to assume that they are mutually independent.

3.4 Formality in Semantics and Soundness in Inference

The formality of a knowledge representation system ensures unambiguous semantics. This can be achieved if the system has a solid mathematical foundation. The formality helps to improve the scalability and robustness of the representation system [10]. However, the advantage of formality is not universal. It may be beneficial for the back-end representation and automated reasoning, but it may turn out to be harmful for the front-end modeling [11].

Unambiguous semantics ensures soundness of inference. An inference mechanism is sound if it always produces valid results given valid premises. In the context of causal reasoning using FCM or BBN, soundness of inference mechanism may refer to the correctness of the results inferred from the given causal model, in response to the stimulus to some variables. In FCM, the stimulus is in the form of a change (increase or decrease) in some variables, and the results are the corresponding change in some other variables. In BBN, the stimulus is in the form of an assignment of probability value to some variables, and the results are the corresponding update of probability value in some other variables.

In BBN, the numeric values represented in the CPTs, and those inferred through Bayesian reasoning are all interpreted as probabilities. They denote the probability of some event given the evidence that some other events have occurred. For example, in the CPT for C, in (Fig. 2), the values 0.8 and 0.2 are probabilities that C will increase and decrease, respectively, given the evidence that A and B have increased. In <Table 1>, the values 0.84 and 0.16 are probabilities that C will increase and decrease, respectively, given the evidence that A has increased. Bayesian reasoning is founded on sound mathematical theorems derivable from well defined basic axioms. Therefore, the results inferred through Bayesian reasoning are provable and the correctness is ensured. This provides the basic foundation for its soundness.

Contrarily, there is no well founded underlying theory, in FCM, for the semantic interpretation of the numeric values represented in the adjacency matrix and those inferred from the vector-matrix multiplication. The values are not associated to any physical quantity but they are merely linear scale factors for the grading of some abstract quantities, such as a change in market demand and an impact on design quality. As shown in (Fig. 1), the values 0.7, 0.4, and 0.5 are not associated to any specific physical quantity, but they are merely linear scale factors for grading the strength of a causal effect between two variables. Since proportionality is implied, a causal effect of 0.8 should be regarded as two times the strength of a causal effect of 0.4. An inference mechanism based on vector-matrix multiplication is rather ad hoc in some aspects. There are operations on numeric values that are lack of sound theoretical foundation. In (Fig. 1), when there is evidence that A has increased by 0.25 and B has decreased by 0.25, the vector-matrix multiplication yields: [0.25, -0.25, 0, 0] × M = [0, 0, 0.275, 0]. The result can be interpreted as C increases by 0.275. If we now double the inputs so that A has increased by 0.5 and B has decreased by 0.5, the vector-matrix multiplication yields: [0.5, -0.5, 0, 0] × M = [0, 0, 0.55, 0]. The result is C increases by 0.55, double the previous result - an indication of the use of proportionality in the inference mechanism. If we again double the inputs so that A has increased by 1 and B has decreased by 1, the vector-matrix multiplication yields: [1, -1, 0, 0] × M = [0, 0, 1.1, 0]. The result is C increases by 1.1, once again double the previous result. However, the result exceeds the threshold value (i.e., 1), and it is arbitrarily truncated to the threshold value. The truncation has produced an inconsistency because it violates the linear relationship between the input and output values, and it is done without having a good justification.

4. Conclusion

In this paper, we have compared the roles of FCM and BBN in the knowledge engineering of causal reasoning systems. The knowledge engineering process includes knowledge acquisition, knowledge representation and causal reasoning. The comparison is done based on some inherent features of the frameworks which are independent of any specific applications. These features, such as usability, expressiveness, reasoning adequacy, formality and soundness, constitute the comparison criteria. The criteria are discrete because a framework is either having or not having a particular feature. Hence, the comparison is done in an objective and qualitative manner. Besides, we have also done a literature survey to compare the roles of the frameworks in the knowledge engineering of some real applications (both research-based and industry-scaled) from which we have derived some conclusions related to the practicality of the frameworks.

The comparison results are summarized in <Table 2>. Overall, except for the modeling of dynamic system, BBN is, in general, more expressive and formal in representation as well as more powerful and sound in reasoning. The expressiveness in representation is attributed to the ability in handling uncertainty. The powerfulness in reasoning is attributed to the ability in performing backward diagnostic reasoning. The formality in semantics and soundness in inference is attributed to its solid foundation on probability theory. In addition, BBN is more superior because it has an efficient evidence propagation mechanism based on conditional independence and a proven track record in industry-scale applications. Unfortunately, BBN suffers from its complexity when used as a front-end modeling tool for capturing causal knowledge from the domain expert. Elicitation of causal knowledge from the domain expert, through the specification of CPTs is both unnatural and tedious. As a complement to it, FCM is an excellent front-end modeling tool. The visual graphical interface of FCM is both friendly and intuitive. It allows the domain expert to work at a higher level of abstraction as it hides the lower level details and focuses on the essentials.

From the comparison results, FCM has shown to be simpler, more intuitive, more high-level, and more user-friendly. These features make it very appropriate to be used at the front-end of knowledge engineering for the acquisition of causal knowledge from human experts. BBN, on the other hand, has shown to be more expressive, powerful, formal and sound. These features make it very appropriate to be used at the back-end of knowledge engineering for the representation and automated reasoning by machine. Our ongoing research work is to integrate the two causal reasoning frameworks, in which FCM is used at the front-end, for the effective modeling or elicitation of causal knowledge from the domain expert and BBN is used at the back-end for the representation and reasoning about causal knowledge. The idea of integration is made possible by transforming FCM into BBN. Two preliminary experiments in the area of assembly design have been conducted to test the idea for the integration. One of them is related to decision support [39] and the other is related to maintenance analysis and fault diagnosis [40]. Both experiments show encouraging result of the integration of the two frameworks. The latter has demonstrated that the integration produces similar result than using BBN alone but with simpler knowledge engineering process. Further research is to formalize a methodology for the integration.

Other future work planned is to get a group of knowledge engineers and domain experts working on a number of real applications, with different nature, using FCM and BBN separately. A comparison of the frameworks can be done based on the statistics of the subjective opinion from the knowledge engineers and the domain experts. The comparison results obtained from this quantitative approach will complement the qualitative comparison results described in this paper.

〈Table 2〉 A Summary of Comparison Results

General Criterion	Specific Distinguishing Question	BBN	FCM	Remark
Usability in Modeling	What to construct essentially?	CPTs	Signed directed graph	
	What type of construction interface?	Tabular	Visual graphical	FCM is more user-friendly
	How to represent a causal relationship?	Probabilistic dependencies between variable states	A causal link between the variables	FCM is more direct in representation
	How to represent a causal strength?	Multiple conditional probability values in the CPT	Single value attached to the causal link	FCM is simpler in representation
	How obvious is the causal structure?	Implicitly represented in the CPTs	Explicitly represented on the graph	FCM is more intuitive
	What is the level of specification?	Variable states	Variables	FCM is more high-level
	How many values are required to specify a combination of causal effects?	The product of the number of possible states of the individual cause and effect variables	The number of cause variables or causal links	FCM is easier to handle
Expressiveness in Representation	Does it allow unequal likelihood of increase and decrease before any evidence?	Yes (user can decide and specify prior probabilities)	No (user has no control over initial likelihood)	BBN is more expressive
	Does it allow unrepresented causes?	Yes (effect of unrepresented causes is reflected in unequal prior probabilities)	No (assume all possible causes are represented)	BBN is more expressive
	Does it allow ignorance of individual causal effects of a combination?	Yes (it is only required to specify combination effect)	No (it is required to specify individual effects)	BBN is more expressive
	Does it allow ignorance of how individual causal effects are combined?	Yes (user estimates total effect if formula is unknown)	No (combination is only based on algebraic sum)	BBN is more expressive
	Does it allow feedback and causal loops?	No	Yes	FCM is more expressive
	Does it allow temporal representation?	No (it only supports static system)	Yes (it supports modeling of dynamic system)	FCM is more expressive
Adequacy in Reasoning	Does it support backward chainning?	Yes	No (it only supports forward chainning)	BBN is more powerful
	Does it support diagnostic reasoning?	Yes	No (it only supports predictive reasoning)	BBN is more powerful
	Does it have an efficient evidence propagation mechanism?	Yes (based on Pearl's conditional independence)	No	BBN is more practical
	Are there many commercially available powerful and efficient reasoning engines?	Yes (Netica, Hugin, etc.)	No	BBN is more practical
	Are there many industry-scale applications?	Yes (by Microsoft, Hewlett Packard, etc.)	No (restricted to research based applications)	BBN is more practical
Formality in Semantics & Soundness in Inference	Is it founded on sound mathematical theorems derivable from well-defined basic axioms?	Yes (founded on probability theory)	No	BBN has formal semantics
	Is the correctness of the inference mechanism provable?	Yes	No (Inference mechanism is rather ad hoc)	BBN has sound inference

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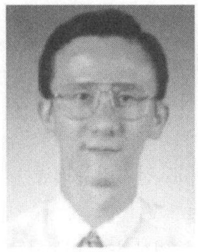

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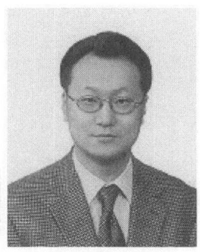

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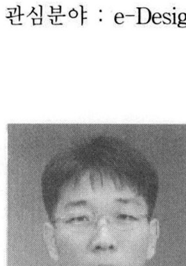

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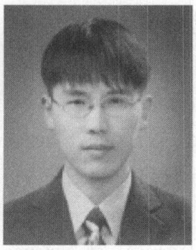

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