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Abstract

Causal map integration is helpful to broaden group member's eyesight and sheds insight on the detection of overall group's cognition tendencies. However the existing causal map integration approaches are either based on human intervention mechanism that is criticized with researcher bias, or based on syntactic mechanism that lacks of semantic. In order to improve the current causal map integration methodology and practice, this study proposes the conceptualization and formalization of an innovative causal map integration approach, automatic semantic causal map integration, *grounded on the Sowa's Conceptual Graph Theory and Kosko's Fuzzy Knowledge Combination Theory. The system prototype with an example is also illustrated.*

Keywords: Causal map, Ontology, Knowledge integration

Introduction

Causal map represents cognition as a system of cause-effect relations for the purpose of capturing the cognitive structure of an individual (Narayanan 2005). During the past two decades of evolution, the tool of causal map has been considered as one of the most effective ways to represent thought and conduct conceptual modeling (Mohanmmed et al. 2000) in the various areas, e.g., managerial and organizational cognition (e.g., Tegarden and Sheetz 2003), strategic management (e.g., Eden and Ackermann 1998), human resources management (e.g., Budhwar and Sparrow 2002), business analysis (e.g.,Xirogiannis and Glykas 2004), software development (e.g., Nelson et al. 2000), etc. Recently, increased interest has been put to study on causal map from individual level to group and/or organizational level (e.g., Hodgkinson and Clarkson 2005; Tegarden et al. 2005). The basic operation to achieve the latter is causal map integration. Previous study has maintained that integrated maps can be used to broaden problem solver's eyesight by taking alternative views into account (Tegarden et al. 2003). Thus, it is critical to juxtapose and integrate different maps to get problem solved especially in the messy problem situation (Vo et al. 2005). Even integrated map may not accurate enough to reflect the views of any one individual, it is still highly insightful to enable the detection of overall group cognition tendencies and permit the study of the overall structure of group and/or organizational level perceptions of a given set of constructs (Hodgkinson et al. 2005).

Prior research has proposed several different integration approaches with different terms, e.g., congregate map, aggregated map, and oval map, but they share the similar integration process (Tegarden et al. 2005). The existing approaches for creating integrated map require the standardization of individuals' concept maps. With such standardized concept maps held, the individual maps are integrated into a higher level, based on either the researchers' own justifications on similar concepts (human-based integration) or computers' identifications on similar syntactic structures (syntactic-based integration). However, the human-based integration has been criticized with researchers' personal bias that potentially influence the final integrated map (Hodgkinson et al. 2005). Moreover, such an integration intervened by humans is labor-intensive and time-consuming (Nelson et al. 2000), it therefore is not applicable for large-scale causal map integration. On the other hand, the syntactic-based integration focuses on the structures of individual maps while sheds little light on the meaning in their causal maps. As a consequence, the syntactic-based integration lacks of the accuracy and is not easy to understand. Causal map integration must combine structural transformation and semantic mapping that lead to the correct merge of individual maps and that allow the problem solvers to query the so-called mediated schema (Croitoru et al. 2005). Therefore, the weaknesses of the existing approaches necessitate a more advanced approach of causal map integration.

This study aims to improve the causal map integration approaches by enabling automatic semantic causal map integration. Our new approach is grounded on knowledge engineering methods. The underpinnings of our proposed integration approach are Sowa's Conceptual Graph Theory (Sowa 1984; Sowa 2000) and Kosko's Fuzzy Knowledge Combination Theory (Kosko 1986b). Due to the fuzzy nature of human cognition, we are interested in fuzzy causal map, a fuzzy extension of causal map where the causal relations are fuzzified (Kosko 1986a). Drawing upon Sowa's Conceptual Graph Theory, we represent the causal map by extending the *support* of conceptual graph, and formalize the causal map generalization, the core operation of semantic causal map integration, by transforming the causal map *support* to the standard conceptual graph *support*. The transformation is relied on the fuzzy equivalence relation generated by calculating the lexical semantic relatedness of concepts. The causal map generalization includes node fusion and link join. Node fusion is formalized by conceptual graph elementary extension, whereas link join is formalized by fuzzy knowledge combination theory. They work together to implement the automatic semantic causal map integration.

In the remainder of the paper, section 2 provides a literature review on causal map and causal map integration. Section 3 elaborates the proposed automatic semantic causal map integration. Section 4 illustrates the prototype and an example of the proposed approach. Finally, the significance of this study and the future directions are discussed.

Current Study on Causal Map Integration

Causal map, originated from the Axelrod (1976)'s cognitive map, represents individuals' causal beliefs so as to explicate and assess the structure and content of their mental models. It is a simplified mathematical model of a belief system. Casual map consists of two basic elements: concepts and causal relationships. Concepts are the variables of the system while the causal relationships refer to the directional linkages among those concepts. Two different types of causal relationships can be represented in the map: positive and negative. In a positive causal relationship, an increase (decrease) of the cause variable will cause a corresponding increase (decrease) of the effect variable. In a negative causal relationship, an increase (decrease) in the cause variable will lead to a decrease (increase) of the effect variable. As the extension of causal map, Kosko (1986a) proposed a fuzzy causal map, where the causal relationships are fuzzified to the interval [-1, 1]. As a result, the causal relationships can be represented with a weight of causality, going beyond the representations with simple positive or negative causality. To account for the fuzzy nature of human cognition, in study we focus on fuzzy causal map integration.

Two main research streams of causal map integration appear in the previous studies. One of the streams is human-based integration which is focused on how to construct an integrated map with the interventions of human experts. The other stream is syntactic-based integration which is focused on how to merge causal map by analyzing the structure of causal map.

For human-based integration, three basic approaches have been identified: aggregate mapping approach (e.g., Eden et al. 1998; Kwahk and Kim 1999; Tegarden et al. 2003), congregate mapping approach (e.g., Bougon 1992) and oval mapping approach (e.g., Huff 1990; Vennix 1996). In the aggregate mapping approach, the focus of the integrated map is on representing all individual maps as fully as possible. All labels and links from each individual causal map are included in the integrated map. As a result, the aggregate map may become quite complex. Although Tegarden et al. (2003) attempted to solve this problem by providing concept categories to simplify the display of integrated map, the categories are still human generated. The congregate mapping approach centers on the identification of key causal loops that drive system dynamics. The study of causal loops or cycles in causal mapping and causal modeling has been emphasized by systems dynamics researchers. In the congregate approach, only labels and links that contribute to forming loops are entered into the integrated map. In the oval mapping approach, the focus is on consensual model building at group level. Group members exchange their perceptions of a problem situation to foster consensus. Concepts are written in piece of ovals and the integrated map is built in group meetings aided by facilitators. The purpose of the oval mapping is to reach agreement on what elements should be entered into the integrated map.

For syntactic-based integration, causal maps are integrated by analyzing their structure. With the help of Graph Theory, causal map is abstract into a graph, and then structural analysis is conducted based on the nodes and links in the graph. Silva (1995) proposed some basic forms to integrate causal maps. Miao et al. (2002) formalized the syntactic analysis of causal map and provided the mathematical way to integrate causal maps. Zhang et al. (2003) introduced a decomposition theory and causal algebra that can be used for causal maps integration. Recently, Croitoru et al. (2005) elaborated a method to conduct hierarchical knowledge integration using layered conceptual graph.

Although various approaches, either human-based integration or syntactic-based integration, have been proposed to integrate causal maps, they share a similar integration process. First, they need to standardize the individual maps before integration. Second, the individual maps are integrated based on common concepts. The two streams differentiate with each other on the way to standardize individual maps, where are exactly their weaknesses. Human-based integration focuses on the procedure and/or methodology to elicit the concepts and validate the semantics of concepts. As a result, the researchers' bias is introduced and the efficiency of the procedure is impaired. Syntactic-based integration can remedy the efficiency problem and can be automatically executed; however the precious semantic information in the causal maps is lost. Therefore a better integration solution should consider both the semantic and syntactic of causal map. With the development of knowledge engineering and ontology engineering, it is the high time to propose the way for automatic semantic casual map integration.

Automatic Semantic Causal Map Integration

In this section, we illustrate the automatic semantic causal map integration approach. The core of automatic semantic causal map integration is causal map generalization and/or specialization which incorporate two important procedures: node fusion (hierarchical node clustering) and link join. When we integrate a set of causal maps, we can establish the single extended map to contain all the individual maps by aggregation approach (Eden et al. 1998), and then we do generalization and/or specialization for the extended map.

The focus of node fusion is to establish the fuzzy equivalence relation among concepts semantically, get the hierarchical clustering of concepts, and then conduct elementary extension and/or restriction based on Conceptual Graph Theory. For link join, the main task is to find weight combination functions based on fuzzy knowledge combination theory.

Using Conceptual Graph to Represent Causal Map

Conceptual graph is a finite, connected, bipartite graph and can be used to represent very complex conceptual structures. Causal map can be deemed as one specific type of conceptual graph. Now we borrow the notions of Chein and Mugnier (1992) to represent the causal map.

Definition 1: Support

A *support* represents general knowledge on a domain. A *support* is a 3-tuple

$$S = (T_C, t_R, M) \tag{1}$$

where,

- T_C , the set of concept types, is a complete graph to reflect their semantic relatedness;
- t_R , the causal relation, is a dyadic relation, T_C and $\{t_R\}$ are disjoint;
- M, is a countable set of individual markers, in addition, there exist a marker called generic ***** and an absurd marker **0**, and $\forall\ m \in M$, $\mathbf{0} < m <$ *****.

Definition 2: S-graph

An *S-graph* represents a single proposition related to this context. An *S-graph* is a bipartite, connected, and finite graph

$$G = (V_C, V_R, N_G) \tag{2}$$

where,

- V_C is the set of concept vertices, which are also called c-vertices;
- V_R is the set of causal relation vertices, which are also called r-vertices;
- V_C and V_R are finite disjoint sets ($V_G = V_C \cup V_R$ is the vertices set of G);
- $N_G : V_R \rightarrow V_C^2$ is a mapping; $V_C^2 = V_C \times V_C$,
  For $r \in V_R$, $N_G(r) = (c_1, c_2)$, $c_1 \in V_C$, $c_2 \in V_C$. Because the relation must be casual relation, the degree of r in G is always 2, and $N_G^1(r) = c_1, N_G^2(r) = c_2$.
- $\forall\ c \in V_C$, $\exists r \in V_R$, $i \in \{1, 2\} \rightarrow c = N_G^i(r)$; ($G$ has no isolated c-vertices).

Definition 3: Causal map (Simple definition)

A *causal map* is a 3-tuple

$$CM = (S, G, \lambda) \tag{3}$$

where,

- S is a *support*;
- G is an *S-graph*;
- λ is a labeling of the vertices of G with elements from the support S
  $\forall\ r \in V_R$, $\lambda(r) \in [-1, 1]$,
  $\forall\ c \in V_C$, $\lambda(c) \in T_C \times (M \cup \{*\})$ (if the second element is *, we can omit it to facilitate representation).

Suppose the following causal map as shown in Figure 1 (omitted the weight of the causal relations) with five concepts labeled 1 to 5 and six links. Then it can be formalized by definition 3 (λ is omitted) which graphical represented by Figure 2.

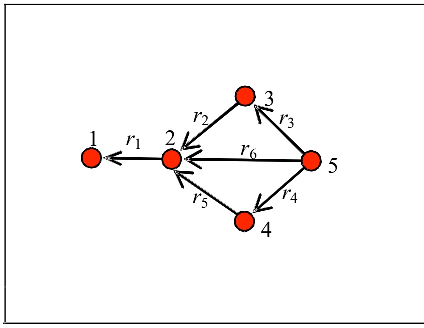


Figure 1: Sample Causal Map

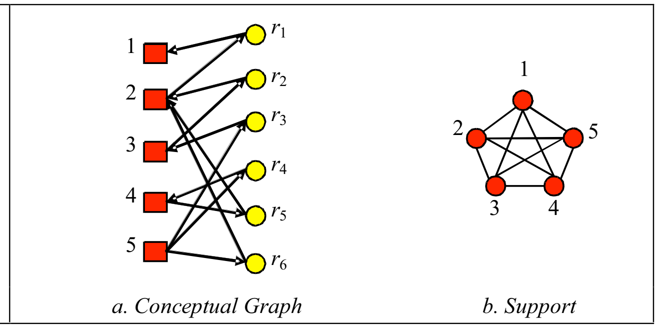


Figure 2: Sample Causal Map's Conceptual Graph Representation

$M = \{*\}$,

$V_C = \{1, \ldots, 5\}$,

$V_R = \{r_1, \ldots, r_6\}$,

$N_G(r_1) = \{2, 1\}$, $N_G(r_2) = \{3, 2\}$, $N_G(r_3) = \{5, 3\}$, …, $N_G(r_6) = \{5, 2\}$ are shown in Figure 2a.

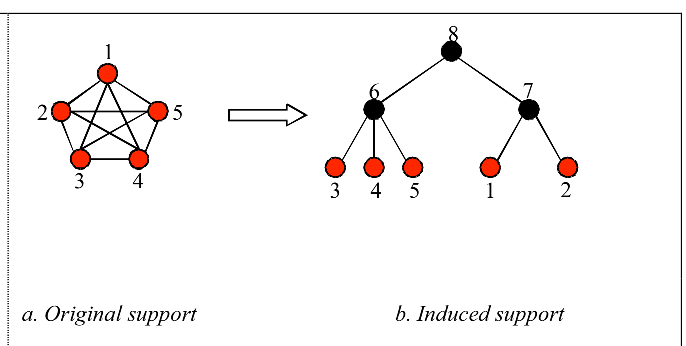
T_C, the concept type complete graph, can be described by a 5×5 symmetric matrix as shown in Figure 2b.

Node Fusion

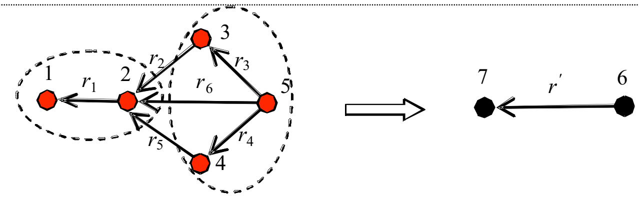
Adopting conceptual graph to represent causal map, the most important modifications we have done is to relax the concept type structure from lattice to complete graph. Such relaxation is because it is not practical to identify the concepts' "*is-a*" relation when we draw the causal map. Concept relatedness represented by network structure instead of hierarchical structure will be a good substitution for the "*is-a*" relation (Budanitsky and Hirst 2006).

However we still need concept lattice to conduct map specialization and/or generalization according to Conceptual Graph Theory. Therefore we transform the current causal map's *support* to standard conceptual graph's *support* (causal map induced *support*) by establishing hierarchical clustering of concept types. After that, we based on the new *support* to conduct map generalization/specification. The process is illustrated as Figure 3.

Step 1. Transform the original *support* to standard conceptual graph's *support* (*induced support*) by establishing hierarchical clustering of concept types. (concept 6,7,8 are new generated concept types based on hierarchical clustering)



Step 2. Based on the *induced support* to conduct map generalization and/or specification according to conceptual graph theory.



c. Original causal map *d. Generalized causal map*

Figure 3: The General Steps of Node Fusion

Definition 4: Causal map induced support

A *causal map induced support* is a standard conceptual map support that generated by hierarchical clustering of causal map concept types. A *causal map induced support* is a 4-tuple

$$CMIS = (IT_C, it_R, IM, conf) \tag{4}$$

where,

- IT_C, the induced concept types, is a finite lattice: **1** as supremum (the universal type), **0** as infimum (the absurd type), $\wedge$ and $\vee$ denoting the lower and upper bounds. The minimal of the set $IT_C \backslash \{\mathbf{0}\}$ should equal to the T_C of causal map's support.
- it_R , the causal relation, is a dyadic relation, IT_C and $\{it_R\}$ are disjoint;
- IM, is a countable set of individual markers, in addition, there exist a marker called generic * and an absurd marker **0**, and $\forall\ m \in IM$, $\mathbf{0} < m <$ *.
- *conf*, the conformity relation, is a predicate on $IT_C \times (IM \cup \{*, \mathbf{0}\})$ satisfying

  $\forall\ m \in IM$ and $\forall\ t, t' \in IT_C$,

  1) $conf(\mathbf{1}, m) \wedge \neg conf(\mathbf{0}, m) \wedge \neg conf(t, \mathbf{0})$,

  2) $t' \leq t \wedge conf(t', m) \rightarrow conf(t, m)$,

  3) $\forall t \in T_C \backslash \{\mathbf{0}\}$, $conf(t, *) \wedge \neg conf(t, \mathbf{0})$.

Therefore we could revise the definition of causal map by adding *induced support*.

Definition 5. Causal Map (Complete definition)

A causal map is a 4-tuple

$$CM = (S, CMIS, G, \lambda) \tag{5}$$

where,

- S is a *support*;
- $CMIS$ is the *induced support*, the standard conceptual graph;
- G is an *S-graph*;
- λ is a labeling of the vertices of G with elements from the support S

  $\forall\ r \in V_R$, $\lambda(r) \in [-1, 1]$,

  $\forall\ c \in V_C$, $\lambda(c) \in IT_C \times (M \cup \{*\})$ (if the second element is *, we can omit it to facilitate representation).

Now we define the causal map projection and morphism.

Definition 6. Causal map projection, morphism, isoprojection and isomorphism

Causal map projection, morphism, isoprojection and isomorphism are both limited by the *induced support*. Given two causal map $CM = (S, CMIS, G, \lambda)$ and $CM' = (S', CMIS, G', \lambda')$,

A *projection* from CM to CM' is a mapping Π from V_C to V'_C, such that

$$\forall c \in V_C,\ \lambda'(\Pi(c)) \leq \lambda(c).$$

A *morphism* from CM to CM' is a mapping Π from V_C to V'_C, such that

$$\forall c \in V_C,\ \lambda'(\Pi(c)) = \lambda(c).$$

if Π is bijective, then the projection is isoprojection, and the morphism is isomorphism.

Following the example in Figure 3, we can have the following projection as shown in Figure 4 from causal map CM to causal map CM', $\Pi = \{(7, 1), (6,5)\}$ under the constraint of the *induced support* showed in Figure 3b.

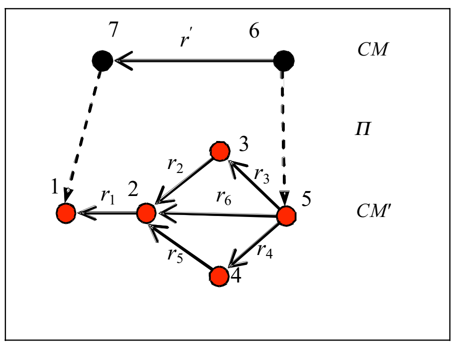


Figure 4: Causal Map Projection

According to the properties of projection and conceptual graph generalization and specialization, we define causal map specialization and generalization as follows:

Definition 7. Causal map specialization and generalization

Given two causal map $CM = (S, CMIS, G, \lambda)$ and $CM' = (S', CMIS, G', \lambda')$, if and only if there exists a projection from CM to CM', CM is a *generalization* of CM' which donates as $CM \geq CM'$, and CM' is a *specialization* of CM, which donates as $CM' \leq CM$.

Therefore, in Figure 4, we can get that causal map CM is a generalization of causal map CM', and causal map CM' is a specialization of causal map CM.

The generalization of causal map needs two operations according to Conceptual Graph Theory: node (c-vertices) fusion and link (r-vertices) join. Here we give the definition of node fusion.

Defintion 8. Node fusion
Given n c-vertices $c_1, \ldots, c_n$, $n \geq 1$ belonging to causal maps $CM_1, \ldots, CM_k$, $k \leq n$, we say that they are upward fusionnable if $conf(e')$ holds, where e' is the upper bound of their labels. A *fusion* of these n c-vertices consists in identifying them in a single vertex whose label, say e', satisfies: $e \leq e'$ and $conf(e')$.

The difficulty to conduct node fusion is to get the *induced support* (hierarchical clustering of concepts). In this study we achieve this by adopting upper ontology WordNet (Fellbaum 1998) with word sense disambiguation (Agirre and Rigau 1996) and fuzzy information retrieval (Cross 1994) approach. First we use WordNet with word sense disambiguation to calculate their lexical semantic relatedness. We first conduct word sense disambiguation based on Agirre et al. (1996)'s conceptual density. Then according to Budanitsky and Hirst (2006), we adopt the formula proposed by Leacock and Chodorow (1998) to calculate the similarity of the words

$$sim(c_1, c_2) = -\log \frac{\mathrm{len}(c_1, c_2)}{2 \times \max\limits_{c \in WordNet} \mathrm{depth}(c)} \qquad (6)$$

where,

$\mathrm{len}(c_1, c_2)$ is the length of the shortest path in WordNet from word c_1 to word c_2, and $\max\limits_{c \in WordNet} \mathrm{depth}(c)$ in WordNet 2.0 is 17.

The word relatedness matrix we get will be used as fuzzy thesauri, and then we use fuzzy information retrieval (Cross 1994) to get the concept similarity matrix. Based on concept similarity matrix, we get the their fuzzy equivalence relation and then generate hierarchical clustering of the set of concepts (Klir and Yuan 1995 p.362-365).

Link Join

After we know which concepts can be fusionnable, we further need to join the links related to these concepts. As shown in Figure 3c and 3d, link join will consider how to join r_2, r_5, and r_6 in Figure 3c to r' in Figure 3d. Although we don't expect the joint weight will accurately reflect every individual's opinion, we try to make the join process objective and informative. Consider the uncertainty of human cognition, we resort to fuzzy knowledge combination theory (Kosko 1986b).

The process to join links can be cast as the process of function-space search. According to Fuzzy Knowledge Combination theory, the process of link combination is function-space search. Let S be a set of *query stimuli* (e.g., how strong one particular causal relation). Let K be a partially ordered set of *knowledge responses* (e.g., [-1, 1] in fuzzy causal map). Define *knowledge sources* (links to be joined) $X_1, \ldots, X_n$ as functions from S to K, i.e., X_i: $S \rightarrow K$. Then for a particular query stimulus $s \in$ S, $X(s) = (X_1(s), \ldots, X_n(s))$ denote the *knowledge* *response vector*. Let $k \in K$ denote the *combined knowledge* of the *epistemic situation* (s, $X(s)$). Then links join problem is to find some knowledge-combination function: ϕ: $K^n \rightarrow K$ such that $\phi\ (X(s)) = k$. According to the suggestion of Fuzzy Knowledge Combination Theory, knowledge-combination function is admissible if it holds boundedness, symmetry, conservatism and nonparametricism. So we choose the following functions.

For unweighted map, $\phi\,(l, m) = \min\,(m, 1 - m + l)$, where

- $l = \min_i X_i(s)$, the least operator,
- $m = \max_i X_i(s)$, the most operator.

For weighted map, $\phi^w(l, m) = \min\,(m^w, 1 - m^w + l^w)$, where

- $l^w = \min_i \max(1 - w_i, X_i(s))$, the weighted least operator,
- $m = \max_i \min(w_i, X_i(s))$, the weighted most operator.
- w_i, the credibility weight of knowledge source X_i

Suppose in Figure 3c we assign three knowledge source $r_2 = 0.25$, $r_5 = 0.5$, and $r_6 = 1$, then for unweighted map, the joined link r' in Figure 3d will be $r' = \phi\ (0.25, 1) = \min\ (1, 0.25) = 0.25$.

System Prototype and Example

We have built automatic semantic causal map integration system based on a famous causal map tools *compendium* (http://www.compendiuminstitute.org) since 2005. Great efforts have been done to make the compendium as a group support system and implement the approaches of automatic semantic causal map integration. The interface is illustrated in Figure 5.

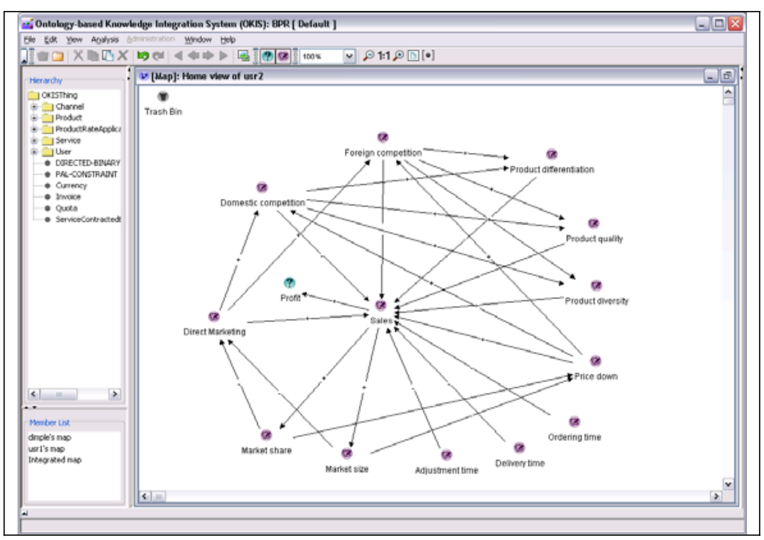
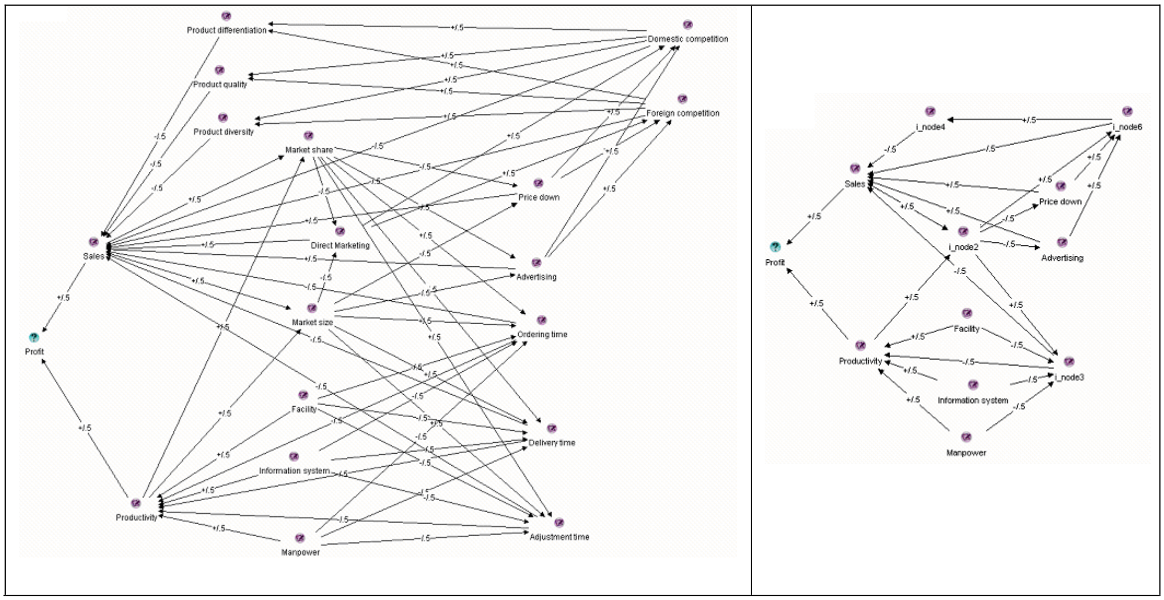


Figure 5: System Interface

Due to lack of alternative approaches to conduct automatic semantic causal map integration, we demonstrate the approach by illustrating the Business Process Reengineering (BPR) case (Kwahk et al. 1999). We choose the case because it provided all individual maps, integrated maps and the suggested semantic clustering of integrated maps. It enables qualitatively assess the system's usability via comparing of the results. The case is related to how to improve the profit by introducing the BPR project. Two perspectives from production department and marketing department are elicited by causal mapping techniques.



a. the most detailed level *b. the level with semantic clustering concepts* (alpha-cut = 1)

Figure 6: Sample integration results

Because our approach is based on hierarchal clustering of concepts, different level of integration can be provided. Two sample results are shown in Figure 6a and Figure 6b. Figure 6a illustrates most detailed level of integration. It is the same with the results reported in Kwahk et al. (1999). Figure 6b describes the integration results with semantic clustering with the concepts (alpha-cut = 1.0). The nodes start with "i_node" is the automatic semantic integrated node. For example, the node "i_node6" semantically incorporates two nodes in individual maps: "Domestic competition" and "Foreign competition".

The fuzzy equivalence relation of the map is illustrated by Table 1 and the hierarchical clustering result is illustrated by Figure 7. When we use the alpha-cut 1, the integration result is quite close to the original clustering of integrated maps.

Beyond that, preliminary usability assessment by 12 domain experts has been done. Survey instrument adapted from Davis (1989) was used to measure the usefulness and ease of use of the system. The result shows that the experts is highly satisfied with the software (score 5.6 out of 7).

Table 1: Fuzzy Equivalence Relation of the Examples

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1.0	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.5	.5	.6	.6	.6	.6	.5
2	.6	1.0	.7	.7	.7	.7	.7	.6	.6	.6	.7	.6	.5	.5	.6	.6	.6	.6	.5
3	.6	.7	1.0	1.0	.7	.7	.7	.6	.6	.6	1.0	.6	.5	.5	.6	.6	.6	.6	.5

4	.6	.7	1.0	1.0	.7	.7	.7	.6	.6	.6	1.0	.6	.5	.5	.6	.6	.6	.6	.5
5	.6	.7	.7	.7	1.0	1.0	1.0	.6	.6	.6	.7	.6	.5	.5	.6	.6	.6	.6	.5
6	.6	.7	.7	.7	1.0	1.0	1.0	.6	.6	.6	.7	.6	.5	.5	.6	.6	.6	.6	.5
7	.6	.7	.7	.7	1.0	1.0	1.0	.6	.6	.6	.7	.6	.5	.5	.6	.6	.6	.6	.5
8	.6	.6	.6	.6	.6	.6	.6	1.0	1.0	1.0	.6	.6	.5	.5	.7	.7	.6	.6	.5
9	.6	.6	.6	.6	.6	.6	.6	1.0	1.0	1.0	.6	.6	.5	.5	.7	.7	.6	.6	.5
10	.6	.6	.6	.6	.6	.6	.6	1.0	1.0	1.0	.6	.6	.5	.5	.7	.7	.6	.6	.5
11	.6	.7	1.0	1.0	.7	.7	.7	.6	.6	.6	1.0	.6	.5	.5	.6	.6	.6	.6	.5
12	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	1.0	.5	.5	.6	.6	.6	.6	.5
13	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	1.0	1.0	.5	.5	.5	.5	.5
14	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	1.0	1.0	.5	.5	.5	.5	.5
15	.6	.6	.6	.6	.6	.6	.6	.7	.7	.7	.6	.6	.5	.5	1.0	.7	.6	.6	.5
16	.6	.6	.6	.6	.6	.6	.6	.7	.7	.7	.6	.6	.5	.5	.7	1.0	.6	.6	.5
17	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.5	.5	.6	.6	1.0	.6	.5
18	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.6	.5	.5	.6	.6	.6	1.0	.5
19	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	1.0

Notes: The number represents the concepts: 1. Profit, 2. Sales, 3. Market size, 4. Market share, 5. Ordering time, 6. Delivery time, 7. Adjustment time, 8. Product differentiation, 9. Product quality, 10. Product diversity, 11. Direct Marketing, 12. Advertising, 13. Domestic competition, 14. Foreign competition, 15. Price down, 16. Productivity, 17. Facility, 18. Information system, 19. Manpower

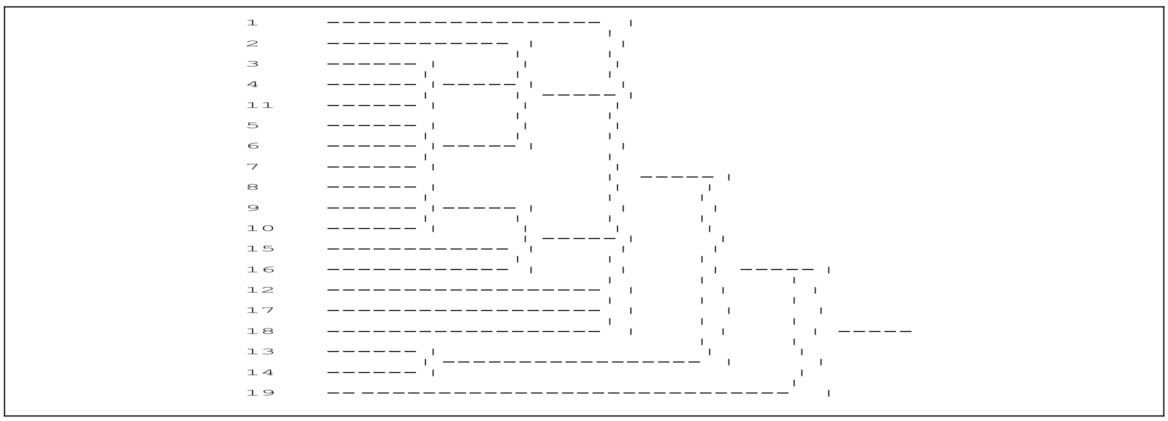


Figure 7: Hierarchical Clustering Results of the Example

Conclusions

The study proposes an ongoing work on automatic semantic causal map integration based on Conceptual Graph Theory and Fuzzy Knowledge Combination Theory. Several practical and evaluative issues still need to be addressed before an implementation can be effectively finalized. However the conceptualization and formalization of semantic causal map integration itself already imply important contributions. Theoretically speaking, we provide the solutions to conduct automatic semantic causal map integration, and we formalize the causal map's representation and semantic integration based on Conceptual Graph Theory and Fuzzy Knowledge Combination Theory. It extends the theory of conceptual graph, as well as causal map. Practically speaking, it can be programmed and applicable, as demonstrated by our prototype, to improve group decision making and problem solving in various business and research context, e.g., strategy development, value management, system dynamics modeling, interview analysis, information gathering, and knowledge structuring.

The study also implies several potential research directions. 1) Research on the evaluation of the proposed approach. The evaluation could be subjective and/or objective. The future study could adopt the methods in usability engineering to subjectively assess the user's reaction to the integration results. We could also conduct an empirical study to objectively compare the automatic integration performance to the integration intervened by human experts. 2) Research on technical improvement of the proposed approach. Our approach contains several important intelligence modules, thus the future study could compare the performance of the alternatives (such as the word sense disambiguation algorithms, map weighting algorithms) and maintain the best practice based on the results of evaluations. 3) Research on empirical assessment of the approach in the business and academic contexts. As a powerful IT artifact, the new approach is expected to proactively change the current practices rather than reactively adapt to the given situations. Therefore the effect of the proposed approach on the decision making and problem solving is suggested to investigate in the future.

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