Use Fuzzy Supervised Algorithm for Clustering and Construct Knowledge Structure to Cognitive Diagnostic Assessment

Jui-Chiao Tseng
Min-Hwei Junior College of Health Care Management, TaiNan 736, Taiwan.

Abstract- The purpose of this study is to provide an integrated method of fuzzy theory basis for individualized concept structure analysis. This method integrates Fuzzy Logic Model of Perception (FLMP) and Interpretive Structural Modeling (ISM). The combined algorithm could analyze individualized concepts structure based on the comparisons with concept structure of expert. The authors provide the empirical data for concepts of Professional and Technical Examination for Registered Nurse from Junior College students of learning deficiencies. The results show that students with different response patterns and total score own varied concept structures. Based on the findings and results, some suggestions and recommendations for future research are provided. The combined algorithm could analyze individualized concepts structure based on the comparisons with concept structure of expert. Fuzzy clustering algorithms are based on Euclidean distance function, which can only be used to detect spherical structural clusters. A Fuzzy C-Means algorithm based on Mahalanobis distance (FCM-M) was proposed to improve those limitations of GG and GK algorithms, but it is not stable enough when some of its covariance matrices are not equal. A new improved Fuzzy C-Means algorithm based on a Normalized Mahalanobis distance (FCM-NM) is proposed. Use the best performance of clustering Algorithm FCM-NM in data analysis and interpretation. Each cluster of data can easily describe features of knowledge structures. Manage the knowledge structures of Mathematics Concepts to construct the model of features in the pattern recognition completely. This procedure will also useful for cognition diagnosis. To sum up, this integrated algorithm could improve the assessment methodology of cognition diagnosis and manage the knowledge structures of Professional and Technical Examination for Registered Nurse's Concepts easily.

Keywords –Fuzzy Supervised Algorithm, Interpretive Structural Modeling, Normalized Mahalanobis distance.

I. INTRODUCTION

The concept structure analysis is an important issue for cognition science and educational psychology [2,3]. Concepts are stored in the form of networks with relationships and hierarchies [7]. Methodologies of concept structure analysis aim to understand the information processing and knowledge storage. There are some methodologies for concept structure analysis but little is known about methodologies of individualized concept structure [1] [3] [10] [11]. Therefore, the development for methodology of individualized concept structure is an important issue and it is essential for cognition diagnosis and pedagogy [12]. In this study, the integrated method of individualized concept structure based on fuzzy logic model of perception (FLMP) and interpretive structural modeling (ISM) will be developed [4] [5] [14]. An example of empirical test data of linear algebra concept for students of learning deficiencies will also be analyzed and discussed.

The well-known ones, such as Bezdek's Fuzzy C-Means (FCM)[15], FCM algorithm was based on Euclidean distance function, which can only be used to detect spherical structural clusters. To overcome the drawback due to Euclidean distance, we could try to extend the distance measure to Mahalanobis distance (MD). However, Krishnapuram and Kim (1999) [16] pointed out that the Mahalanobis distance can not be used directly in clustering algorithm. Gustafson-Kessel (GK) clustering algorithm [17] and Gath-Geva (GG) clustering algorithm [18] were developed to detect non-spherical structural clusters. In GK-algorithm, a modified Mahalanobis distance with preserved volume was used. However, the added fuzzy covariance matrices in their distance measure were not directly derived from the objective function. In GG algorithm, the Gaussian distance can only be used for the data with multivariate normal distribution.We know Gustafson-Kessel clustering algorithm and Gath-Geva clustering algorithm, were developed to detect non-spherical structural clusters, but both of them based on semi-supervised Mahalanobis distance, these two algorithms fail to consider the relationships between cluster centers in the objective function, needing additional prior information. Added a regulating factor of covariance matrix, , to each class in objective function, the fuzzy covariance matrices in the Mahalanobis distance can be directly derived by minimizing the objective function, but the clustering results of this algorithm is still not stable enough. For improving the stability of the clustering results, we replace all of the covariance matrices with the same common covariance matrix in the objective function in the FCM-M algorithm, and then, an improve fuzzy clustering method, called the Fuzzy C-Means algorithm based on Normalized Mahalanobis distance (FCM-NM), is proposed. Zadeh developed fuzzy theory and it flourishes methodologies in many fields [19] [20]. One of these fields is cognition diagnosis and it help represent knowledge structure [21] [22] [23]. It is a common viewpoint that human knowledge is stored in the form of structural relationship among concepts and their subordinate relationship is fuzzy, not crisp. There are some methodologies for concept structure analysis but little is known about methodologies of individualized concept structure [24-27] . Therefore, the development for methodology of individualized concept structure is an important issue and it is essential for cognition diagnosis and pedagogy [28]. In this study, the integrated method of individualized concept structure based on fuzzy logic model of perception (FLMP) and interpretive structural modeling (ISM) will be developed [29-32] . An example of empirical test data of linear algebra concept for students of learning deficiencies will also be analyzed and discussed. For the feasibility of remedial instruction based on the cognition diagnosis, clustering method is needed so that students within the same cluster own similar knowledge structures and students among different clusters have the most variance on knowledge structures [33-42].

II. Proposed Algorithm

2.1 FCM-NM Algorithm –

In this paper, not only z-score normalizing for each feature in the objective function in the FCM-CM algorithm, but also replacing the threshold D where

$$D = \sum_{i=1}^{c}\sum_{j=1}^{n}\left[\mu_{ij}^{(0)}\right]^{m}\left[\left(\underline{x}_j - \underline{a}_i^{(0)}\right)'\left(\underline{x}_j - \underline{a}_i^{(0)}\right)\right] > 0 \qquad (1)$$

With the determinant value of the crisp correlation matrix, and then, the new fuzzy clustering method, called the Fuzzy C-Means algorithm based on normalized Mahalanobis distance (FCM-NM) is proposed. We can obtain the objective function of FCM-NM as following:

$$J_{FCM-NM}^{m}\left(U,A,R,Z\right) = \sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{m}d^{2}\left(z_j,\underline{a}_i\right) \qquad (2)$$

Ωηερε $X = \left[\underline{x}_1,\underline{x}_2,\ldots,\underline{x}_n\right],\ \underline{x}_j \in R^{p},\ j = 1,2,\ldots,n$ (3)

$$\underline{z}_j = \left(z_{1j},z_{2j},\ldots,z_{pj}\right)',\ z_{tj} = \frac{x_{tj}-\overline{x}_t}{s_t},\ j=1,2,\ldots,n,\ t=1,2,\ldots,p \qquad (4)$$

$$\overline{x}_t = \frac{1}{n}\sum_{j=1}^{n}x_{tj},\ s_t = \frac{1}{n}\sum_{j=1}^{n}\left(x_{tj}-\overline{x}_t\right)^2,\quad t=1,2,\ldots,p \qquad (5)$$

Conditions for FCM-NM are

$$m\in[1,\infty);\ U=\left[\mu_{ij}\right]_{c\times n};\ \mu_{ij}\in\left[0,1\right],\ i=1,2,\ldots,c,\ j=1,2,\ldots,n$$
$$\sum_{i=1}^{c}\mu_{ij}=1,\ j=1,2,\ldots,n,\ 0<\sum_{j=1}^{n}\mu_{ij}<n,\ i=1,2,\ldots,c \qquad (6)$$

$$d^2\left(\underline{z}_j,\underline{a}_i\right)=\begin{cases}\left(\underline{z}_j-\underline{a}_i\right)'R^{-1}\left(\underline{z}_j-\underline{a}_i\right)-\ln\left|\Sigma^{-1}\right| & if\left(\underline{z}_j-\underline{a}_i\right)'R^{-1}\left(\underline{z}_j-\underline{a}_i\right)-\ln\left|R^{-1}\right|\geq 0\\ 0 & if\left(\underline{z}_j-\underline{a}_i\right)'R^{-1}\left(\underline{z}_j-\underline{a}_i\right)-\ln\left|R^{-1}\right|<0\end{cases} \qquad (7)$$

the threshold of FCM-NM is a dynamic value rather than a constant, it is different from which of FCM-SM in our previous work [33], and the convergent process is different from all of before mentioned algorithms.

2.2. Method of Fuzzy Approach on Concept Structure Analysis –

The integrated algorithms consist of three steps of algorithms, AMC, ASC and AFISM. Suppose there be M ($m=1,2,\cdots,M$) items which measures A ($a=1,2,\cdots,A$) concepts. There are N task-takers ($n=1,2,\cdots,N$) who take this test. The response data matrix is denoted by $\mathbf{X}=(x_{nm})_{N\times M}$. $x_{nm}=1$ means task-taker n gives correct answer on item m and $x_{nm}=0$ means it doesn't. The item attribute matrix is denoted by $\mathbf{Y}=(y_{ma})_{M\times A}$. $y_{ma}=1$ means item m exactly measures concept a while $y_{ma}=0$ means it doesn't. These A concepts construct 2^A ideal concept vectors, which are denoted by $\mathbf{z}_i=(z_{ia})_{1\times A}=(z_{i1},\ z_{i2},\ \cdots,\ z_{iA})$, $i=1,2,\cdots,I$ and $I=2^A$. Each ideal concept vector expresses one certain kind of concept structure. $z_{ia}=1$ means the ideal concept vector $\mathbf{z}_i$ contains concept a while $z_{ia}=0$ means it doesn't. These ideal concept vectors construct a matrix

$\mathbf{Z} = (z_{ia})_{I\times A}$ .Only the two matrices $\mathbf{X} = (x_{nm})_{N\times M}$ and $\mathbf{Y} = (y_{ma})_{M\times A}$ are known already. The following subsections of algorithms, which are AMC, ASC and AFISM, describe the steps to analyze individualized concept structures.

2.2.1Algorithm for Mater of Concepts (AMC)

(1)The ideal response matrix $R = (r_{im})_{I\times M}$ is defined as follows.

$$r_{im} = \begin{cases} 1 & , \quad (z_{ia})(y_{ma}) = y_{ma} \ , \forall\ a = 1,2,\cdots,A \\ 0 & , \quad \text{else} \end{cases} \tag{8}$$

(2) The closeness between response pattern of task-taker n and ideal response vector $\mathbf{r}_i$ is c_{ni} and

$$c_{ni} = \sum_{m=1}^{M} (x_{nm}) \circ (r_{im}) \Big/ M \quad \text{where} \quad (x_{nm}) \circ (r_{im}) = \begin{cases} 1 & , \quad x_{nm} = r_{im} \\ 0 & , \quad x_{nm} \neq r_{im} \end{cases} \tag{9}$$

(3) The standardized closeness sc_{ni} of task-taker n is based on two conditions.

(i) If K ($K \geq 1$) different c_{ni} values satisfy $c_{ni} = 1$, the crisp recognition is

$$sc_{ni} = \begin{cases} 1/K & , \quad \forall\ c_{ni} = 1 \\ 0 & , \quad else \end{cases} \tag{10}$$

(ii) If $c_{ni} \neq 1 \ \ \forall \ \ i = 1,2,\cdots,I$, the fuzzy recognition is

$$sc_{ni} = c_{ni} \Big/ \sum_{i=1}^{I} c_{ni} \tag{11}$$

2.2.2 Algorithm for Subordination of Concepts (ASC)

(1) d_{na} denotes the magnitude of master for task-taker n on concept a and

$$d_{na} = \sum_{i=1}^{I} (sc_{ni})(z_{ia}) \quad \text{and} \quad 0 \leq d_{na} \leq 1 \tag{12}$$

(2) Based on FLMP, the probability of concept a being precondition of concept a' for task-taker n is

$$P_{aa'} = \begin{cases} 1 & , \quad d_{na} = d_{na'} = 1 \\ 0 & , \quad d_{na} = d_{na'} = 0 \\ \dfrac{(d_{na})(1-d_{na'})}{(d_{na})(1-d_{na'}) + (1-d_{na})(d_{na'})} & , \quad else \end{cases} \tag{13}$$

2.2.3 Algorithm for Fuzzy ISM (AFISM)

The fuzzy relation matrix of task-taker n got from the ASC algorithm is $F_n(p_{aa'})_{A\times A}$. α -cut ($0 \leq \alpha \leq 1$) is applied so that the corresponding binary relation matrix F_n^{α} is acquired [7] . It is

$$F_n^{\alpha} = (p_{aa'}^{\alpha})_{A\times A} \quad \text{and} \quad p_{aa'}^{\alpha} = \begin{cases} 1 & , \quad p_{aa'} \geq \alpha \\ 0 & , \quad p_{aa'} < \alpha \end{cases} \tag{14}$$

For binary relation matrix $F_n^{\alpha} = (p_{aa'}^{\alpha})_{A\times A}$ of task-taker n , the ISM is applied so that the hierarchical graph represent the individualized concept structures.

III. Experiment and Result

The balance Iris Data [30] with sample size 150 which features of the Iris data contains Length of Sepal, Width of Sepal, Length of Petal, and Width of Petal. The samples were assigned the original 3 clusters based on the clustering analysis. The characteristics of 3 clusters for Iris data were shown in Table 1

Table 1. The characteristics of 3 clusters for Iris Data

clusters	species
1	Setosa
2	Versicolor
3	Virginica

The performances of clustering Algorithm FCM, and FCM-NM all with the fuzzifier m=2, are compared in these experiments.

Table 2 The Accuracies of four Algorithms

Algorithms	Accuracies
FCM	0.8400
FCM-NM	0.8595

The results of FCM are obtained by applying the Matlab toolbox developed by [31].The software and linear algebra test are implemented by authors. FCM-NM is simultaneously better than which of FCM algorithm in the datasets.

3.1 The Experiments with Professional and Technical Examination for Registered Nurse Data.

The test includes 19 items with 730 task-takers of Junior College students. The data set comes from the National Taichung University of Education used in the empirical study with learning Abstract Algebra. There are 7 concept attributes within each item and they are depicted in Table3.

Table 3. The Details of The Used Datasets

Classes	Characters about Concepts
1	Basic Nursing
2	Basic Medical
3	Surgical Nursing
4	Production Pediatric Nursing 1
5	Production Pediatric Nursing 2
6	Community spirit Nursing 1
7	Community spirit Nursing 2

The Mean clustering Accuracies of 100 different initial value sets of FCM and FCM-NM for the Dataset was shown in TABLE 4. From this table, we can find that the Accuracies of FCM is worse than the FCM-NM in the dataset.

Table 4 The Accuracies of four Algorithms

Algorithms	Accuracies
FCM	0.538
FCM-NM	0.654

The performances of our proposed FCM-NM algorithms, FCM-NM is simultaneously better than which of FCM algorithm in the datasets.

3.2 Knowledge Structures

There are 7 concept attribute within each item and depicted in Table 5. Although the combined algorithm of FLMP and ISM could provide the concept structure of each task-taker respectively, it is unfeasible to display the concept structure of all task-takers in this paper.

Table 5. Concept Attributes of Test

Classes	Characters about Concepts
1	Basic Nursing
2	Basic Medical

3	Surgical Nursing
4	Production Pediatric Nursing 1
5	Production Pediatric Nursing 2
6	Community spirit Nursing 1
7	Community spirit Nursing 2

Each item was selected in the AFISM step. The abstract algebra test is designed by the author for abstract algebra course of university students in this study. There are 730fifth-year Junior College students participating in the test. The algebra test includes 19 items and each item contains one concept. The conceptifth attribute within each item are depicted in Table 6. All these items are dichotomous.

Table 6. Item- Concept Matrix of Test

Item	1	2	3	4	5	6	7
1	1	0	0	0	0	0	0
2	1	0	0	0	0	0	0
3	1	0	0	0	0	0	0
4	1	0	0	0	0	0	0
5	0	1	0	0	0	0	0
6	0	0	1	0	0	0	0
7	0	0	1	0	0	0	0
8	0	0	1	0	0	0	0
9	0	0	0	1	0	0	0
10	0	0	0	1	0	0	0
11	0	0	0	1	0	0	0
12	0	0	0	1	0	0	0
13	0	0	0	0	1	0	0
14	0	0	0	0	1	0	0
15	0	0	0	0	0	1	0
16	0	0	0	0	0	1	0
17	0	0	0	0	0	0	1
18	0	0	0	0	0	0	1
19	0	0	0	0	0	0	1

As show in Fig. 1, the numbers on the right side are the correct ratios of the items of each level. The item 10 and 14 are on the bottom level of the knowledge structure. It means that, for some students, The item is more easier than others. Item 10 is belongs to concept attribute of Production Pediatric Nursing 1. Item 14 is belongs to concept attribute of Production Pediatric Nursing 2.

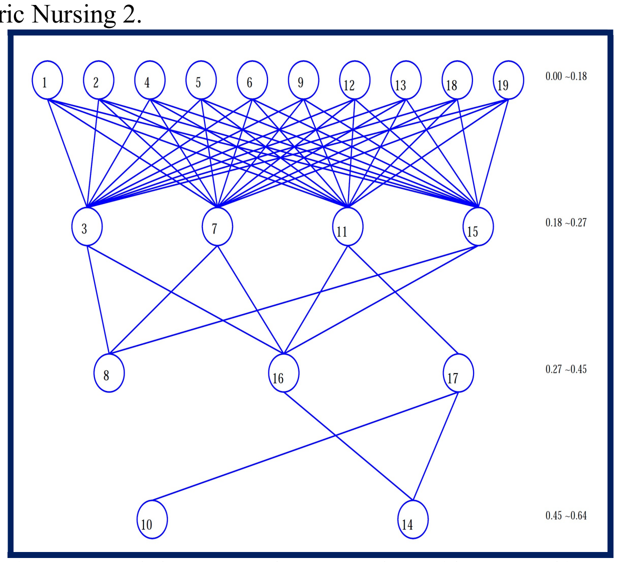

Figure 1. Knowledge structure for some students with Measured items.

As show in Fig. 2, The item 4 is on the bottom level of the knowledge structure. It means that, for some students, the item is more easier than others. Item 4 is belongs to concept attribute of Groups and Subgroups.

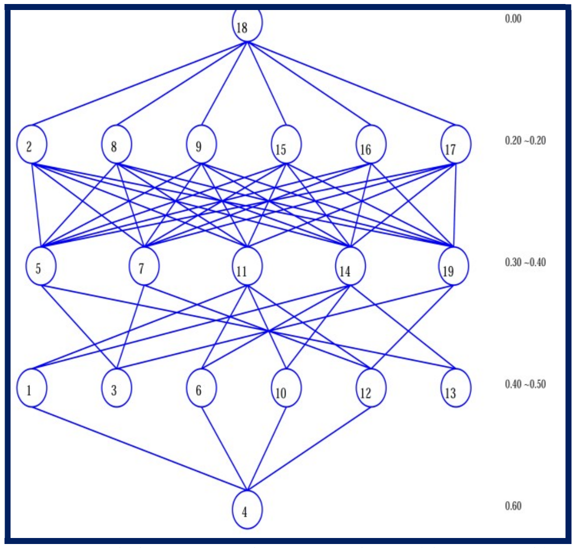

Figure 2. Knowledge structure for some students with Measured items.

As shown from Figure 3, one student is randomly selected from the sample. As to student 9, mastery of concept 1 which is 0.55 The concept of Groups and Subgroups is the basis for concept 2 ,3, 4, 5, 6, 7.

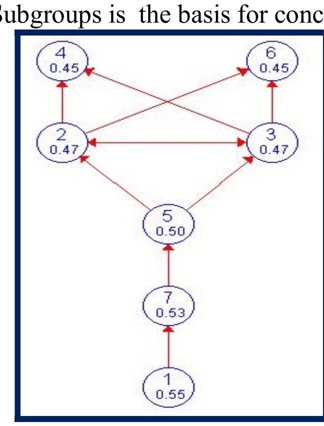

Fig.3 . Knowledge Structure of Student 119

As shown from Figure 4, As to student 11, mastery of concept 1 and 6 which is 0.50 The concept of Groups and Subgroups and Fields and Extension Fields are the basis for concept 2 ,3, 4, 5, 7.

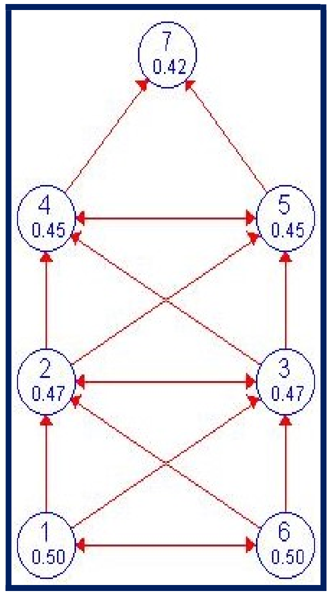

Fig.4 . Knowledge Structure of Student 389

IV.CONCLUSION

FCM is based on Euclidean distance function, which can only be used to detect spherical structural clusters. GK algorithm and GG algorithm were developed to detect non-spherical structural clusters. However, GK algorithm needs added constraint of fuzzy covariance matrix, GG algorithm can only be used for the data with multivariate Gaussian distribution. A Fuzzy C-Means algorithm based on Mahalanobis distance (FCM-M) was proposed to improve those limitations of above two algorithms, but it is not stable enough when some of its covariance matrices are not equal. An improved Fuzzy C-Means algorithm based on Normalized Mahalanobis distance (FCM-NM) is proposed. The experimental results of two real data sets consistently show that the performance of our proposed FCM-NM algorithm is better than those of the FCM algorithms. In this paper, each cluster of data can easily describe features of knowledge structures. We can manage the knowledge structures of Abstract Algebra Concepts to construct the model of features in the pattern recognition completely. An integrated method of FLMP and ISM for analyzing individualized concept structure is provided. With this integrated algorithm, the graphs of concept structures will display the characteristics of knowledge structure. This result corresponds with foundation of cognition diagnosis in psychometrics [43]. This study investigates an integrated methodology to display knowledge structures based on fuzzy clustering with Mahalanobis Distances. In addition, empirical test data of abstract algebra for university students are discussed. It shows that knowledge structures will be feasible for remedial instruction [44]. This procedure will also useful for cognition diagnosis. To sum up, this integrated algorithm could improve the assessment methodology of cognition diagnosis and manage the knowledge structures of Abstract Algebra Concepts easily.An integrated method of FLMP and ISM for analyzing individualized concept structure is provided in this study. With this integrated algorithm, the graphs of concept structures will display the characteristics of knowledge structure. It shows that students with different total score own varied concept structure. Moreover, students have the same total score with different response pattern display distinct concept structure. This results corresponds with foundation of cognition diagnosis in psychometrics [45]. To sum up, this integrated algorithm could improve the assessment methodology of cognition diagnosis.

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