Concept Structure based on Response Pattern Detection of S-P Chart with Application in Algebra Learning

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Abstract: The main purpose of this study is to provide an integrated method for personal concept structure analysis. Based on the utility of S-P chart (student problem chart) to deal with classification for learning style, students of different learning style display its own features of concept structure. In this study, S-P chart is used to classify learning styles of students. Concept structure analysis (CSA) could display personalized concept structure. CSA algorithm is the major methodology and its foundation is fuzzy logic model of perception (FLMP) and interpretive structural modeling (ISM). CSA could clearly represent hierarchies and linkage among concepts. Therefore, CSA will be effectively to display features of personal concept structures. In this study, an empirical data for concepts of linear algebra from university students is discussed. The results show that students of varied learning styles own distinct knowledge structures. CSA combined with S-P chart could be feasible for cognitive diagnosis. According to the findings and results, some suggestions and recommendations for future research are discussed.

Key-Words: concept structure, cognitive diagnosis, FLMP, ISM, S-P chart

1 Background and Motivation

Development of cognitive diagnosis is widely discussed in recent years. One benefit of cognitive diagnosis is to improve the utility of remedial instruction in education environments [7]. Research of cognitive cognition also influences methodology on integration of multi-disciplines [8][12]. These disciplines include cognition science, educational measurement, computer science and technology [1][2][5][40].

Response pattern provides important information for cognitive diagnosis [9][21][34]. Besides, clustering is usually required so that students within the same cluster own similar features of cognition structures and students among different clusters have the most variance [19]. As to this point, Student problem chart (S-P Chart) is one branch of cognitive diagnosis and it focuses on the analysis of response pattern [28]. S-P chart provides disparity index, student caution index and problem caution index, to help diagnose learning style of students and characteristics of items [30]. According to results of S-P chart analysis, all examinee could be classified into six learning styles. Moreover, each learning style represents specific features of cognitive information, which could be references for remedial and adaptive instruction [27][33]. However, little is known about concept structure of each learning style from S-P chart except to the caution index of students. Therefore, integration from another discipline and provides further diagnostic information on concept structures will be prospective [14][15][20][22].

There exist some different approaches of methodologies about concept structures [23][24]. However, most of these methods could not display personal concept structure in the form of graphic representation [16]. Information about mastery of concepts is also limited. Therefore, a method called concept structure analysis (CSA) will be developed in this study. This concept structure analysis combines with S-P chart so as to display information of cognitive diagnosis in more effect way. An empirical testing data on concepts of linear algebra from university students will be analyzed and discussed.

2 Literature Review

S-P chart and CSA are the main algorithms. CSA is based on the foundation of fuzzy logic model of perception (FLMP), interpretive structural modeling (ISM). All the related foundation for S-P chart and CSA will be discussed as follows [43].

2.1 S-P Chart

Foundation of S-P chart is the analysis of response pattern. For a test of dichotomous items, suppose there be N ($n=1,2,...N$) students and M ($m=1,2,...M$) items. The response matrix is $Y=(y_{nm})_{N\times M}$, where $y_{nm}=1$ or $y_{nm}=0$. $y_{nm}=1$ indicates student n has correct answer on item m ; otherwise, it is $y_{nm}=0$ when student n answers item m incorrectly. Moreover, the matrix $Y=(y_{nm})_{N\times M}$ has been sorted by marginal sum. That is, it is $y_{n\bullet}=\sum_{m=1}^{M} y_{nm}$ and $y_{\bullet m}=\sum_{n=1}^{N} y_{nm}$ with $y_{1\bullet}\ge y_{2\bullet}...\ge y_{N\bullet}$ and $y_{\bullet 1}\ge y_{\bullet 2}...\ge y_{\bullet M}$. u' is the average number of examinee who has correct answer on item m. Therefore, it is $u'=\sum_{m=1}^{M} y_{\bullet m} \Big/ M$. The student caution index CS_n is [4][13][32]

$$CS_n = 1-\frac{\sum_{m=1}^{M}(y_{nm})(y_{\bullet m})-(y_{n\bullet})(u')}{\sum_{m=1}^{y_{n\bullet}} y_{\bullet m}-(y_{n\bullet})(u')} \tag{1}$$

Student caution is to detect the aberrant response patterns. This index helps teachers diagnose the aberrant performance of students [35]. The higher student caution index students have, the greater aberrance on response students have. Based on the two indices of caution index for students and correct ratio on items, one plane coordinates is built. The plane coordinates is established and all students could be classified into six learning styles, which are A, A', B, B', C, and C'. It is depicted in Figure 1. Meaning of these six learning styles is as follows [36].

A: These students have good performance and high stability on test.

B: These students have generally good stability but should work a bit harder.

C: These students have poor learning and low proficiency and they must work harder a lot.

A': These students have almost good performance on test but sometimes give incorrect response due to carelessness.

B': These students have fair mastery on concepts and sometimes make errors due to carelessness.

C': These students have quite low stability and proficiency. They have poor mastery on concepts.

The correct ratio on items		
100% – 75%	Effective Learning **A**	Much Carelessness **A'**
75% – 50%	General Fine and Need Diligence **B**	A little Carelessness and Need Diligence **B'**
50% –	Insufficient Learning **C**	Unstable Learning **C'**
	Student caution index < 0.50	Student caution index ≥ 0.50

Fig. 1. Meaning of Six Classification for Students

2.2 Fuzzy Logic Model of Perception

FLMP is a paradigm for psychological measurement research [10]. It embraces the existence of multiple sources of information and the problem of their integration in perception [44][45].

Suppose there be a combination from two factors C and O to decide the prototype. There are I levels and J levels within factor C and O respectively. The fuzzy true value c_i ($i=1,2,\cdots I$) and o_j ($j=1,2,\cdots J$) of levels are to express the degree for the combination of two levels from distinct factor to support prototype. The probability $p(c_i , o_j)$ of the prototype from this combination is as follows [11].

$$p(c_i , o_j)=\frac{c_i o_j}{c_i o_j+(1-c_i)(1-o_j)} \tag{2}$$

Application research of FLMP includes attention, reading, letter recognition, speech perception, visual perception and feature evaluation [42]. It is proved that FLMP is equivalent to a version of Rasch Model, a one-parameter logistic item response model. Therefore, FLMP can be reparameterized as a simple 2-category logit model and facilitate interpretation of its measurement scales and allow access data analysis. In this study, FLMP is used to calculate the probability of prototype for subordinate relationship of two concepts.

2.3 Interpretive Structural Modeling

The utility of interpretive structural modeling (ISM) is to construct graphic relationship among elements within a complex system [6][25][26][29]. Discrete mathematics and graph is the foundation of ISM. For a subordinate matrix of a system, ISM will arrange elements in the form of hierarchical structure. Suppose there be K elements within a complex system and $A=(a_{ij})_{K\times K}$ is the subordinate matrix among K elements. $a_{ij}=1$ means element i is the precondition of element j; otherwise $a_{ij}=0$ means element i is not the precondition of element j. $\hat{A}$ is the transitive closure of A and R is the reachability matrix of A. According to A and R, the hierarchical graph could be established [18][39]. An example of subordinate matrix A is demonstrated as follows and there are 8 elements within a complex system. As shown in Fig. 2., it is an hierarchical graph of ISM in the form of structural relationship to represent the hierarchy and linkage.

$$A=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

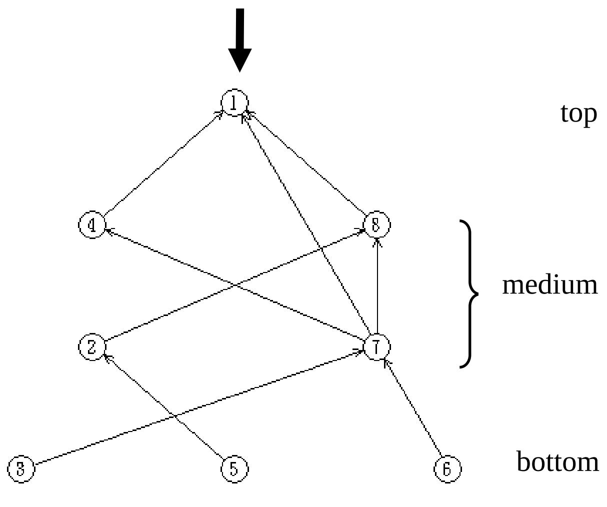

Fig. 2. The Hierarchial Graph of ISM for 8 Elements

There are four levels in the Fig. 2. From bottom to top, the first level is bottom level and these elements located in the first level are the precondition of the other elements. Therefore, elements 3, 5, 6 are the preconditions of elements 2, 7. The second and the third level are medium levels. They include elements 2, 7, 4, 8. Finally, the top level contains element 1.

3 Integrated Procedure and Algorithm

The integrated procedure is depicted in Figure 3. Firstly, S-P chart is to classify examinee based on their response patterns. Secondly, concept structure analysis (CSA) is to analyze individualized knowledge structures. CSA includes three algorithms, which are AMC (algorithm for mastery of concept), ASC (algorithm for subordination of concepts) and AFISM (algorithm for fuzzy ISM). By the integrated procedure, all examinee of the same learning style represent similar concept structures and remedial instruction could be feasible based on the information of cognitive diagnosis for the same learning style.

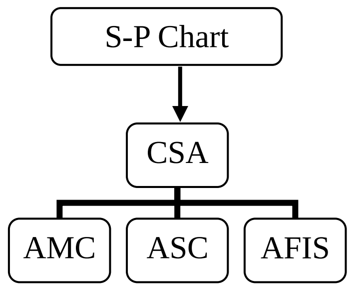

Fig. 3. Procedure of the Integrated Algorithm

The three algorithms are AMC, ASC and AFISM. They are combined so as to analyze personal concept structure. The basic definitions are as follows.

(1) There exist M ($m=1,2,\cdots,M$) items in a test which measures A ($a=1,2,\cdots,A$) concepts. There are N ($n=1,2,\cdots,N$) examinee who take the test.

(2) $\mathbf{X}=(x_{nm})_{N\times M}$ is the response matrix of all examinee on the test. It is $x_{nm}=1$ when student n gives correct answer on item m; otherwise $x_{nm}=0$ means student n gives wrong answer on item m.

(3) $\mathrm{Y}=(y_{ma})_{M\times A}$ means item-concept matrix. It is $y_{ma}=1$ if item m exactly measures concept

a ; otherwise $y_{ma}=0$ means item m does not measure concept a [37].

(4) There are 2^A ideal concept vectors according to A concepts and let the ideal concept matrix be $\mathbf{Z}=(z_{ia})_{I\times A}$ with $\mathbf{z}_i=(z_{i1},z_{i2},\cdots,z_{iA})$, $i=1,2,\cdots,I$, $I=2^A$. $z_{ia}=1$ means the ideal concept vector $\mathbf{z}_i$ contains concept a ; otherwise $z_{ia}=0$ means the ideal concept vector $\mathbf{z}_i$ does not contain concept a.

(5) Let $\mathbf{r}_i=(r_{im})_{1\times M}$ be the ideal response vector and it is the response pattern on all items based on corresponding ideal concept vector $\mathbf{z}_i$. It is $r_{im}=1$ if ideal concept vector $\mathbf{z}_i$ could provide correct answer on item m ; otherwise it is $r_{im}=0$. The ideal response matrix is $\mathbf{R}=(r_{im})_{I\times M}$.

(6) sc_{ni} is the standardized closeness between response vector $(x_{n1},x_{n2},\cdots,x_{nM})$ and ideal response vector $\mathbf{r}_i=(r_{i1},r_{i2},\cdots,r_{iM})$. Greater sc_{ni} means more similarity between $(x_{n1},x_{n2},\cdots,x_{nM})$ and $(r_{i1},r_{i2},\cdots,r_{iM})$. $\mathbf{SC}=(sc_{ni})_{N\times I}$ is the standardized closeness matrix.

$\mathbf{X}=(x_{nm})_{N\times M}$ and $\mathbf{Y}=(y_{ma})_{M\times A}$ are known and the following three algorithms, AMC, ASC and AFISM, are to analyze individualized concept structures.

3.1 AMC

(1) Based on $\mathbf{Y}=(y_{ma})_{M\times A}$ and $\mathbf{Z}=(z_{ia})_{I\times A}$, $\mathbf{R}=(r_{im})_{I\times M}$ is defined

$$r_{im}=\begin{cases}1 & , \quad (z_{ia})(y_{ma})=y_{ma}\ ,\ \forall\ a=1,2,\cdots,A \\ 0 & , \quad \text{else}\end{cases} \tag{3}$$

(2) c_{ni} is the closeness between the response pattern of student n and ideal response vector $\mathbf{r}_i$. It is

$$c_{ni}=\sum_{m=1}^{M}(x_{nm})\circ(r_{im})\Big/M \tag{4}$$

where $(x_{nm})\circ(r_{im})=\begin{cases}1 & , \quad x_{nm}=r_{im}\\ 0 & , \quad x_{nm}\neq r_{im}\end{cases}$

(3) The standardized closeness sc_{ni} is defined as follows.

a) It is crisp recognition if K ($K\geq 1$) different c_{ni} values satisfy $c_{ni}=1$, and

$$sc_{ni}=\begin{cases}1/K & , \quad \forall\ c_{ni}=1\\ 0 & , \quad else\end{cases} \tag{5}$$

b) It is fuzzy recognition if $c_{ni}\neq 1$ $\forall\, i=1,2,\cdots,I$, and

$$sc_{ni}=c_{ni}\Big/\sum_{i=1}^{I}c_{ni} \tag{6}$$

In the above definition, the standardized closeness satisfies $0\leq sc_{ni}\leq 1$ and $\sum_{i=1}^{I}sc_{ni}=1$.

3.2 ASC

(1) Let $\mathbf{D}=(d_{na})_{N\times A}=(\mathbf{SC})(\mathbf{Z})$ be the matrix of mastery on concepts. For student n on concept a, it is

$$d_{na}=\sum_{i=1}^{I}(sc_{ni})(z_{ia})\ \text{ and }\ 0\leq d_{na}\leq 1 \tag{7}$$

(2) In terms of FLMP, the probability of concept a to be the precondition of concept a' for student n is

$$p_{aa'}=\begin{cases}1 & , \quad d_{na}=d_{na'}=1\\ 0 & , \quad d_{na}=d_{na'}=0\\ \dfrac{(d_{na})(1-d_{na'})}{(d_{na})(1-d_{na'})+(1-d_{na})(d_{na'})} & , \quad else\end{cases} \tag{8}$$

3.3 AFISM

(1) α value ($0\leq\alpha\leq 1$) is determined for student n. Fuzzy relation matrix from ASC is $F_n(p_{aa'})_{A\times A}$ and the binary relation matrix F_n^{α} is

$$F_n^{\alpha}=(p_{aa'}^{\alpha})_{A\times A}\ \text{ and }\ p_{aa'}^{\alpha}=\begin{cases}1 & , \quad p_{aa'}\geq\alpha\\ 0 & , \quad p_{aa'}<\alpha\end{cases} \tag{9}$$

(2)The adjacent value between concept a and a' is

$$p_{aa'}^{\alpha}=\begin{cases}1 & , \quad p_{aa'}\geq\alpha\\ 0 & , \quad p_{aa'}<\alpha\end{cases}\quad ,\quad 0\leq\alpha\leq 1 \tag{10}$$

(3) ISM is used to construct the individualized and hierarchical concept structures based on matrix $F_n^{\alpha}=(p_{aa'}^{\alpha})_{A\times A}$.

4 Data Resource

A linear algebra test for university students is designed by author. This instrument consists of 19 dichotomous items which measure 6 concepts. The sample includes 933 university students from Taiwan. Concept attributes are depicted in Table 1.

Table 1. Concept Attributes of Test

Concepts	Concept Attributes
1	Operation of matrix
2	System of linear equations
3	Determinants
4	Vector space and the property of R^n
5	Eigen value and eigen vector
6	Geometry of linear algebra

Item- concept matrix $\mathbf{Y} = (y_{ma})_{M\times A}$ and correct ratio of each item are depicted in Table 2. $\alpha = .65$ is selected in the AFISM step.

Table 2. Item- Concept Matrix of Test

Item	Concept						Correct Ratio
	1	2	3	4	5	6	
1	1	0	0	0	0	0	.8328
2	1	0	0	0	0	0	.8071
3	1	0	0	0	0	0	.4544
4	1	0	0	0	0	0	.4009
5	0	1	0	0	0	0	.6806
6	0	1	0	0	0	0	.3323
7	0	1	0	0	0	0	.6356
8	0	1	0	0	0	0	.0139
9	0	0	1	0	0	0	.1061
10	0	0	1	0	0	0	.5520
11	0	0	1	0	0	0	.4566
12	0	0	0	1	0	0	.3901
13	0	0	0	1	0	0	.4019
14	0	0	0	1	0	0	.2444
15	0	0	0	0	1	0	.0171
16	0	0	0	0	1	0	.2444
17	0	0	0	0	1	0	.1490
18	0	0	0	0	0	1	.1179
19	0	0	0	0	0	1	.1854

5 Results and Discussion

In accordance with S-P chart, all examinee could be classified into six learning styles. It is impossible to display concept structure of each examinee. Consequently, two students are randomly selected from each learning style to represent the features of concept structures. The following two session will discuss S-P chart analysis and concept structures based on S-P chart.

5.1 S-P Chart Analysis

Table 3 depicts the number of students within each learning style. As shown in Table 3, there are the most number of students for learning style C. However, there are quite few students for learning style A and learning style A` .

Table 3. Number of Students within Each Cluster

Learning Style	Number of Students
A	4
B	177
C	552
A`	2
B`	22
C`	176
Total	933

5.2 Concept Structures based on S-P Chart

There are six concepts in this study. As shown in Table 1, there exist preconditions among these concepts in the viewpoints of experts. Namely, from concept 1 to concept 6 in Table 1, the concepts of smaller number are the precondition of concepts denoted in greater number. For example, concept 1 is the precondition of concept 2, 3, 4, 5, 6. Also, concept 2 is the precondition of concept 3, 4, 5, 6.

As shown from Figure 4 to Figure 15, two students are randomly selected from each learning type respectively. Explanation of concept structure must stand on its hierarchical level, linkage and mastery. For example, in Fig. 4, there are three levels. From bottom to up, the first level is concept 1. The second level is concept 2 and 3. The third level is concept 4, 5 and 6. Besides, mastery of concept 1 is 0.61 and it is the preconditions of concept 2, 4, 5 and 6. One is obvious that hierarchies and linkages in concept structures of these six learning style are quite different.

As to Fig. 4 and Fig. 5, two students A-01 and A-02 of learning style A display concept structures similar to expert. Characteristics of learning style A is effective learning. Firstly, all the prerequisite linkages obey the conditions that the concepts of smaller number are the precondition of concepts denoted in greater number. Therefore, it is considered that there doesn't exist misconception for student A-01 and A-02. Moreover, for most concepts of these two students, mastery of concepts is quite high.

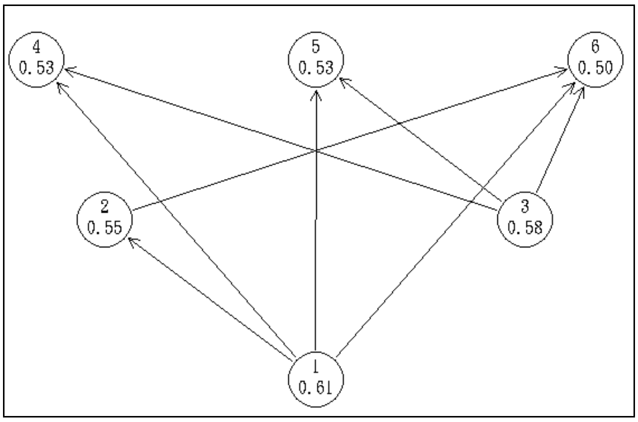

Fig. 4. Concept Structure of Student A-01 (Learning Style A)

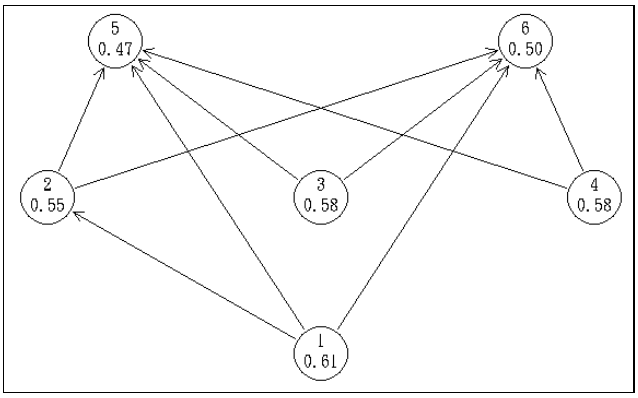

Fig. 5. Concept Structure of Student A-02 (Learning Style A)

As to Fig. 6 and Fig. 7, the students AP-01 and AP-02 are learning style A`. Characteristics of the learning style A` is much carelessness in learning process. In Fig. 6. and Fig. 7., their concept structures are almost similar to expert. However, it shows aberrant linkage from concept 6 to concept 5. Therefore, maybe these exists much negligence in concept 5 and concept 6. It is necessary to detect their learning process or design remedial instruction on these two concepts of learning style A`.

Another possible explanation is the understanding of concept 5 and concept 6. Concept 5 is eigen value and eigen vector. Concept 6 is geometry of linear algebra. One common learning path is that eigen value and eigen vector could be the foundation of learning geometry of linear algebra. On the other hand, another feasible learning path is that learning geometry of linear algebra can improve realization of eigen value and eigen vector. In any case, number of learning A` is just 2 and this kind of students are quite few.

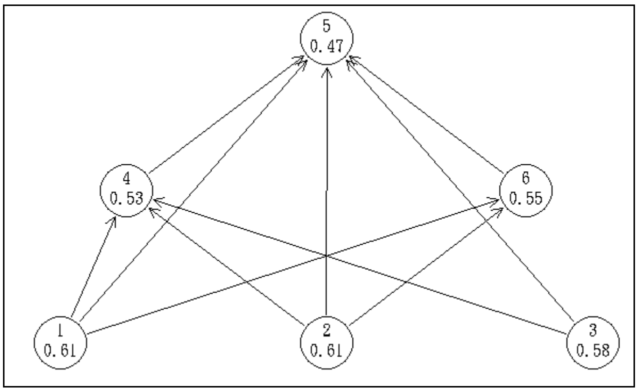

Fig. 6. Concept Structure of Student AP-01(Learning Style A`)

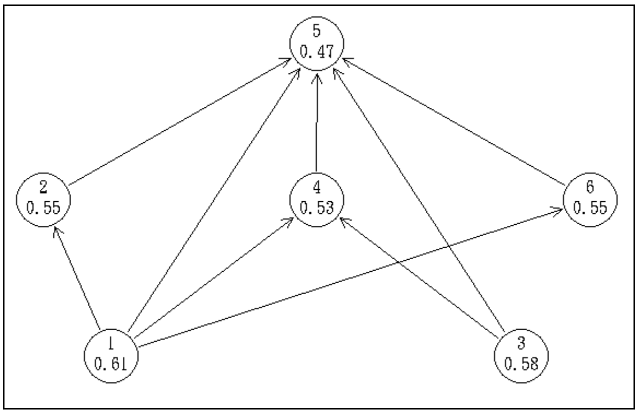

Fig. 7. Concept Structure of Student AP-02 (Learning Style A`)

As shown in Fig. 8 and Fig. 9, the students B-01 and B-02 are learning style B. Characteristics of learning style B is general fine but they need more diligence in learning process. In Fig. 8. and Fig. 9., most linkage in concept structures look like expert. Only the linkage from concept 4 to concept 3 shows erroneous relationship. For that reason, it is necessary to detect their learning process on concept 3 and concept 4. Refined design on remedial instruction for these two concepts should be feasible. In any case, since number of learning B is quite large, further investigation on concept 3 and concept 4 is necessary.

One important point is that number of hierarchical levels in Fig. 8. and Fig. 9 vary. Fig. 8 owns three hierarchical levels but Fig. 9 has four hierarchical levels. Concepts located in levels are also little different. For example, the bottom level in Fig. 8 contains concept 1, 2, 3. However, the bottom level in Fig. 9 contains only concept 1. The above discussion means students will also have different concept structures although they are the same learning styles. In sum, information of personally cognitive diagnosis from concept structure should be useful.

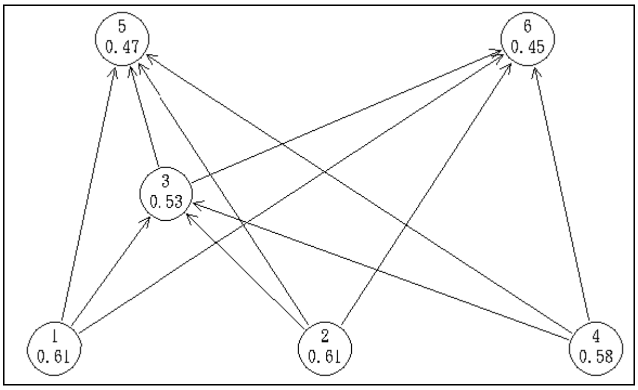

Fig. 8. Concept Structure of Student B-01 (Learning Style B)

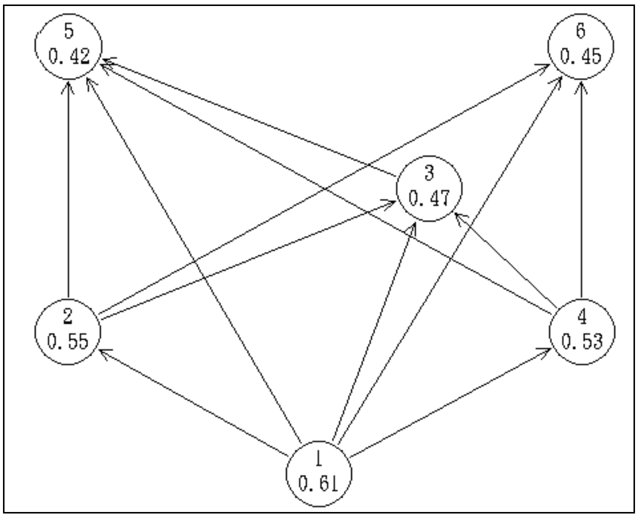

Fig. 9. Concept Structure of Student B-02 (Learning Style B)

As depicted Fig. 10 and Fig. 11, the students BP-01 and BP-02 are learning style B`. Meaning of learning style B` is a little carelessness and they need diligence in learning process. Concept structures of both students reveal some erroneous linkages among concepts. In Fig. 10, the erroneous linkage is from concept 4 to concept 3 and from concept 5 to concept 3. In Fig. 11, the aberrant linkage is from concept 2 to concept 1 and from concept 4 to concept 3. Their common aberrant linkage is from concept 4 to concept 3, which is the same as learning style B.

Therefore, in addition to the aberrant linkage happened to learning style B，concept structure of learning style B` own more another erroneous linkage.

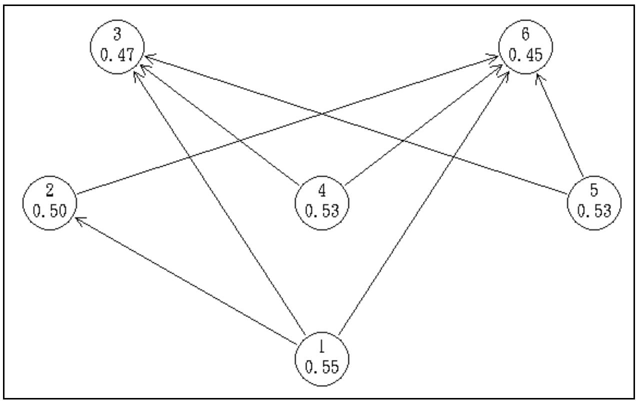

Fig. 10. Concept Structure of Student BP-01 (Learning Style B`)

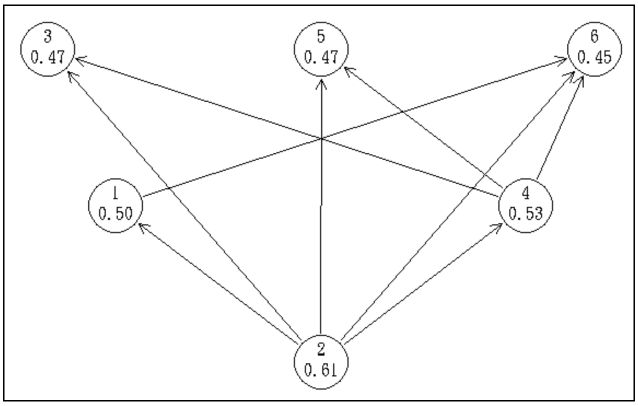

Fig. 11. Concept Structure of Student BP-02 (Learning Style B`)

Fig. 12 and Fig. 13 display concept structures of the students C-01 and C-02 who are learning style C. Characteristics of learning style C is insufficient learning when they construct and organize concepts. Both students represent some erroneous linkages. In Fig. 12, the erroneous linkage is from concept 6 to concept 2. In Fig. 13, the erroneous linkage is from concept 6 to concept 2 and from concept 3 to concept 2. Their common erroneous linkage is from concept 6 to concept 2. Remedial instruction for learning style C should focus on the improvement of these two concepts.

In addition to a little difference on erroneous concept linkage, concepts within each level also vary a little. For example, concept 6 is located in the medium level for student C-01. Nevertheless, concept 6 and concept 3 are located in the medium level for student C-02. All these personal information on cognitive diagnosis improve feasibility of adaptively remedial instruction.

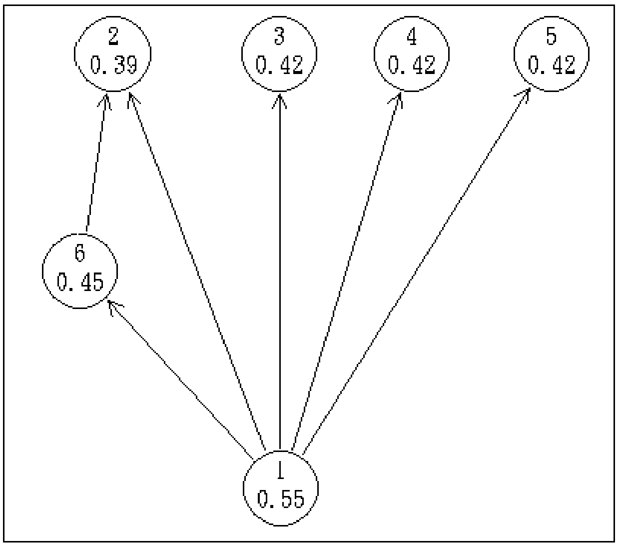

Fig. 12. Concept Structure of Student C-01 (Learning Style C)

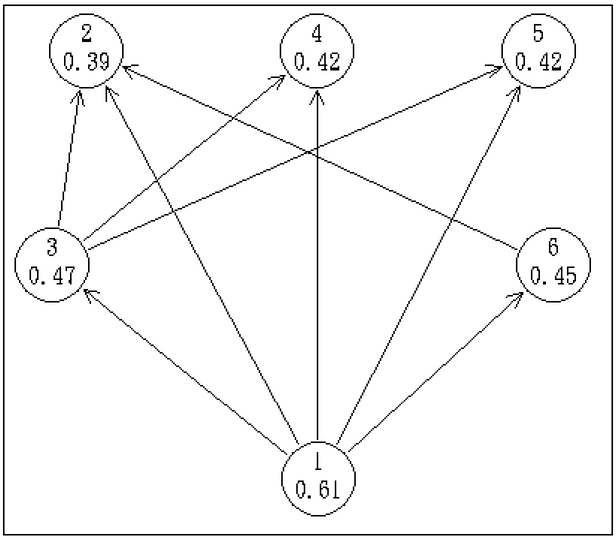

Fig. 13. Concept Structure of Student C-02 (Learning Style C)

Fig. 14 and Fig. 15 show the concept structures of the students CP-01 and CP-02 who are learning style C`. Learning without stability is the major characteristics of learning style C`. That is, when students of learning style C` construct concept structures, they are easy to organize knowledge without careful logic or meta-cognition.

Both students represent quite a few erroneous linkages and this phenomenon corresponds with the meaning of learning style C`. In Fig. 14, there exist four erroneous linkages. They are from concept 3 to concept 1, from concept 4 to concept 2, from concept 5 to concept 2 and from concept 6 to concept 2. In Fig. 15, there are also four erroneous linkages. They are from concept 3 to concept 2, from concept 5 to concept 2, from concept 6 to concept 2 and from concept 5 to concept 4.

Both the two students have common erroneous linkages which are from concept 5 to concept 2 and from concept 6 to concept 2. Personally remedial instruction for learning style C` should focus on the promotion of these concepts of erroneous linkages. On the other hand, the hierarchy and concepts within each level also vary. For instance, concept 3 is located in the bottom level for student CP-01, but it is located in the medium level for student CP-02. All these features of personal concept structure could improve practice of adaptively remedial instruction.

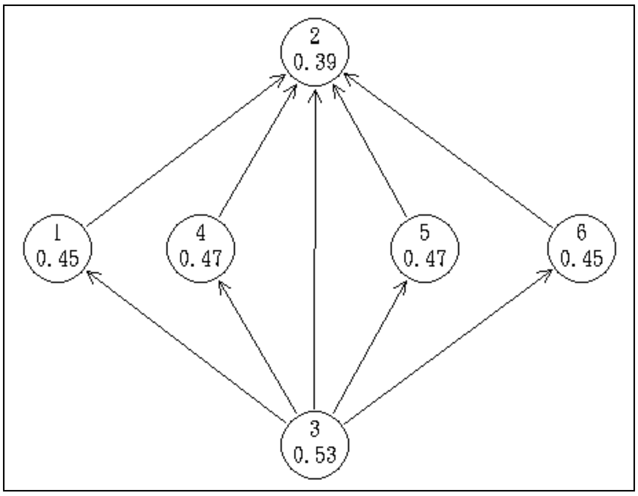

Fig. 14. Concept Structure of Student CP-01 (Learning Style C`)

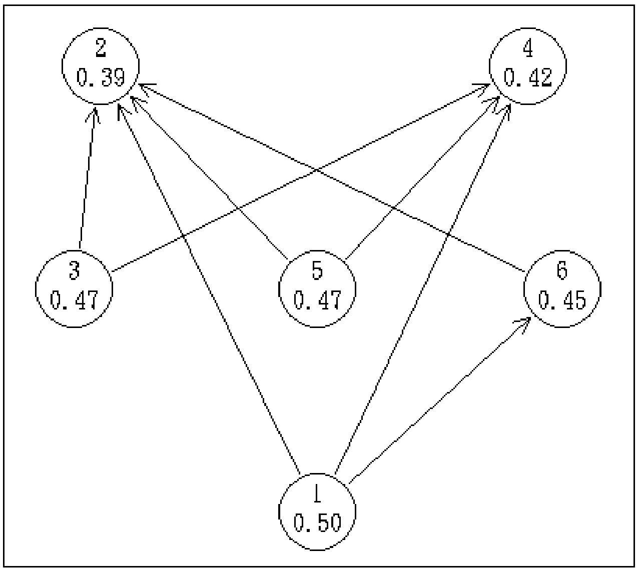

Fig. 15. Concept Structure of Student CP-02 (Learning Style C`)

6 Conclusions

This study investigates an integrated methodology to display concept structures based on response pattern detection of S-P Chart. One benefit of this method is to classify students into proper learning style. Each learning style will display features of cognitive information so that adaptively remedial instruction in group will be practicable [41]. Another benefit of this method is the graphic representation of concept structure will improve realization of misconceptions or poorly structural linkages among concepts.

An empirical test data of linear algebra for university students are investigated and discussed. It shows that cognitively diagnostic information could help design remedial instruction [31]. Future study could extend this method to other fields and develop this method into internet system [3][17][38].

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