Chang, K.-E., Sung, Y.-T., Chang, R.-B., & Lin, S.-C. (2005). A New Assessment for Computer-based Concept Mapping. *Educational Technology & Society*, 8 (3), 138-148.

A New Assessment for Computer-based Concept Mapping

Kuo-En Chang
Professor, Department of Information and Computer Education
National Taiwan Normal University, Taipei, Taiwan
Tel: +886223622841
Fax: +886223512772
kchang@ice.ntnu.edu.tw

Yao-Ting Sung
Associate professor, Department of Educational Psychology and Counseling
National Taiwan Normal University, Taipei, Taiwan
Tel: +886223952445
Fax: +886223413865
sungtc@cc.ntnu.edu.tw

Rey-Bin Chang
Ms. student, Department of Information and Computer Education
National Taiwan Normal University, Taipei, Taiwan
Tel: +886223622841
Fax: +886223512772
rbchang@ice.ntnu.edu.tw

Shui-Cheng Lin
Phd. student, Department of Information and Computer Education
National Taiwan Normal University, Taipei, Taiwan
Tel: +886223622841
Fax: +886223512772
shui@mail.ccsh.tp.edu.tw

ABSTRACT

Concept maps are widely used in education, and have been acclaimed for their excellent results. For efficiently using concept maps in education, computer-based concept mapping systems have been developed. However these computer-based concept mapping systems are limited in their assessment algorithms. The assessment takes only concept nodes as the primary basis, with relation links playing only a minor role. To address this problem, this study proposes a new style of concept map, called the weighted concept map, which assigns a weight to each proposition in a concept map to represent its importance. This study proposes a new assessment based on a weighted concept map and diagnosis analysis. Two studies are conducted to evaluate the methods of assessment.

Keywords

Concept map, Assessment, Computer-based assessment

Introduction

Although it has been over thirty years since Novak proposed the idea of a concept map in 1971, researchers are still impressed by its versatility in curriculum design (Edmondson, 1995; Ferry, Hedberg, and Harper, 1997; Moen and Boersma, 1997; Starr and Krajcik, 1990), teaching strategy (Briscoe and LaMaster, 1991; Nakhleh and Krajcik, 1994; Schmid and Telaro, 1990), and evaluation of teaching (Beyerbach and Smith, 1990; Goldsmith, Johnson, and Acton, 1991; Novak and Gowin, 1984; Ruiz-Primo and Schavelson, 1996). A concept map consists of a set of propositions, which are made up of a pair of concepts (nodes) and a relation (link) connecting them. Take the statement "Main memory includes ROM; ROM is read-only and cannot be written to" as an example. We can represent the statement with a concept map as shown in Figure 1. In the figure, there are propositions in the concept map, such as "Main memory *includes* ROM", "ROM *may* read", or "ROM *may not* write".

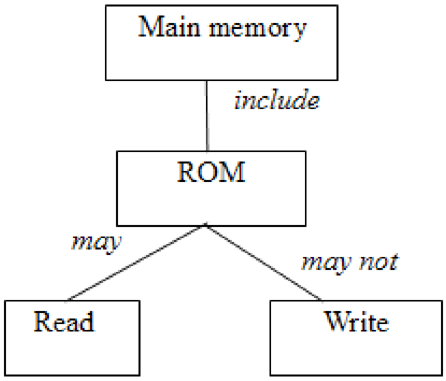

Figure. 1. An example of concept map

Although many researchers have reported that concept mapping is a useful tool for learning and instruction, constructing concept maps using pencil and paper has some obvious disadvantages (Chang, Sung, and Chen, 2001). These include:

It is inconvenient for a teacher to provide appropriate feedback to students during concept mapping.
The construction of a concept map is complex and difficult for students, especially novice students.
Concept maps constructed using pencil and paper are difficult to revise.
The 'pencil-and-paper' concept map is not an efficient tool for evaluation.

Because of the above difficulties, researchers have built computer-based concept mapping systems to help students construct concept maps more easily (Chang, Sung, and Chen, 2001; Fisher, 1990; Fisher, et. al., 1990; Reader and Hammond, 1994).

A concept map is a description of how propositions are organized. Concept maps reflect how ideas, opinions, and propositions are organized in the knowledge structure of students who construct the concept maps, and give observations on students' states. From the observations a teacher can assess the knowledge structure of students.

As an unconventional assessment tool concept maps can visualize the structure of abstract knowledge (Laffey and Singer, 1997; Rafferty and Fleschner, 1993). It can also enable students to clearly express their knowledge and concepts thereby leading them to the learning of higher-level cognitive abilities. Moreover, it allows assessment with greater ease. Scholars have proposed various scoring schemes for assessing concept maps. Generally speaking, there are three major approaches (Ruiz-Primo & Schavelson, 1996). The first one is scoring a student's map component, like propositions, hierarchy, crosslinks and examples in Novak and Gowin scheme. The second approach is using a criterion map and comparing students map with that criterion map. The closeness index use in Acton, Johnson, and Goldsmith (1994) is a typical example. The third approach combines both the component of a generated map and a criterion map.

A proposition is the smallest unit in the constitution of knowledge (Anderson, 1983; Novak and Gowin, 1984). In the past however, there did not seem to be a convincing algorithm for assessment based on propositions. For example, the closeness index *C* proposed by Goldsmith et al. (Acton et al., 1994; Goldsmith, Johnson, and Acton, 1991) was usually used in computer-based concept mapping. The idea of assessment is about connectivity among concept nodes, but it pays no attention to relation links between concept nodes. Such assessment criteria do not fully discover whether the students have learned the topic being taught. The idea of fuzzy closeness index proposed by Chen et al. (2001) makes its assessment based on concepts, but also partly based on links. Still, the assessment criteria do not take a whole proposition into consideration. To address this deficiency, this study proposes the idea of a concept map with weighted propositions (called weighted concept map) and its assessment method.

In studies up to now, the results of concept map assessment have been no more than quantitative analysis. The quantitative analysis is a similarity value found in the comparison of concept maps drawn by students and an expert concept map drawn by a teacher. The similarity value only helps illustrate how well students know a given subject, and does not clearly measure students' learning state. Such assessment results do not fully depict the difference of learning states in different students (Stuart, 1985). For example, two students with the same similarity value in an assessment may have different states of comprehension. Since there is no way of deciding the difference of learning results when the similarity value is the same, the feedback provided by the similarity value does not give appropriate help for the students. The proposed assessment first finds the learning states of all propositions in a student concept map, and then calculates the similarity value by comparing the weights on propositions in student and expert concept maps based on learning states of all propositions.

Weighted concept map

Mislevy and Gitomer (1996) argued that the importance of each proposition is different; some are more important than others in learning. Teachers need to determine the importance of each proposition based on their professional knowledge, and each proposition is given a weight ranging from 0 to 1. A concept map which uses weighted propositions is what we term a "weighted concept map." The higher a proposition ranks in importance, the higher the weight it is assigned. For example, Figure 2 shows a weighted concept map derived from the concept map shown in Figure 1.

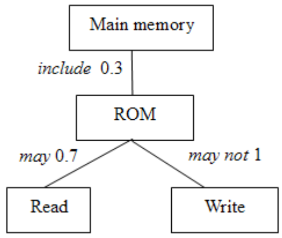

Figure. 2. An example of weighted concept map

From the three propositions in Figure 2, the teacher thinks "ROM *may not* write" is the most important, and assigns it the maximum weight.

Assessment

To measure how well a student learns a given subject, we need to have teachers draw their concept maps of the subject, which are called the expert concept maps. By comparing concept maps drawn by the students with the expert concept maps, the students' comprehension of each proposition can be determined. A student's comprehension has one the following learning states: the proposition is learned, partially learned, unlearned, or the student has a misconception about the proposition. First, we describe the assessment method for the closeness index, and then explain the comparison method of the weighted concept map.

Closeness index

We use Figure 3 as an example to illustrate the comparison method proposed by Goldsmith et al. Figure 3(a) is an expert concept map, $G_e=(V_e, E_e)$, where V_e and E_e are the sets of concept nodes and relation links in the map, respectively. Figure 3(b) is a student concept map, $G_s=(V_s, E_s)$. To compare the maps, we first search in each of them for concept nodes that are connected to each node n from $V = V_e \cup V_s$. The sets of such nodes are represented as $N_n^{(E)}$ and $N_n^{(S)}$. For instance, in Figure 3 node A has links to nodes B and C in G_E, but in G_S A is connected to nodes C, D, and E. Therefore, $N_A^{(E)}$= {B, C} and $N_A^{(S)}$= {C, D, E}. After the sets of adjacent nodes for a given node are determined, the intersection of the two sets ($I_n = N_n^{(E)} \cap N_n^{(S)}$) and their union ($U_n = N_n^{(E)} \cup N_n^{(S)}$) are determined. Going back to the example above, the intersection of $N_A^{(E)}$ and $N_A^{(S)}$ is I_A = {C}, and their union is U_A = {B, C, D, E}. Now that we have I_n and U_n, we define the closeness index for node *n* as $C_n = \dfrac{|I_n|}{|U_n|}$, where $|\cdot|$ means the number of nodes in the set. By this definition, the closeness index for node A in Figure 3 can be calculated as $C_A = \dfrac{|I_A|}{|U_A|} = \dfrac{1}{4}$ = 0.25. After the closeness indexes for all nodes in the two concept maps are calculated, we can define the closeness index of the two concept maps as:

$$C\,(G_e, G_s) = \frac{1}{|V|}\sum_{i\in V} C_i \quad \text{, where } V = V_e \cup V_s\,.$$

Table 1 shows all the steps of computation for Figure 3.

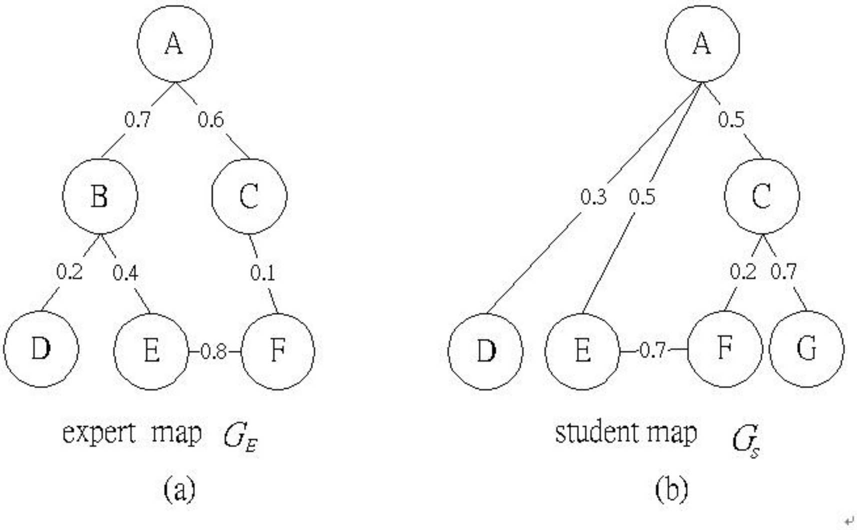

Figure 3. (a) Expert concept map and (b) student concept map

Table 1. Calculation of closeness index for the two concept maps in Figure 3

n	$N_n^{(E)}$	$N_n^{(S)}$	I_n	U_n	C_n
	$\{B,C\}$	$\{C,D,E\}$	$\{C\}$	$\{B,C,D,E\}$	0.250
B	$\{A,D,E\}$	ϕ	ϕ	$\{A,D,E\}$	0
C	$\{A,F\}$	$\{A,F,G\}$	$\{A,F\}$	$\{A,F,G\}$	0.667
D	$\{B\}$	$\{A\}$	ϕ	$\{A,B\}$	0
E	$\{B,F\}$	$\{A,F\}$	$\{F\}$	$\{A,B,F\}$	0.333
F	$\{C,E\}$	$\{C,E\}$	$\{C,E\}$	$\{C,E\}$	1
G	ϕ	$\{C\}$	ϕ	$\{C\}$	0

$C = 0.321$

Similarity index

Calculation of closeness index does not take propositions into consideration. Our proposed method considers propositions based on weighted concept maps.

Let $G_e=(V_e, E_e)$ be an expert concept map. If $(v_i, v_j)\in V_e$ and $e_{ij}\in E_e$, then (v_i, e_{ij}, v_j) represents a proposition in G_e if the relation link e_{ij} connects two concept nodes v_i and v_j. Any proposition (v_i, e_{ij}, v_j) can be compared with the propositions in a student concept map. From the resulting comparison, it is possible to decide if the proposition (v_i, e_{ij}, v_j) is learned, partially learned, unlearned, or if the student has a misconception. The following procedure shows how the comparison is performed:

(1) If there is a proposition (v_i, e_{ij}^*, v_j) in the student concept map, then
   - (i) If $e_{ij}^* = e_{ij}$, (v_i, e_{ij}, v_j) is learned.
   - (ii) If $e_{ij}^* = \phi$, (v_i, e_{ij}, v_j) is partially learned.
   - (iii) If $e_{ij}^* \neq e_{ij}$, the student has misconception about (v_i, e_{ij}, v_j).

(2) If there is a proposition (v_j, e_{ij}^*, v_i) in the student concept map, then
   - (i) If $e_{ij}^* = e_{ij}$ or $e_{ij}^* = \phi$, (v_i, e_{ij}, v_j) is partially learned.
   - (ii) If $e_{ij}^* \neq e_{ij}$, the student has misconception about (v_i, e_{ij}, v_j).

(3) If the proposition (v_i, e_{ij}^*, v_j) or (v_j, e_{ij}^*, v_i) does not exist in the student concept map, then (v_i, e_{ij}, v_j) is not learned.

In order to quantify the similarity between the student and expert concept maps, we score propositions according to the student's learning state for the propositions. If proposition $v_{p_i}^* = (v_i, e_{ij}^*, v_j)$ constructed by the student is correct, $v_{p_i}^*$ is scored by the weight of the corresponding proposition defined in the expert concept map. If the student's proposition $v_{p_i}^*$ is partially correct, $v_{p_i}^*$ is scored by half the weight of the expert's proposition. If $v_{p_i}^*$ does not belong to either of the types mentioned above, this proposition receives a score of zero.

By applying the above principles, we can define $score(v_{p_i}^*)$ as the score assigned to the proposition $v_{p_i}^*$. The formula for calculating $score(v_{p_i}^*)$ is one of the following three conditions. Assume that v_{p_i} is a proposition in the expert concept map and $w(v_{p_i})$ is its weight.

(1) If $v_{p_i}^*$ is a correct proposition, $score(v_{p_i}^*) = w(v_{p_i})$.

(2) If $v_{p_i}^*$ is a partially correct proposition, $score(v_{p_i}^*) = \frac{1}{2} \times w(v_{p_i})$.

(3) If $v_{p_i}^*$ is neither a correct proposition nor a partially correct proposition, $score(v_{p_i}^*) = 0$.

After calculating the scores for all student propositions, we define the similarity index as

$$S = \frac{\sum_{for\ all\ i,j} score(v_{p_i}^*)}{\sum_{for\ all\ v_{p_i}\in V_p} w(v_{p_i})}, \quad 0 \le S \le 1$$

S is used to measure how similar the student's knowledge structure is to the expert's. The larger the index, the more the similarity.

In order to further distinguish the difference between S and C, we give an example. Figure 4 is an expert concept map for "types of memory and their characteristics", and Figure 5 is a concept map built by a student. Table 2 lists the intersection and union of the adjacent nodes for each corresponding node in Figures 4 and 5. Table 3 gives the student's learning states and scores for propositions after the comparison of propositions in Figures 4 and 5.

Applying the assessment method of the closeness index, we see in Table 2 that the total score for all nodes in Figure 5 is 8. Because there are 13 concept nodes in the expert concept map in Figure 4, the closeness of the concept maps in Figures 4 and 5 is *C*=8/13=0.615.

Table 3 shows that the total score for the propositions constructed by the student is: 0.7 + 0.4 + 0.35 + 0.8 = 2.25. Meanwhile, the total of weights for all propositions in the expert concept map in Figure 4 is 8.3. According to our definition, *S* = 2.25/8.3 = 0.271.

This example demonstrates that the closeness index may produce on absurd assessment because it does not take into consideration the correctness of propositions.

Table 2. Intersection and union of adjacent nodes for each node in Figures 4 and 5

Concept node	Intersection of adjacent concept nodes	Union of adjacent concept nodes	Number of intersections/union
Main memory	Smaller capacity and higher speed, RAM, ROM, memory	Smaller capacity and higher speed, RAM, ROM, memory	1
Smaller capacity and higher speed	Main memory	Main memory	1
RAM	Main memory, read, overwrite	Main memory, read, overwrite, data erased	3/4
ROM	Main memory, read, overwrite	Main memory, read, overwrite, data retained	3/4
memory	Main memory, auxilary memory	Main memory, auxilary memory	1
Auxilary memory	Memory, larger capacity and lower speed	Memory, larger capacity and lower speed, disk, tape	2/4
Overwrite	RAM, ROM	RAM, ROM	1
Read	RAM, ROM	RAM, ROM	1
Larger capacity, lower speed	Auxilary memory	Auxilary memory	1

Table 3. Student's learning states and scores for the propositions

Student proposition($v^*_{p_i}$)	Learning state of for the proposition	$score(v^*_{p_i})$
Main memory *characterized by* Smaller capacity and higher speed	Learned	0.7
Main memory *may not* RAM	Misconception	0
Main memory *may not* ROM	Misconception	0
Memory *consists of* Main memory	Learned	0.4
RAM *may not* Write	Misconception	0
RAM ??? Read	Partially learned	0.35
ROM *may* Write	Misconception	0
ROM *may not* Read	Misconception	0

Empirical Evaluation and Discussion

We performed two studies using 84 first-graders from two classes of a senior high school in Taipei as subjects. The material used in the first study is a unit entitled 'An introduction to memory,' which is a part of the course of 'Introduction to Computer and Information Technology.' Students practice concept mapping for fifty minutes before the experiment. In the study, students use the system revised from Chang, Sung & Chen (2001) to construct their concept maps for fifty minutes. The system includes a concept list, a relation list, a toolbar to edit and save maps, and hint and evaluation buttons. The concept and relation lists contain all of the given concepts and relations to be used. Students select concepts or relations from the concept or relation list, and put them into the editing area using the editing tools in the toolbar. The students then gradually create a map composed of nodes and links. The students can press the evaluation button to compare the expert concept map with the student concept map for calculating two evaluation scores *C* and *S*. After the study, the students were given an achievement test.

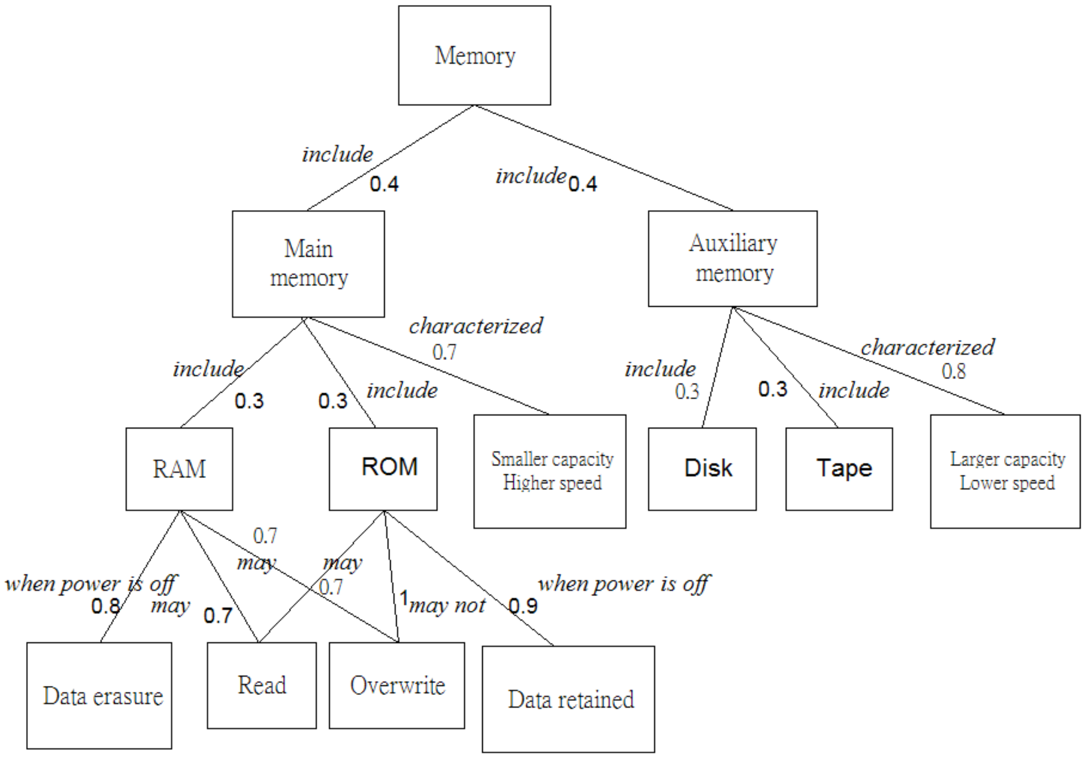

Figure 4. An expert concept map for "types of memory and their characteristics"

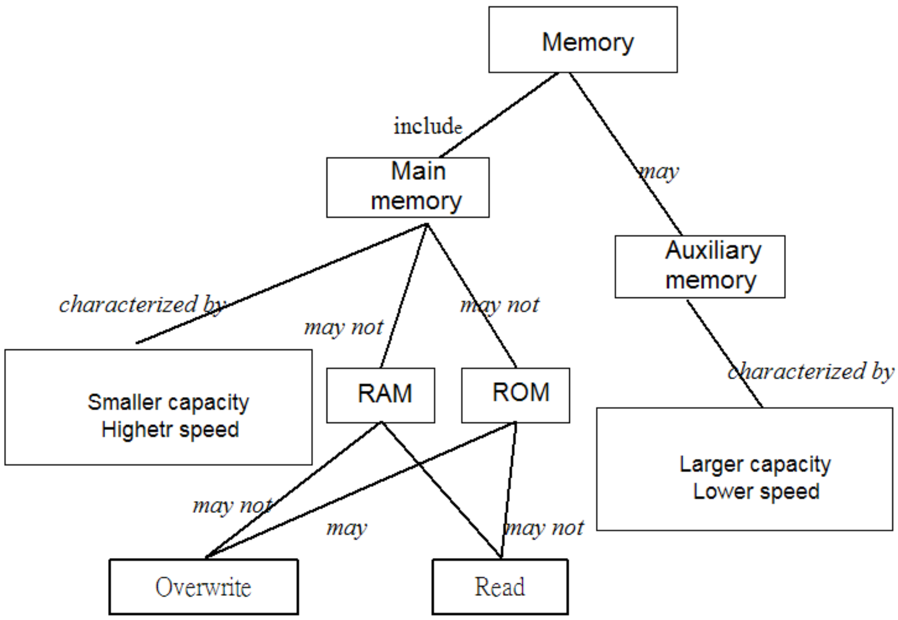

Figure 5. A student concept map

In the study we analyze the relations between the scores on students' achievement tests and the closeness and similarity indices of the students' concept maps. From the analysis we know the predictive effect on students' test scores by the two indices. The data collected in this experiment are *C* and *S*. The outcome of predicting the test scores by *C* and *S* is discussed. Using simple regression analysis, we find the explanatory quantity for the two indices on the variation in achievement. In the regression analysis, the larger R^2 is, the larger the explanatory quantity for variation in the 'An introduction to memory' posttest.

Table 4 is the Pearson Correlation Matrix of *C* and *S* and achievement test scores. Table 5 is the result of regression analysis of *C* about the test scores and Table 6 shows the same for *S*.

Table 4 shows that the relevance of *C* to the test score is significant (r=0.48, p<0.01). The relevance of *S* to the score is also significant (r=0.63, p<0.01). We can conclude that both *C* and *S* have significant predictive power for learning achievement. Additionally, the relatedness of *C* and *S* is also significant (r=0.94, p<0.01). Tables 5 and 6 show that the explanatory power of *S* (R^2) in predicting the variation in test scores is 40.1%, which is superior to the 22.8% for *C*.

Table 4. The Pearson Correlation Matrix of *C*, *S*, and test scores (N=84)

	C	**S**	Test score
C	1.00		
S	0.94**	1.00	
Posttest score	0.48**	0.63**	1.00

** p < 0.01

Table 5. A regression analysis of using C as a predictor and test scores as criteria (Unit 'memory,' N=84)

Source of variation	Sum of squares (SS)	Degree of Freedom (df)	Mean squares (MS)	F value	R^2
Regression	2985.7	1	2985.7	24.2**	0.228
Residual	10126.7	82	123.5		
Total	13112.4	83			

** p <0.01

Table 6. A regression analysis of using S as a predictor and test scores as criteria (unit 'memory,' N=84)

Source of variation	Sum of squares (SS)	Degree of Freedom(df)	Mean squares (MS)	F value	R^2
Regression	5260.8	1	5260.8	54.9**	0.401
Residual	7851.6	82	95.8		
Total	13112.4	83			

** p <0.01

In the second study, the participants, procedure, and data analyses are the same study one. However, the domain knowledge was substituted with a unit entitled 'Metamorphism,' (Figure 6) which was adopted from the course of 'Earth Sciences.' Table 7 and Table 8 are the result of regression analyses of *C* and S on the test scores. Tables 7 and 8 show that the explanatory power of *S* (R^2) in predicting the variation in test scores is 40.3%, which is superior to the 33.9% for *C*.

The analyses demonstrate that both *C* and *S* have significant predictive powers for learning achievement, and the predictive power of *S* is superior to that of *C*. We explain the reason for this. The calculation of *C* is based on concepts. The assessment criterion for *C* is the correctness of the connections between adjacent concepts, but it overlooks the question of whether the student really understands the proposition composed of two adjacent concepts and their link. On the other hand, *S* is based on propositions, which indicates that *S* not only takes the correctness of a proposition into consideration but also weights the importance of the proposition. Therefore, *S* is more precise and predictive than *C*.

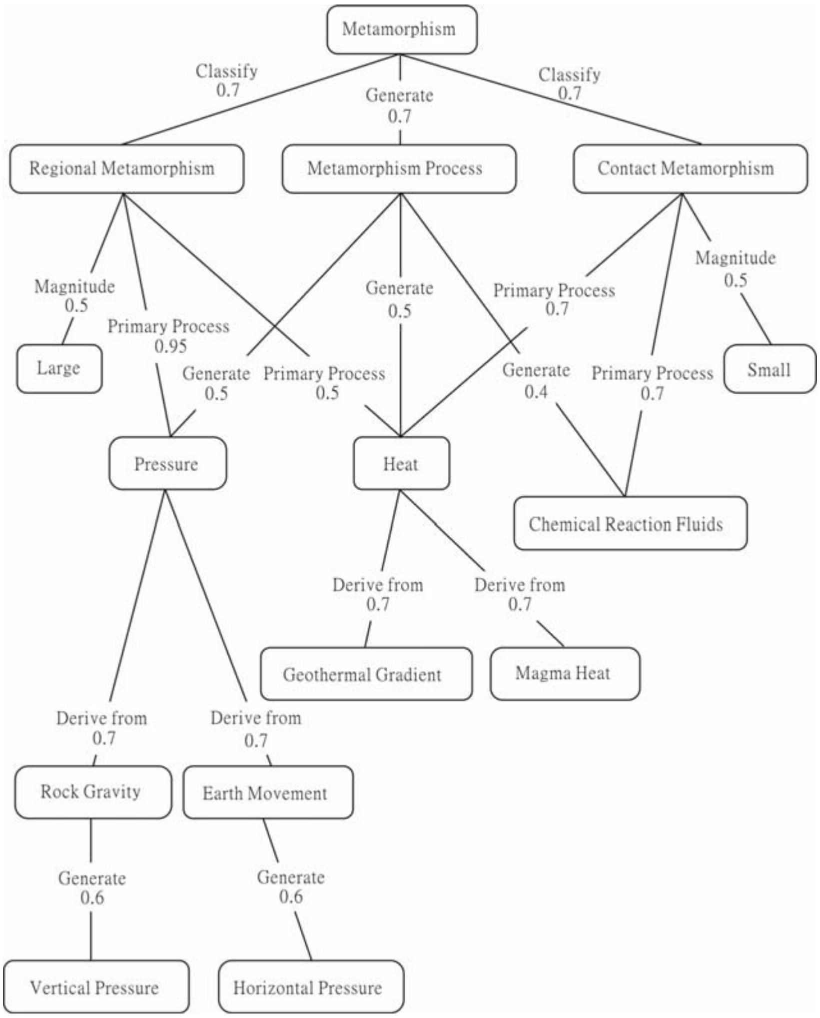

Figure 6. A concept map for the unit of "Metamorphism"

Table 7. A regression analysis of using C as a predictor and test scores as criteria (unit 'Metamorphism,' N=84)

Source of variation	Sum of squares (SS)	Degree of Freedom (df)	Mean squares (MS)	F value	R^2
Regression	8980.0	1	8980.0	42.1**	0.339
Residual	13225.0	82	178.9		
Total	22205.0	83			

** p <0.01

Table 8. A regression analysis of using S as a predictor and test scores as criteria (unit 'Metamorphism,' N=84)

Source of variation	Sum of squares (SS)	Degree of Freedom(df)	Mean squares (MS)	F value	R^2
Regression	8953.7	1	8953.7	55.4**	0.403
Residual	13251.3	82	161.6		
Total	22205.0	83			

** p <0.01

Conclusions and future work

Concept maps have been widely applied in education. In the past some of the assessment criteria for concept maps considered only concept nodes, while others were based on concept nodes with relation links used in only an auxiliary role. This study concludes that those assessment criteria are not fully convincing because the assessment results do not detect the true the state of students learning. To address this problem, this study suggests that a weighted concept map be used as the criteria for assessment. Furthermore, this study proposes a method to compare weighted concept maps. The students' concept maps are contrasted with those of experts to assess students' learning states, and then indices are computed according to students' learning states for a given proposition. That will help students construct their concept maps, and the similarity index of the student's and the expert's knowledge structures can be obtained. From the experimental results we reached the following conclusions: Both the similarity and closeness indices, which are indicators for assessing the similarity of student's and expert's knowledge structures, can effectively predict students' learning results. But the predictive power of the similarity index is superior to that of the closeness index.

For the convenience of assessment, most concept mapping systems pre-store all known concepts and relations in the system. Students choose only from those predefined concept nodes and relation links to construct their maps. Based on the predefined concept nodes and relation links, the similarity index and closeness index are calculated. But, requiring students to construct their concept maps using predefined concepts and links hinders students from completely expressing their ideas. Improving assessment methods to provide students with more freedom in the construction environment may be even more helpful for students' learning and assessment. Therefore, developing more flexible methods for comparing concept maps with synonyms in concept nodes or relation-links is an important issue for future research.

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