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Learner Model for Automatic Detection of Learning Style Using FCM in Adaptive E-Learning System

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Abstract : *The aim of this paper is to introduce an automatic student modeling approach for identifying learning style in learning management systems according to Felder Silverman Learning Style Model (FSLSM).This paper proposes the use of fuzzy cognitive maps FCMs as a tool for identifying learner's learning style to individualizing each learner's according to their needs. FCMs are a soft computing tool which is a combination of fuzzy logic and neural network. Result shows that according to this model student learning style can be detected which give high precision value.*
Keywords: *Adaptive e-learning, Fuzzy cognitive map, Individualize, Learning Process, Personalized Learning*

I. Introduction

In order to optimize and facilitate learners' interaction with a web-based educational system, one must first decide on the human factors that have been taken into consideration and precisely identify the real needs of the students. The focus of this paper is on learning style as one individual is different from the others in many ways which play an important role in learning, according to educational psychologists. Learning style refers to the individual's traits in which a learner approaches a learning task [2] and learning process. Learning styles which refer to learner's preferred ways to learn can play an important role in adaptive e- learning systems [3]. With the knowledge of different styles, the system can provide personalized adaptive recommendations to the learners to optimize learning process and improve effectiveness. Moreover, e-learning system which allows computerized and statistical algorithms opens the opportunity to overcome drawbacks of the traditional detection method that uses mainly questionnaire[3].There are many learning style models described in literature[4][5][6], which show that every individual prefers to learn in different learning style. According to above theories, adaptive e-learning system can also strengthen above concept so that incorporating student learning style definitely enhances the learning process of learner [1]. In this paper, authors describe how learning process influenced by learning styles because preferred mode of input varies from individual to individual. In this paper, a new method is proposed that automatically detect' learning styles with respect to the Felder- Silverman Learning Style Model based on their learning behaviors in e-learning course[1]. A fuzzy cognitive Map (FCM), a soft computing technique, is used for learner model in this research work. Rest of the paper is divided into four sections. Second section describes related work done so far in this domain. Third section explains the concept of proposed model. Fourth section is an experimental section which gives the results and related discussion. Last section concludes the whole work and gives the future aspects of the paper should explain the nature of the problem, previous work, purpose and the contribution of the paper. The contents of each section may be provided in simple way to understand easily the facts discussed in the paper.

II. Related Works

Several studies have been carried out on automatic approach; some of them are worth mentioning in the following literatures:

- Graf, et al.in[1], an automatic approach for detecting learning style preferences according to the Felder-Silverman learning style model (FSLSM), which can be used to find the FSLSM learning style based on learning behavior of the students in LMS.
- Bahiah and Mariam in[2], providing parameters for identification of FSLSM learning style dimension from e-Learning activities;
- Khan, et. al. in[3] an automatic identification for learning styles and affective states in web-based learning management systems;
- Dung and Florea in[4], an approach for detecting FSLSM learning styles in learning management systems based on students behaviors.
- Georgiou and Botsios applied FCM to learning style recognition[5]. They proposed a three-layer FCM schema to allow experienced educators or cognitive psychology to tune up the system's parameters to adjust the accuracy of the learning style recognition[6]. The inner layer is composed of the learning styles, the middle one the learning activity factors, and the outer layer the 48 statements of the learning style inventory.

2.1 The Felder-Silverman Learning Style Model

Research on the integration of learning styles in educational hypermedia began relatively recently and only a few systems that attempted to adapt to learning styles have been developed[7]. Consequently, "it still is unclear which aspects of learning styles are worth modeling and what can be done differently for users with different learning styles"[8]. However, scientists agree that taking these student characteristics into account, one can lead to an increased learning performance, greater enjoyment, enhanced motivation and reduced learning time[7]. In order to make our literature based approach applicable for LMSs in general, only commonly used learning activities and features in LMSs were selected for patterns analysis. These features include: content objects, outlines, examples, self- assessment tests, exercises, and discussion forums. Furthermore, the navigational behaviour of learner's in the course was also considered. In the next subsections, the bahaviours of each learning style with respect to FSLSM are described in table 1 and the relevant patterns for identifying learning styles for the given dimensions are presented, using the literature regarding FSLSM[9] as basis. It had already proved that all engineering students are inductive so we eliminated the organization dimension from our study and consider only Felder four learning style dimensions.

Table 1. Characteristics of each learning style with respect to FSLSM

Preferred Learning Style	Dimension
Sensory-concrete material, more practical, std procedure	Perception
Intuitive-abstract material, innovative, challenges	
Visual-learning from picture	Input
Verbal-learning from words	
Inductive- It has proved that engg. students are Inductive	Organization
Deductive	
Active-Learning by doing, group work	Processing
Reflective-learning by thinking work alone	
Sequential-learn in linear steps, use partial knowledge	Understanding
Global-learn in large leaps, need big picture	

2.2 Mathematical Representation of Fuzzy Cognitive Maps

Fuzzy Cognitive Maps are fuzzy signed graphs with feedback (Stylios et al., 1997a). FCM consists of nodes represented by concepts $\mathbf{C_i}$ and interconnections strength $\mathbf{e_{ij}}$ between concept $\mathbf{C_i}$ and concept$\mathbf{C_j}$. A Fuzzy Cognitive Map forms a dynamic model. It is in fact a complex system consists of collection of concepts and there are cause and effect relationship between them. A simple illustration of a Fuzzy Cognitive Map is depicted in Figure1: as below, which consists of five nodes-concepts:

Interconnection's strength value e_{ij} among concepts is characterized by a weight w_{ij}. It is described as the grade of causality between two concepts. Weights take fuzzy values in the interval [-1, 1]. The sign of the weight indicates positive causality, then $w_{ij} > 0$ between concept C_i and concept C_j, i.e. an increase of the value of concept C_i causes an increase in the value of concept C_j and similarly a decrease of the value of concept C_i causes decrease in the value of conceptC_j. When there is negative causality between two concepts, then $w_{ij} < 0$; the increase in the first concept means the decrease in the value of the second concept and vice-versa[10].

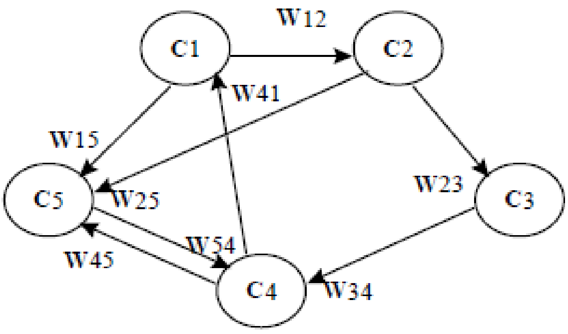

Fig. 1. Simple FCM Structure

The value of each concept is calculated by applying the calculation rule of equation as given in equation (1) where influence of one concept on another is also computed simultaneously:

$$x_i(t) = f\left(\sum_{\substack{j=1 \\ j\neq 1}}^{n} (x_j(t-1)w_{ji}\right) \quad (1)$$

Where $x_i(t)$ = the value of concept C_i at time t,
$x_j(t-1)$ = the value of concept C_j at time$t-1$,
w_{ji} is the weight of the interconnected concepts C_j and C_i and
f = sigmoid function where $f = \frac{1}{1+e^{-\lambda x}}$

Other proposed squeezing functions are the $\tanh(x)$,$\tanh\left(x/_2\right)$ and they convert the result of the multiplication into the fuzzy interval [0,1] or [-1,1], where concepts can take any values in between.
At each time interval, values for all concepts of Fuzzy Cognitive Map change and process recalculation as per equation (1). The calculation rule for each simulation step of FCM includes newly calculated values for all the concepts. It consists of n $x1$ vector X which gathers the values of n concepts, and the matrix $W = \left[w_{ij}\right]_{1\le i,j\le n}$ which gathers the values of the causal edge weights for the Fuzzy Cognitive Map, where the dimension of the matrices is equal to the number n of the distinct concepts used in the map. So the new state vector X of the FCM at time t is calculated according to the equation:

$$X(t) = f\left(W^T X(t-1)\right) \qquad (2)$$

2.3 Construction and Learning for FCM I

Experts who have knowledge and experience on the operation and behaviour of the system are involved in the determination of concepts, interconnections and assigning casual fuzzy weights to the interconnections (Kosko, 1992; Stylios and Groumpos, 1999). Generally, Fuzzy Cognitive Maps can be understood using learning algorithms in a similar way as in the neural networks theory. Proposed learning algorithms are categorized as the unsupervised learning algorithms.
During the training period of FCM, the weights of the map change with a first-order learning law based on the correlation or differential Hebbian learning law:

$$W' = -W_{ij} + x'_i\, x'_j \qquad (3)$$

So $x'_i\, x'_j > 0$ if values of concepts C_i C_j move in the same direction and
$x'_i\, x'_j < 0$ if values of concepts C_i C_j move in opposite directions;
Therefore, concepts which tend to be positive or negative at the same time have strong positive weights, while those that tend to be opposite have strong negative weights.

III. Proposed FCM Approach For Detecting Learning Style

The proposed model is literature based. Recorded data of learners' behaviors during their interactions with learning objects and learning activities have been used and corresponding mapping rules infer learning styles with respect to the Felder-Silverman Learning Style Model. So, basically we apply rule based fuzzy cognitive map. The development of learner model takes an active and challenging part in next generation adaptive e-learning environments[11],[12]. The purpose of learner models is to drive personalization based on learner and learning characteristics that are considered as important for the learning process, such as cognitive, affective and behavioural variables. Modeling learning styles with FCM that proposed in this paper aims to find a mapping between students 'actions in the system and the learning style that they best fit. To achieve this goal, the inputs of the network are required to be identified and its outputs and the meaning of their possible values are to be deciphered.

3.1 Labeling Learning object/ Relevant features of behavior pattern

Learning style of a learner is a way how a learner collects, processes and organizes information [12]. This paper is based on Felder-Silverman learning style model. According to FSLSM, each learner has a preferred learning style measured in four dimensions (active/reflective, sensing/intuitive, visual/verbal, sequential/global)[13],[5].The concept for providing adaptivity based on learning styles aims to individualized each learner according to their needs and learning styles[4].The paper annotates each learning objects or learning activity to each of the one learning style of among 16.Given table 2 shows the mapping of learning activity or learning objects with learning style in processing dimension.

Table 2. Learning styles to learning object (activity) mapping for processing dimension

Preferred Learning Style	Dimension
Sensory-concrete material, more practical,std procedure	Perception
Intuitive-abstract material, innovative ,challenges	
Visual-leaming from picture	Input
Verbal-leaming from words	
Inductive- It has proved that eng. students are Inductive	Organization
Deductive	
Active-Leaming by doing, group work	Processing
Reflective-leaming by thinking work alone	
Sequential-leam in linear steps, use partial knowledge	Understanding
Global-leam in large leaps, need big picture	

3.2 Collecting and processing information

Here, we measure measurable learning objects like theory, example, exercise, audio, video, assignments etc. It is pertinent to mention that some input data and activity variables in terms of learning objects cannot be mapped like touch, feel, taste, smell etc. The recorded learners' interactive data and their preferences at perceiving and processing information could be considered as fuzzy sets and the relations among them and learning styles can be considered as fuzzy relationships. In this way, the appropriateness of Fuzzy cognitive maps for diagnosing user learner style is evident and very much relevant.

3.3 Input layer

When learners interact with the system all the interactive and activity data are automatically captured and stored by the system in terms of log file. During interaction learner interact with different learning objects /activitiesof set {L1, L2….Ln}.

The input data captured are on the basis of number of visits, time period and order of visiting the learning material. These captured data produce a large number of sets having measurable patterns. Here, only relevant data patterns are taken into consideration for analyzing learner's behavior for monitoring aspects. These patterns are analyzed by learning style diagnostic module. So, learner model basically refers to learning style diagnosis module. To represent the input of the network, it is proposed to use one processing unit (neuron) in the input layer per observed action in the system. For example, time spent on learning objects or learning activity, number of hits on learning objects or activity, types of learning materials and format, marks on self-assessment, exam delivery time etc.

3.4 Output layer

The output of the network should approximate the learning style of the students based on the actions presented at the input layer.

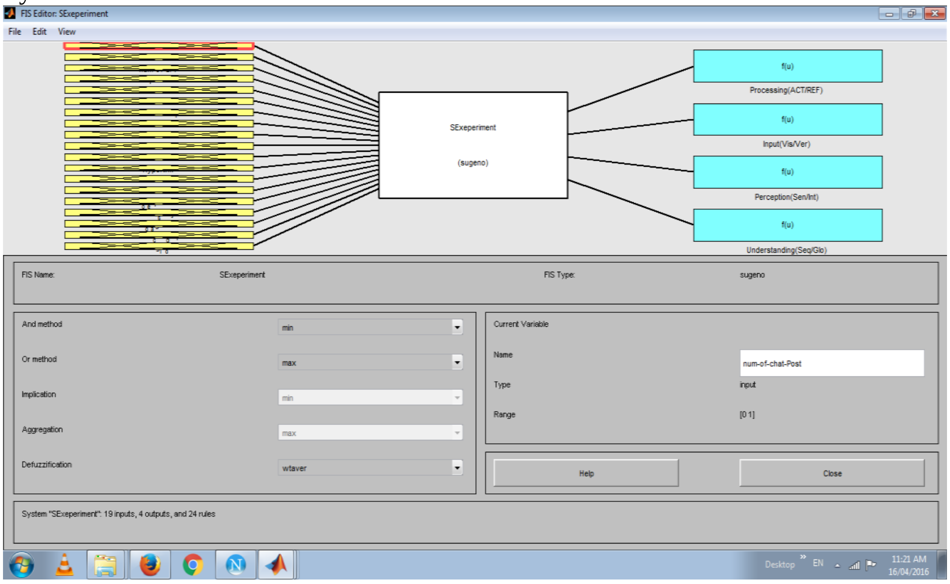

Fig. 2. Sugeno Fuzzy Inference System

IV. Automatic Detection Of Learner's Learning Style In E-Learning

This work is the extended version of my paper already published in literature[12]. For simplicity, fuzzy variables are taken in three degrees of linguistic variable (low medium & high) for measurement of learning style. Six degrees of linguistic variables may also be taken into the proposed framework. Threshold membership values for classification of linguistic variables may be taken as per literature[15][16].Range varies from [0 1] positive term define one pole of each learning style as follow :

0.00 to 0-0.3 weak,

0.3 to 0.7-moderate,

0.7 to 1.0 -strong.

With help of applying FCM learning algorithm, learning styles are identified by incorporating fuzzy rules. To explain these approaches the following related definitions are mapped to above sets.

- the set of elements $c_i \in \Theta$, where $\Theta=\{L\}$;
- A, a linguistic term of a linguistic variable (e.g. almost absolute cause);
- A measurable numerical assignment compact interval $X \in (-\infty, \infty)$;
- $V \in X$, a linguistic variable which is a label for $c_i \in \Theta$;

$\mu A(c_i)$ and the membership value of c_i represent the degree of membership of θi to elements of the sets determined by linguistic term A.

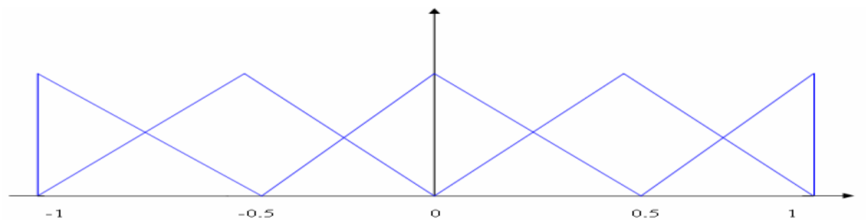

Fig. 3. Membership Function range from [-1 1]

The proposed fuzzy sets and their corresponding membership functions are:

- Mweak(weak) the fuzzy set for concept value around 0-30% (0-0.3) with membership function μw.
- Mmoderate (Moderate) the fuzzy set for concept value around 30-70% (0.3-0.7) with membership function μm.
- Mhigh(high) the fuzzy set for concept value around 70-100% (0.7-1)with membership function μh.

V. Experiment And Result

Implementation of this approach basically uses multiple resources because not only one resource has all features, which gives the best result. The authors had provided 4 week C++ course taking 80 learning objects or activities in account among 60 students. Moodle is used in this work because it is one of the best open source software for providing to create powerful, flexible and engaging online courses and experiences in learning management system[2]. The data gathered by APIE LMS based on Moodle require less amount of work in data pre-processing than data collected by other systems because it stored all the relevant and authenticate web usages. The results of this model obtained through an experimental on MATLAB fuzzy inference system and it was compared with those obtained through the Index of Learning Style questionnaire given by Felder-Silverman. The comparison showed high precision values of proposed method in identifying learning styles. Moreover, the method does not depend on a particular LMS. These characteristics indicate that the proposed method is promising and capable for wide use.

5.1 Fuzzy Inference System

Sugeno fuzzy inference system is applied to implement the functions of this module Inference Stage: if-than rule for approximation reasoning, for example- if the time spend to read text is short and if time spend to view video is high and number of frequency to hit video lecture is high and the number of correct answer in SA is high and if few attempts to find the correct answer have been made than the student learning rate is fast and student is visual. Representative picture of inference model is given in fig.2.
After fuzzy inference, the calculated linguistic variables are defuzzified using Center of Area (CoA) in crisp values. The crisp values are linked with the diagnosed learning styles in all four dimensions as per Felder Silver learning Style Model.
Table 3: shows an example of membership values obtain in each dimension of a student. Most important derivation is that higher value gives the degree of belongings and negative and positive sign give the learning style.

Table 3. Membership value in each learning style of a learner

Dimension 1		Dimension 2		Dimension 3		Dimension 4	
ACT	REF	SEN	INT	SEQ	GLO	VIS	VER
0.77	0.1	0.2	0.35	0.8	0.2	0.75	0.3

Table 4. Classification of learning styles on the basis of threshold membership value.

Dimension 1		Dimension 2		Dimension 3		Dimension 4	
ACT	REF	SEN	INT	SEQ	GLO	VIS	VER
S	W	W	M	S	W	S	W

Table 4: shows an example of learning style of a student in all four dimension i.e.Strong Act/Modeate Int/Strong seq/Strong visual.

VI. Comparison of precision value of FCM with Felder Index of learning style (ILS)

After pattern analysis and using fuzzy rule based cognitive map technique, learning styles were detected. The authors compared the predicted learning styles to the results obtained using the ILS questionnaire using precision formula given by [17].

$$\text{Precision} = \frac{\sum_1^n \text{Sim}\,(\text{LS}_{\text{FCM}}, \text{LS}_{\text{ILS}})}{n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; eq(A)$$

In this equation

- Sim is 1 if the values obtained with the FCM and ILS are equal,
- Sim 0 if they are opposite and
- Sim 0.5 if one is neutral and the other an extreme value;

n is the number of students studied.
Experimentally, we obtain precision value in all dimensions
Precision: (71.25%, 76.12%, 75.25%, 77.35%) for Act/Ref, Sen/Int, Vis/Vrb, and Seq/Glo .

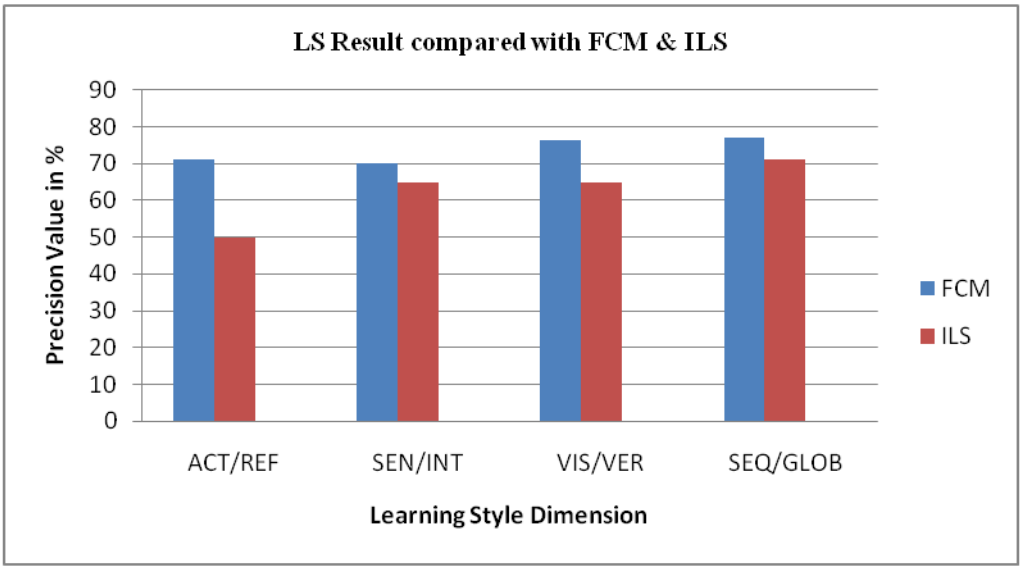

Fig 4: Comparison of precision value of FCM with ILS

VII. Conclusion

This paper presents an approach to develop learner Model to detect learning style of students to individualizing students according to their student's learning style. This system is a learner centric instead of teacher centric which could increase the students' autonomy. In future, we are working on to obtain complete learner's information's and provide personalized environment. The model recommends those required activities and or resources that would favour and improve their learning process and integrate learning styles into Adaptive e-learning system to assess the effect of adapting educational system.

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