SEQUENTIAL PATTERN ANALYSIS: METHOD AND APPLICATION IN EXPLORING HOW STUDENTS DEVELOP CONCEPT MAPS

Chiung-Hui Chiu (Corresponding author), Chien-Liang Lin
Graduate Institute of Information and Computer Education
National Taiwan Normal University
Taiwan
cchui@ntnu.edu.tw

ABSTRACT

Concept mapping is a technique that represents knowledge in graphs. It has been widely adopted in science education and cognitive psychology to aid learning and assessment. To realize the sequential manner in which students develop concept maps, most research relies upon human-dependent, qualitative approaches. This article proposes a method for sequential pattern analysis, inspired by sequential pattern mining algorithms generally applied to commercial forecast and decision supports. The method can be programmed for automatic execution and thus reasonably fast, yielding reproducible results. To validate the proposed method, 187 college students were recruited to create respective concept maps on a computerized concept mapping system. While the concept mapping data was analyzed by the sequential pattern analysis method, it was found that the mapping sequences used by students that created superior concept maps were similar and had a pattern in which propositions were formed in a temporal order from more inclusive to less inclusive. Conversely, no similarity was found in the concept mapping sequences by those who created inferior concept maps. The findings support theoretical expectations about concept mapping and are consistent with qualitative evidence based on student self-reports.

INTRODUCTION

Concept mapping is a technique developed by Prof. Joseph D. Novak at Cornell University in the 1960s to visually represent an individual's knowledge structure about a particular topic. The generated concept map is composed of nodes and links. The nodes represent concepts, while the links represent the relationships between the concepts. The concepts and propositions should be hierarchically structured. More inclusive, more general concepts and propositions are positioned at the top of the map (Novak & Gowin, 1984). Concept mapping is based on Ausubel's theory of meaningful learning. In the concept mapping process the learner is required to make a conscious effort to identify the key concepts in new information and relate them to concepts in his/her existing knowledge structure. Concept mapping has frequently been used as an instructional aid to promote learning and retention of new information. The map produced during the instruction would reflect the structure of the students' ideas and display the interrelationships among these ideas. Concept mapping, thus, could also be used to assess the varying degrees of student understanding (e.g., Hay, 2007; Markham, Mintzes, & Jones, 1994; Moreira, 1979, 1985; Schmid & Telaro, 1990).

Many studies showed that the concept maps of divergent learner groups exhibited different representational structures. Fraser and Edwards (1985), Novak (1988), and Winitzky, Kauchak, and Kelly (1994, p. 127) found that experts' concept maps presented more thorough, elaborate, complex, interconnected and hierarchical ordering. Novices' concept maps were less complex, less structured and organized in isolated bits or small chunks. Kinchin, Hay, and Adams et al. (2000) found that student concept maps could be categorized into three major patterns, including spoke, chain and net structures. The "spoke" structure is a radial structure in which all related concepts are linked directly to the core concept, but not linked directly to each other. The "chain" is a linear sequence of concepts in which each concept is linked to those immediately above and below. A logical sequence exists from beginning to end, but the hierarchical relation of many links is invalid. The "net" is a highly integrated and hierarchical network. To quantitatively assess such difference between concept maps, Novak and Gowin's (1984) scoring scheme has been often adopted. Experts would be expected to score higher on their concept maps than novices. This scheme scores the structural features of a concept map involving propositions, hierarchy, cross links and examples. The construct validity can be established because these features represent different aspects of meaningful learning, specifically concept differentiation and integration (Shaka & Bitner, 1996). Although subsequent researchers have made minor modifications (e.g. such as adding a branch count), all tended toward an aggregate score for the structural elements (e.g., Dorough & Rye, 1997).

While most studies emphasize measuring the produced concept map, some (e.g., Deguchi, Yamaguchi, Funaoi, & Inagaki, 2004; Karvonen, Rautama, Tarhio, & Turkia, 2001; McAleese, 1998; Rautama, Sutinen, & Tarhio, 1997; Wong, 1998) take notice of the importance of probing the manner in which a student proceeded to generate his/her respective concept map. It was suggested that examining the concept mapping process would help determine the mental activity and knowledge processing that led to the given results. Wong (1998) thus

asked students to recall and provide their actions in generating a concept map. The student responses showed that both high achievers (scored at high levels on achievement tests) and low achievers knew what the components of a concept map should be, the need to consider how the concepts were related and that concepts should be positioned hierarchically. However, their thoughts and actions during generating a concept map seemed inconsistent. When asked how they went about organizing concepts and deciding on the links between concepts, high achievers emphasized the importance of understanding the concepts and forming meaningful relationships between the concepts. High achievers made an effort to identify the meanings and distinguish the concept features, organize the concepts into clusters of related concepts, form correct links between concepts in a cluster and between concepts in different clusters, and organize the concepts in the map hierarchically. Low achievers did not put in as much effort as the high achievers in identifying the meanings of concepts and forming meaningful relationships between concepts. Their responses showed a lack of understanding the concepts and their links, and a lack of effort at in-depth knowledge processing. This probably explains why the concept maps produced by low achievers were incomplete and had more inappropriate concepts, inappropriate links and incorrect hierarchical structure. Karvonen et al. (2001) and Rautama et al. (1997) also considered a concept map as a process rather than an image. They suggested implementing computing techniques to present this concept mapping process. A computer-aided design was proposed in 1997 and implemented in 2001 to trace, record, preserve and visualize a continuous set of mapping actions. The mapping process information was presented as a script that consisted of operations, like adding a new concept to the map and linking it to other concepts. Biswas and Sulcer (2010) and Deguchi, Yamaguchi, Funaoi, and Inagaki (2004) further developed computer programs that allowed playback of the mapping process. They expected that learners would study their own knowledge construction approaches and the teachers could inspect the students' learning problems through reviewing the mapping sequences. It is laborious and difficult for teachers and students to examine or realize concept mapping details. This paper therefore proposes an approach that could efficiently, reliably and validly disclose the pattern and useful information concerning student concept mapping sequences.

A METHOD FOR ANALYZING CONCEPT MAPPING SEQUENCES

Inspired by sequential pattern mining techniques in a large customer transactions database, an approach for exploring student sequential patterns in constructing concept maps is proposed. The sequential pattern is a temporal ordered list of elements that appear together in the concept mapping sequences produced by the involved or concerned students. The Direct Sequential pattern Generation (DSG), a graph-based algorithm proposed by Yen and Chen (1996) is borrowed and transformed in this work. Other discovering data sequences techniques (e.g., Agrawal & Srikant, 1995; Gomathi, Moorthi, & Duraiswamy, 2008; Tsai & Shieh, 2009) may also be suitable for use. This method is composed of the following stages.

Stage 1. Build temporal sequences consisting of theoretically meaningful actions. Because the proposition (i.e. concept-relationship-concept triple) is the basic unit of meaning in a concept map (Dochy, 1996), a proposition is taken as the essential element for processing mapping-sequence analysis. Therefore, at the first stage the log data by each student during concept mapping, consisting of low level events (e.g., forming concepts or relation-links), is organized into *a sequence of propositions* ordered by increasing proposition-generating-time. As shown in Figure 1, V_i, V_j and V_k are created concept nodes, e_{ij} and e_{jk} are created relation-links, and $\{V_i, e_{ij}, V_j\}$ and $\{V_j, e_{jk}, V_k\}$ are the formed propositions. These two propositions could be converted into two connected proposition nodes P_{ij} and P_{jk}. There is a common joint concept V_j between the propositions P_{ij} and P_{jk}. The direction of the link between P_{ij} and P_{jk} is determined by the proposition formation time.
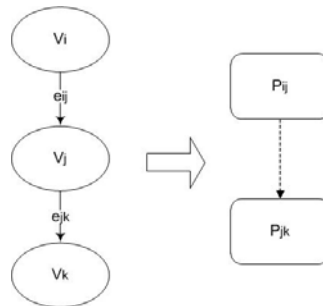

Figure 1: Build proposition-based sequences

Stage 2. Generate large 1-sequences and transform student-sequences. The following definitions are derived from Agrawal and Srikant (1995). It is defined that a student supports a sequence *s* if *s* is contained in his/her mapping sequence. The *support for a sequence* is the fraction of the total number of students that support this sequence. Each sequence that satisfies a certain minimum support threshold is a *large sequence*. A sequence of

www.manaraa.com

length *k* is called a *k-sequence* and a large sequence of length *k* a *large k-sequence*. To discover the sequential patterns is to find the maximal large sequence(s) among all large sequences. The stage involves finding all large 1-sequences. Afterward, each student-sequence is converted into a transformed student-sequence that is an ordered list of large 1-sequences. Table 1 presents an example of students' (No. 1-5) mapping sequences and illustrates how the original student-sequences are transformed to large 1-sequences with the support set to 100%.

Table 1: Concept mapping sequences of five exemplary students

Student	No. 1	No. 2	No. 3	No. 4	No. 5
Mapping sequence	ABCDE	BFACDE	ACGFBD	BGACD	GAECBD
Transformed mapping sequence	A, B, C, D	B, A, C, D	A, C, B, D	B, A, C, D	A, C, B, D

Note. A, B, C, D, E, F and G stand for proposition nodes

Stage 3. Construct association graph. This stage combines two large-1 sequences to generate a 2-sequence and scans all of the transformed student-sequences. When the support for a 2-sequence achieves the minimum support threshold, it is viewed as a large 2-sequence. A directed edge is then created from the first large 1-sequence to the second large 1-sequene. If the *support* is set at 100%, the 2-sequence appeared in all transformed student-sequences. The algorithm can be simplified as follows:

LS1 = { large 1-sequences }
LS2 = ∅
if *LS1* ≠ ∅ **then begin**
forall permutation *1x1y*, where *1x* and *1y* are selected from *LS1* **do**
    if *1x 1y* appears in the same order in all transformed student-sequences **then**
      LS2= *LS2*∪{<*1x1y* >} * generate large 2-sequences *\
      CreateEdge (*1x, 1y*) * create an edge from 1x to 1y in the association graph *\
end

Using the example in Stage 2, all possible directed edges can be created to construct the association graph as shown in Figure 2(2).

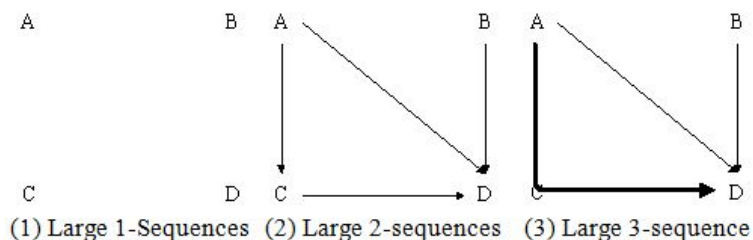(1) Large 1-Sequences (2) Large 2-sequences (3) Large 3-sequence
Figure 2: Procedure for discovering the sequential patterns in Table 1

Stage 4. Generate sequential patterns. Based on the association graph, a large n-sequence (n>2) can be generated. If there is a directed edge from the last large 1-sequence of a large 2-sequence found in stage 3 to another large 1-sequence, the large 2-sequence will be extended to a large 3-sequence. The sequence length is extended until no large k-sequence can be generated. As in the example in stage 2, the large 2-sequence <A→C> can be extended as shown by the bold lines in Figure 2(3). The resulting <A→C→D> is a large 3-sequence. After finding all large sequences, the large sequences that are subsequences of the other large sequences are deleted. The remaining large sequences are maximal large sequences, that is, they indicate student sequential patterns during concept mapping.

The sequential pattern analysis method can be programmed for automatic execution. The automated method can produce a computationally efficient and reliable analysis for unveiling student concept mapping sequences. It corrects some of the problems with reliability and computational inefficiency commonly observed with human-dependent approaches.

AN EVALUATION OF THE SEQUENTIAL PATTERN ANALYSIS METHOD FOR CONCEPT MAPPING

To evaluate the proposed method for probing student concept mapping sequences, a concept mapping activity on the topic of electrical energy was arranged. A computer system was utilized to support this activity and collect students' concept mapping data. In addition, students' concept map data were scored to estimate their understanding of electrical energy.

PARTICIPANTS

One hundred and eighty-seven students volunteered to participate in this study. They were enrolled in an elementary teacher preparation program at a teachers college in southern Taiwan, and were taking educational theory, curriculum design, and technology integration courses. The teacher preparation program was designed to cultivate elementary generalists because an elementary school teacher in Taiwan usually needs to teach many different school subjects. These students were all capable of using a word processing program, a painting program and an Internet browser.

CONCEPT MAPPING ACTIVITY

The participants attended a "selected terms" concept mapping (Schau, Mattern, Zeilik, Teague, & Weber, 2001) activity on electrical energy. Each participant was given 23 concepts and 6 links, and was asked to independently generate a concept map using only these concepts and links. The given concepts and links were extracted from an expert concept map negotiated by two college professors with expertise in electrical energy and elementary science education. Figure 3 presents the expert concept map. The concepts are arranged in a hierarchy with "electrical energy" at the top. As one travels down a map, the concepts become more and more specific and the map is anchored with examples.
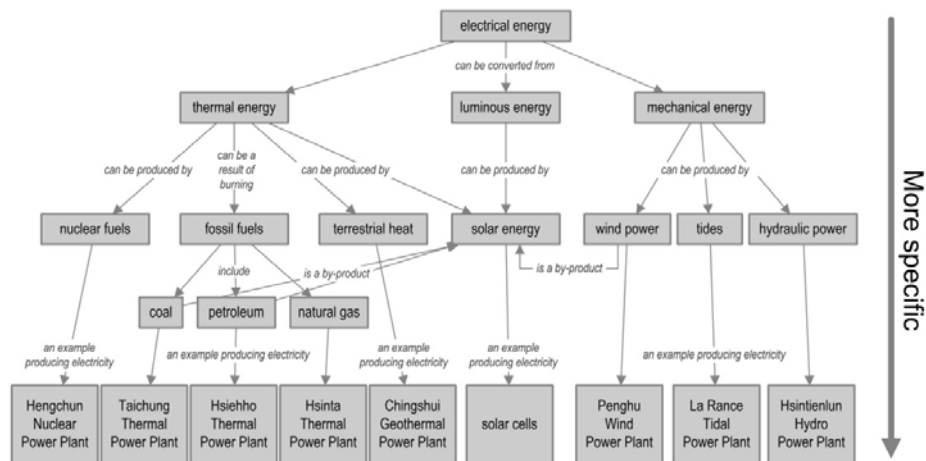

Figure 3: The expert concept map on the topic of electrical energy

CONCEPT MAPPING PLATFORM

A web-based concept mapping system was adopted to support the experimental activity. Figure 4 shows the user interface. The system modules used in this study are detailed as follows.
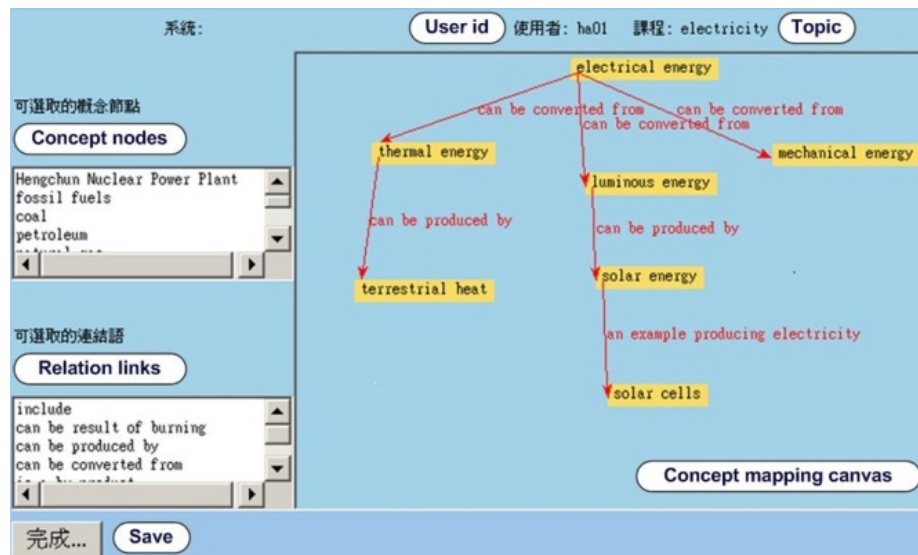
www.manaraa.com

Figure 4: Interface for the web-based concept mapping system

Mapping module. The mapping module provided functions to generate a concept map on a computer screen. A user could arbitrarily add, change, delete, position or move concept nodes and relation links using a keyboard and a mouse. To decrease the cognitive demand in producing a complete concept map, this system could predefine concepts/links, or provide a partial map (fill-in-the-map) in advance.

Tracing module. The tracing module was used to trace and record the entire data in a concept mapping activity. The traced data included every action (such as adding, deleting, positioning and repositioning concept and link objects), the action time and the map generated by each individual user or collaborative group. The system stored these data in its database.

Scoring module. A scoring module was used to semi-automatically score a concept map in real time. The system evaluated the four structural components of a concept map, including the propositions, hierarchy levels, cross links and examples. The concept map to be scored was compared with a criterion concept map. The portions in the former map that also existed in the latter would be given numerical scores. However, it should be noted that not all scoring method take into considering all four components. Multiple combinations can be found from scoring methods that consider all components (Novak & Gowin, 1984) to methods that only consider propositions (McClure & Bell, 1990). In this evaluation study, the expert concept map (Figure 3) was used as the criterion concept map. The professors that provided the expert map determined the scoring rules as follows: (a) a valid proposition scored 1 point, (b) a valid hierarchy level scored 5 points, (c) a valid cross link scored 2 points, and (d) a valid example scored 1 point. The expert concept map scored 51 points according to the rules.

PROCEDURE
One by one the participant classes were arranged to carry out the concept mapping activity in a computer laboratory at the participants' college. The laboratory had IBM-compatible computers. Each participant was required to work independently on an assigned computer. Two sessions were allocated for each class. The first session was mainly used to introduce the participants to the concept mapping technique and how to use the concept mapping system to construct individual concept maps. This took about 30 minutes. In addition, a reference article on electrical energy was supplied to the participants to help them recall the related existing knowledge. Ten minutes was given for reading the reference. The second session was used for the formal concept mapping activity. The participants took 40 minutes to generate respective concept maps on electrical energy.

RESULTS
The concept mapping data sets, including mapping sequences and end map products, generated by the 187 participants were analyzed. The concept map products were scored numerically, with concept mapping sequences examined for sequential patterns. The results show that the mean concept map score was 24.87 (*SD* = 8.90). The range was 40, with the highest score = 40, and the lowest score = 0. Those maps with a score in the top 27 percentile (score ≥ 32) were classified as high score students. Those whose score was in the lower 27

percentile (score ≤ 19) were identified as low score students. The mean of the high score students (n = 52) was 34.38 (*SD* = 2.03), while the mean of the low score students (n = 52) was 13.21 (*SD* = 5.61). The mean for correct proposition numbers produced by the high score students was 16.79 (*SD* = 1.71) and the mean for the low score students was 6.58 (*SD* = 2.70). The mean length for the maximal large sequences by the high score students identical to that of experts was 6.83 (*SD* = 1.49), and the mean by the low score students was 3.10 (*SD* = 1.48). While the concept mapping sequences of the concept maps with a score of 40 were analyzed, it was found that 18 identical propositions appeared in student sequences and there existed a specific sequential pattern (the maximal large sequence) with length 11. The sequence analysis was reiterated by consolidating the next highest score mapping data (score=39). It was found that the number of identical propositions appearing in the mapping data was 18, but the length of the maximal large sequence dropped to 7. While the sequence analysis was reiterated by downward consolidating the third-highest score data (score=38), the fourth-highest score mapping data (score=37), and the fifth-highest score mapping data (score=36), the results show that the number of identical propositions appearing in concept mapping was 17, 12, and 9 respectively and the length of the maximal large sequence was 4, 2, and 0. The analysis iteration was terminated at the fifth-highest score data, because further consolidating lower score data would not generate any large sequences. Figure 5 presents the sequential pattern example by the students whose maps achieved higher scores.
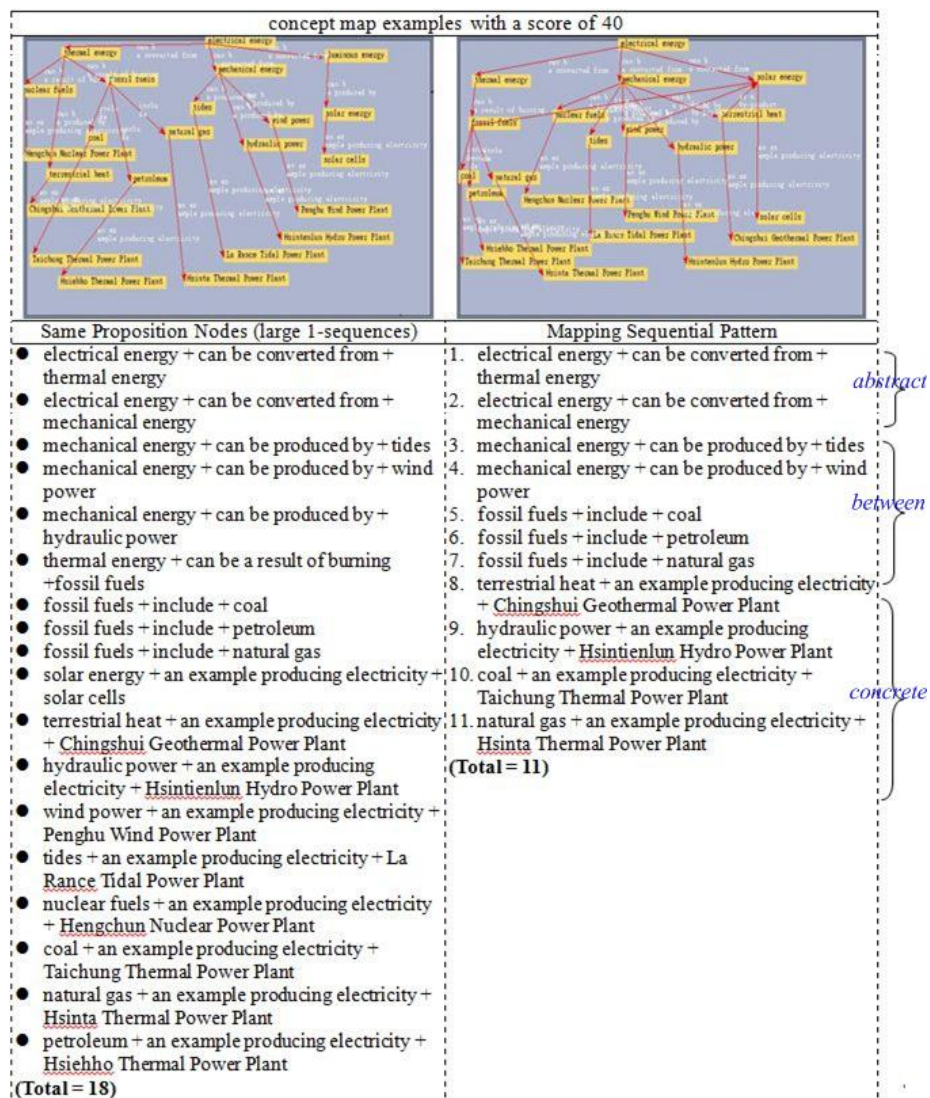

Figure 5: Sequential pattern example for superior concept maps

Comparatively, data sets with the lowest five scores were analyzed. The maps scored 0 shared no generated proposition similarity. No large k-sequences were found, i.e. they shared no common mapping sequences. If these data sets were consolidated with any other mapping data, the large sequence length would remain zero.

Therefore, 0-score data sets were excluded from the follow-up sequential pattern analyses. Still no common propositions and mapping sequences were found in the second- and third-lowest score (2 & 3) mapping data. The forth lowest score was 4. The analyses showed that an identical proposition existed with no identical mapping sequences. The fifth lowest score was 8. It was found that 6 identical propositions existed and the maximal large sequence length was 4 (see Figure 6).

Score	Same Proposition Nodes (large 1-sequences)	Mapping Sequential Pattern
0	empty	empty
2 3	empty	empty
4	● nuclear fuels + an example producing electricity + Hengchun Nuclear Power Plant (Total = 1)	empty
8	● thermal energy + an example producing electricity + Hsinta Thermal Power Plant ● thermal energy + an example producing electricity + Taichung Thermal Power Plant ● thermal energy + an example producing electricity + Hsiehho Thermal Power Plant ● terrestrial heat + an example producing electricity + Chingshui Geothermal Power Plant ● hydraulic power + an example producing electricity + Hsintienlun Hydro Power Plant ● wind power + an example producing electricity + Penghu Wind Power Plant (Total = 6)	1. thermal energy + an example producing electricity + Hsinta Thermal Power Plant 2. thermal energy + an example producing electricity + Taichung Thermal Power Plant 3. thermal energy + an example producing electricity + Hsiehho Thermal Power Plant 4. terrestrial heat + an example producing electricity + Chingshui Geothermal Power Plant *concrete* (Total = 4)

Figure 6: Sequential pattern example for inferior concept maps

DISCUSSION

By applying the sequential pattern analysis method proposed in this paper to the practical student concept mapping data, differences were found in the sequential patterns between students generating higher and lower-score concept maps. The sequential patterns among higher-score students were longer in length. Further, the higher-score students tended to established propositions from more inclusive ones to less inclusive ones in temporal order. To illustrate the finding, the mapping sequential pattern in two 40-score cases was taken as an example. Numbers 1 to 11, as shown in Figure 5, denote the temporal order of the composed proposition items. While referring to the hierarchy of the expert concept map on electrical energy (see Figure 3), the proposition items contained in the mapping sequential pattern can be roughly classified into three groups. Items No. 1 and No. 2 are subordinate directly to the concept "electrical energy" and are most inclusive, general and abstract in the subject domain electrical energy. Items No. 8 to No. 11 describe the relations with specific examples included in the subject domain electrical energy and thus are the least inclusive, most specific and most concrete. Comparatively, the other five items, from No. 3 to No. 7, are less inclusive than propositions No. 1 and No. 2, and are more inclusive than propositions No. 8 to No. 11. From the mapping sequential pattern, denoted by No. 1 to No. 11, the 40-score students showed a tendency to construct concept maps starting from more inclusive propositions to less inclusive ones. The mapping sequential patterns of 37-40 score, 38-40 score, and 39-40 score students also unanimously showed this trait. These high-score students first identified and selected the main idea of the concept mapping activity, "electrical energy," as the most super-ordinate concept of all other concepts. They then identified the concept categories under the super-ordinate concept. Coordinate concepts such as "thermal energy," "mechanical energy," or "luminous energy" were specified. These coordinate concepts were spaced below the super-ordinate and each was connected to it by a line to represent a relationship. After that, specific concepts related to one another within individual coordinate level categories were listed. These concepts were subordinate concepts. A line was drawn from each subordinate concept to its coordinate level concept and their relationships were specified. The sequential analysis indicated that subordinate terms like "wind power," "tides" and "hydraulic power" were first connected to their coordinate level concept, "mechanical energy"; and then "solar energy" to "luminous energy." However, the sequences connecting "terrestrial heat," "fossil fuels," "nuclear fuels" and "solar energy" with "thermal energy" were inconsistent. The students appeared indecisive in making these connections. Finally, they chose and linked appropriate examples to each specific concept, for instance, "solar cells" to "solar energy." These students could easily include and connect relevant examples. In contrast to the higher-scoring students, the mapping

www.manaraa.com

sequences produced by the lower-score students were quite different. The mapping sequences, starting points, and anchoring points among these students also varied from one another. However, they shared a feature that their first and the following correct propositions revolved around more subordinate concepts and examples. Although these students were given the same time as others for creating their respective maps, they could form propositions only for more concrete concepts. Their concept maps had more incorrect propositions and inappropriate structure types. This was probably because they were limited in their ability to identify the meanings of concepts, particularly at a more abstract level, and form meaningful relationships between concepts. The differences between high and low score students in their concept mapping sequence corresponds with the viewpoints of Novak and Gowin (1984, p. 98). They suggested that starting from more super-ordinate concepts, then gradually adding more subordinate concepts could lead to a well-organized, hierarchically structured concept map that would attain a high score if measured using Novak and Gowin's scoring scheme. The findings are also consistent with those from Wong (1998) that more knowledgeable students self-reported that they "identified the most inclusive concept or major concept (first)…Next identified the second most inclusive concept" in constructing a concept map. By comparing the concept mapping sequence of high score students, a teacher could determine whether a student is choosing an inappropriate starting point or taking a dissimilar sequence for composing a concept map. This student is very likely to create a dissatisfactory concept map and can be spotted in an earlier stage through the comparison. Whether this student is decisive in choosing concepts or making connections could help to judge whether he/she has a problem, conflicting interpretation, misconception, or complete ignorance about specific concepts or connections. Concept mapping sequences by higher-score students could be referenced to judge what portion (concepts or connections) of a concept map by the lower-score student should be dealt with and what priorities should be taken. The lower-score student might need to have those concepts or connections explicitly stated through didactic exposition and reinforced through practice and feedback. The teacher could use a created map with its construction sequence from higher-score students as an instructional aid when guiding a lower-score student during concept map development. Alternatively, the teacher could set up heterogeneous pairs and require them to strive for consensus regarding their maps' appearance. The difference in their original concept maps and mapping sequences allows students to weigh their own and others' perspectives, and then be able to justify, confirm or modify their concepts and conceptual relationships.

CONCLUSIONS

Understanding student concept mapping sequences is important. This information helps understand student learning performance. If students learn in an appropriate manner, student problems can be detected at an early stage and specific sequences could be made explicit for students. Recurring student sequential patterns might indicate some problem with instruction and thus could suggest directions for instructional improvement. This paper proposes a method for discovering concept mapping sequences. The sequential method is derived by transforming a sequential pattern mining algorithm used in scientific and commercial domains. The proposed method was implemented as a computer program to automatically yield results. Uncovering student concept mapping sequences has traditionally relied upon manual tracing of students' self-reports or concept mapping data logged by computer. Those techniques are labor intensive, not practical for large data sets and subject to individual bias. The sequential method presented in this paper is clearly superior to any method that requires human intervention. Attributable to the automated nature of the program, the proposed method could analyze large data sets in a fraction of the time previously required and moreover yield objective results that are reliable and reproducible. While applying the sequential method to practical student concept mapping data it was found that the mapping sequences produced by higher-score students were similar. These sequences showed a pattern in which most of the constituted propositions were the same and formed progressively from more inclusive to less inclusive. This pattern would become obscure in lower-score students. Low-score students' concept mapping sequences appeared very diverse. The findings substantiate the theoretical expectations (Novak & Gowin, 1984) and correspond to the qualitative research findings based on student self-reports (Wong, 1998). Although real data rather than artificial data was used for the evaluation makes the efficacy of the sequential method more worthy of recognition, this study was carried out using specific and limited participants. This would suggest further evaluation with larger, different and diverse populations. In addition, the real student data was collected in a concept mapping activity with some constraints ("selected terms" concept mapping). It is suggested that this method be also tested on the monitoring and analysis of students engaged in more open-ended concept mapping activities.

ACKNOWLEDGEMENTS

REFERENCES

Agrawal, R., & Srikant, R. (1995). *Mining sequential patterns*. Paper presented at the the Eleventh International Conference on Data Engineering, Taipei, Taiwan.

Biswas, G., & Sulcer, B. (2010). *Visual exploratory data analysis methods to characterize student progress in intelligent learning environments*. Paper presented at the 2010 International Conference on Technology for Education (T4E), IIT Bombay, Mumbai.

Deguchi, A., Yamaguchi, E., Funaoi, H., & Inagaki, S. (2004). *Concept mapping software to reconstruct learning processes: Enhancement based on the teachers' requests and its evaluation from the viewpoint of teachers*. Paper presented at the International Conference on Computers in Education, Melbourne, Australia. Retrieved from http://plum.yuntech.edu.tw/icce2004/Theme4/Ch113_Deguchi.pdf

Dochy, F. J. R. C. (1996). Assessment of domain-specific and domain-transcending prior knowledge: Entry assessment and the use of profile analysis. In M. Birenbaum & F. J. R. C. Dochy (Eds.), *Alternatives in Assessment of Achievements, Learning Process and Prior Knowledge* (pp. 93-129). Boston, MA: Kluwer Academic Publishers.

Dorough, D. K., & Rye, J. A. (1997). Mapping for understanding. *The Science Teacher, 64*(1), 36-41.

Fraser, K., & Edwards, J. (1985). The effects of training in concept mapping on student achievement in traditional classroom tests. *Research in Science Education, 15*(1), 158-165. doi: 10.1007/BF02356538

Gomathi, C., Moorthi, M., & Duraiswamy, K. (2008). Web access pattern algorithms in education domain. *Computer and Information Science, 1*(4), 183-186.

Hay, D. (2007). Using concept maps to measure deep, surface and non-learning outcomes. *Studies in Higher Education, 32*(1), 39-57. doi: 10.1080/03075070601099432

Karvonen, A., Rautama, E., Tarhio, J., & Turkia, J. (2001). *Versatile concept map viewing on the Web*. Paper presented at the the Sixth Annual Conference on Innovation and Technology in Computer Science Education, Canterbury, UK.

Kinchin, I. M., Hay, D. B., & Adams, A. (2000). How a qualitative approach to concept map analysis can be used to aid learning by illustrating patterns of conceptual development. *Educational Research, 42*(1), 43-57.

Markham, K. M., Mintzes, J. J., & Jones, M. G. (1994). The concept map as a research and evaluation tool: Further evidence of validity. *Journal of Research in Science Teaching, 31*(1), 91-101. doi: 10.1002/tea.3660310109

McAleese, R. (1998). The knowledge arena as an extension to the concept map: Reflectionin action. *Interactive Learning Environments, 6*(3), 251. doi: 10.1076/ilee.6.3.251.3602

McClure, J. R., & Bell, P. E. (1990). *Effects of an Environmental Education-Related STS Approach Instruction on Cognitive Structures of Preservice Science Teachers*. Universty Park, PA: Pennsylvania State University. (ERIC Document Reproduction Service No. ED 341582).

Moreira, M. A. (1979). Concept maps as tools for teaching. *Journal of College Science Teaching, 8*(5), 283-286.

Moreira, M. A. (1985). Concept mapping: An alternative strategy for evaluation. *Assessment & Evaluation in Higher Education, 10*(2), 159-168. doi: 10.1080/0260293850100206

Novak, J. D. (1988). Learning science and the science of learning. *Studies in Science Education, 15*(1), 77-101. doi: 10.1080/03057268808559949

Novak, J. D., & Gowin, D. B. (1984). *Learning how to learn*. New York: Cambridge University Press.

Rautama, E., Sutinen, E., & Tarhio, J. (1997). Supporting learning process with concept map scripts. *Journal of Interactive Learning Research, 8*(3), 407-420. doi: 10.1145/268809.268829

Schau, C., Mattern, N., Zeilik, M., Teague, K. W., & Weber, R. J. (2001). Select-and-fill-in concept map scores as a measure of students' connected understanding of science. *Educational and Psychological Measurement, 61*(1), 136-158. doi: 10.1177/00131640121971112

Schmid, R. F., & Telaro, G. (1990). Concept mapping as an instructional strategy for high school biology. *Journal of Educational Research, 84*(2), 78-85.

Shaka, L. F., & Bitner, B. L. (1996). *Construction and validation of a rubric for scoring concept maps*. Paper presented at the the 1996 Annual International Conference of the Association for the Education of Teachers in Science, Seattle, WA. Retrieved from http://www2.ed.psu.edu/CI/journals/96pap43.htm

Tsai, C.-Y., & Shieh, Y.-C. (2009). A change detection method for sequential patterns. *Decision Support Systems, 46*(2), 501-511. doi: 10.1016/j.dss.2008.09.003

Winitzky, N., Kauchak, D., & Kelly, M. (1994). Measuring teachers' structural knowledge. *Teaching and Teacher Education, 10*(2), 125-139. doi: 10.1016/0742-051X(94)90008-6

Wong, M. S.-L. (1998). An investigation into high-achiever and low-achiever knowledge organisation and knowledge processing in concept mapping: A case study. *Research in Science Education, 28*(3), 337-352. doi: 10.1007/bf02461567

Yen, S. J., & Chen, A. L. P. (1996). *An efficient approach to discovering knowledge from large databases*. Paper presented at the the Fourth International Conference on Parallel and Distributed Information Systems.