Learning Style Diagnosis Using Fuzzy Cognitive Maps

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Abstract

There is a crucial issue in Adaptive Educational Hypermedia, concerning the machine's ability to recognize the learner's style and profile to the purpose of providing the learning material tailored to the learner's specific needs. In this paper an approach to this problem is presented, based on methodologies one can find in Fuzzy Logic and Neural Networks. The so called Fuzzy Cognitive Map becomes a powerful tool in this case, as it has been proved in other applications to. The reason which leads to such approach is mainly the observation of uncertainty in learner's profile description. Therefore, classes in any classification of learner's profile are considered as fuzzy sets and are represented as vertices of a Fuzzy Cognitive Map.

Keywords: fuzzy cognitive maps, learning style, decision support systems.

Introduction

The proposed method of learner's profile and style recognition is based on Fuzzy Cognitive Maps (FCM) which are a soft computing methodology that has been successfully used to model complex systems [Craiger],[D&K], and to support making decisions Papageorgiou et. Al. [P&S&G]. A system designed to diagnose in the best possible way the learner's profile as it has been classified by the experts in the field, can be considered a complex system. FCM methodology

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INTRODUCTION

With the rapid development of computer based online education, learners are gaining increasing autonomy, and instructional applications are reaching an unprecedented diversity of users. Consequently, personalized learning plays a crucial role in Web-based learning. Adaptive functionalities in e-learning are of great importance with respect to the Semantic Web [H&N], and associated to the Adaptive Web [M&C]. Adaptive functionalities are capable to know like a personal agent the specific requirements of a user, to take goals and to recognize his preferences on the actual context into account in order to optimize the access to electronic information. To this end we present an interesting application of Fuzzy Cognitive Maps within Adaptive Hypermedia. This application results to an intelligent model which expresses, derives and draws conclusions about the characteristics of users. User model has been established by modelling typical groups of learners that represent users' stereotypes (i.e. users with similar behavior or requirements, etc). One of the learner's model components is the Learning Style (L.S.).

++Learning Styles are simply different approaches or ways of learning In other words, Learning Styles are the preferable general tendencies to process information in different ways. Therefore, the primary use of Learning Styles is as a metaphor for thinking about individual differences. As far as educational technologies will focus on the individualization in learning the Learning Styles diagnosis will remain one of the basic questions. There is a numerous of Learning Styles classifications (HILL'S cognitive style mapping DUNN&DUNN, Grasha –riechmann,Gregorc learning styles, Kolb's Learning style). Learning Style Inventories which are diagnostic tests (in the form of questionnaires which gather self reported data) have been proposed in order to identify student's preferences. No matter the classification in hands, the resulting Learning Style characterization should rather be characterized by their fuzziness than by their compactness.

Σχόλιο [NN1]: Να αναφερθούν οι εργασίες στα References

The proposed method is based on Fuzzy Cognitive Maps (FCM) methodology. A Fuzzy Cognitive Map is a soft computing tool, which can be considered as a combination of fuzzy logic and neural network techniques. It has been used to model complex systems [references of studied paper 3 : 5,7,46-48] and to support decisions making [references of studied paper 3 :29] . An FCM structure represents quantitative , as well as data about the factors , the characteristics and the components of a complex system. Within this structure the human knowledge about the system and its behavior is exploited.

Σχόλιο [NN2]: Να αναφερθούν οι εργασίες στα References

Σχόλιο [NN3]: Να αναφερθούν οι εργασίες στα References

In this paper we present some basic information on Kolb's Learning Styles classification. The Kolb's classification has been chosen for use in this investigation, but it is worth to mention that other classifications can be applied in analogous manner.

The structure of this paper is….(section 1 describes …section 2……

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SECTION 1: LEARNING STYLES

In literacy one can find a number of learning styles classifications. In most cases the classifications have very little in common. To the best of author's knowledge, the Felders and Silverman classification, as it appears in [8], has been cited more than any other related paper. Felder's paper, which originally formulated in collaboration with Linda Silverman, presents a model of learning styles and a parallel model of teaching styles that seems to apply well to students in technical disciplines. Kolb classified L.P in a two-dimensional space, and proposed an easy method to diagnose the L.P. Several methods for diagnosing individual learning styles are in use. Some of them have been already used in AEHS. For example Honey and Munford [H&M1] introduced a procedure, which has been recently used by K.Papanikolaou and M. Grigoriadou [15]. In table 1 a number of classifications appear altogether with learner's characterizations that are taken under consideration in each class. It reflects the Jonassen D., Grabowski [10] work on known Learning Styles. Fartermore, table 1 corresponds certain L.A. to specific teaching procedures . For example, in the Dunn and Dunn model, one can find 3 pairs of characteristics like Left/Right, Intuctive /deductive, and Sequential/Global which results 8 permutations. In order to design a software tool for the L.S. recognition, one could consider any given L.P. classification like the one proposed by Kolb [12] or Felder and Silverman [8], or any other's proposed one. For reasons of simplicity we make use of the Kolb's classification.

Σχόλιο [A.4]: Να βάλω και άλλες περιγραφές.

Despite the numerous classifications on the learner's style that have been proposed so far, one easily recognize the difficulty to classify many learners as of a certain kind in any given classification. No matter the classification in hands, the subsets should rather be characterized by their fuzziness than by their compactness. To the purpose of the presentation of a classification by Fuzzy Cognitive Map, we consider as learning style model, introduced by Kolb, according to whom "we learn by conceiving and transforming our experiences". The proposed method can be easily applied to other classifications of learner's style in an analogous manner.

To the purpose of the presentation of a classification by Fuzzy Cognitive Map, we consider as learning style model, introduced by Kolb, according to whom "we learn by conceiving and transforming our experiences". The proposed method can be easily applied to other classifications of learner's style in an analogous manner. According to Kolb's classification, conception and elaboration of information are the two dimensions of learning process. It has also been pointed out that each dimension of the learning process presents us with a choice. For example, it is virtually impossible to drive a car (Concrete Experience) and at the same time to analyze a driver's manual about the car's function (Abstract Conceptualization). Therefore, we resolve the conflict by choosing. Hence, in order to conceive information one has to choose between Concrete Experience and Abstract Conceptualization. As a matter of information elaboration one has to choose among Reflective Observation or Active Experimentation. Such choices determine the learning style. According to Kolb's model, the four learning styles and the corresponding per learning dimension choices are presented at the following table [Jonassen & Grabowski]. Taking a step further, one should realise the incompleteness of having a concrete classification of the four classes. Diverger and Assimilator have RO in common, as Assimilator has common characteristics to Converger and so on.

	Active Experimentation (AE)	Abstract Conceptualization (AC)	Reflective Observation (RO)	Concrete Experience (CE)
Diverger			X	X
Assimilator		X	X	
Converger	X	X		
Accommodator	X			X

Table 1

Instruments (Learning Style Inventories) that are proposed in order to identify student's preferences are questionnaires that gather self reported data.

Users are given sentences that describe behaviors and tendencies during learning situations and they are called to rank these sentences according to how well they think each sentence fits best to the way they learn.

Thus the recorded User 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.

Table 1 shows some basic factors that correspond to learner's behaviors. The factors are presented in a comparative way that expresses how much the learner exhibit the corresponding behavior, which is taken into account in order to classify learners into the appropriate learning style. The used linguistic terms to indicate this amount of preference –tendency in a certain behavior or property are: very strong, strong , ordinary and weak which are considered as fuzzy variables.

Imaginative intuition	
Diverger	**VERY STRONG-**Very good
converger	**WEAK-**Unimaginative
Accommodator	**ORDINARY-**Rather poor
Assimilator	**STRONG-**Less artistic
Decision making	
Diverger	**WEAK-**(Less able)
converger	**STRONG-**(Very good)
Accommodator	**EXTREMELY STRONG** (Very good /risk taking)
Assimilator	**WEAK** (Less able)
Understanding symbols and abbreviation	
Diverger	Needs concrete examples (rather poor)
converger	Very good
Accommodator	Good
Assimilator	maximum

Table 2

Boredom effectiveness /patience	
Diverger	
converger	
Accommodator	**WEAK-** minimum
Assimilator	**VERY STRONG-**maximum
Ability to get things done	
Diverger	
converger	**VERY STRONG-**Very good/apply ideas
Accommodator	**STRONG-** Carries out plans
Assimilator	**WEAK**-Rather hesitant
Authority Treatment	
Diverger	Doubts **WEAK**
converger	Skepticism **ORDINARY**
Accommodator	Seeks for **VERY STRONG**
Assimilator	appreciate **STRONG**
Scientific/systematic approach	
Diverger	Less **WEAK**
converger	Very good- **STRONG**
Accommodator	Less-**WEAK**
Assimilator	maximum-**EXTREMELY STRONG**
Self directed learning vs guidance need	
Diverger	Very good at self …./ self diagnostic-**STRONG**
converger	Good at self..-**ORDINARY**
Accommodator	Needs guidance-**WEAK**
Assimilator	Maximum – **EXTREMELY STRONG**
Collaborative learning	
Diverger	**STRONG-** Prefers
converger	**ORDINARY**
Accommodator	**EXTREMELY STRONG –** Strongly prefers
Assimilator	**WEAK-** Do not prefers
Emotionally involved	
Diverger	**STRONG-**Oriented towards
converger	
Accommodator	
Assimilator	**ORDINARY**-Less oriented
Risk Taking	
Diverger	
converger	
Accommodator	**EXTREMELY STRONG**
Assimilator	
leadership	
Diverger	
converger	
Accommodator	**EXTREMELY STRONG**
Assimilator	

SECTION 2: FUZZY COGNITIVE MAPS

Fuzzy Cognitive Maps (FCM) is a soft computing tool which can be considered as a combination of fuzzy logic and neural networks techniques. FCM representation is as simple as an oriented and weighted compact graph. For example the simple FCM which is depicted in figure 1 consists of seven nodes which represent five concepts. Concepts represent key factors and characteristics of the modeled system and stand for inputs, outputs, variables, states, events, actions goals and trends of the system. Each concept C_i is characterized by a numeric value $V(C_i)$ which indicates the quantitative measure of the concept's presence in the model. Each two distinct nodes are joined by at most one weighted arc. The arcs represent the causal relationships that relate pairs of concepts. The degree of causality of concept c_i to concept c_j is expressed by the value of the corresponding weight w_{ij}. Experts describe this degree using linguistic variables for every weight, so this weight w_{ij} for any interconnection can range from –1 to 1.
There are three types of causal relationships expressing the type of influence among

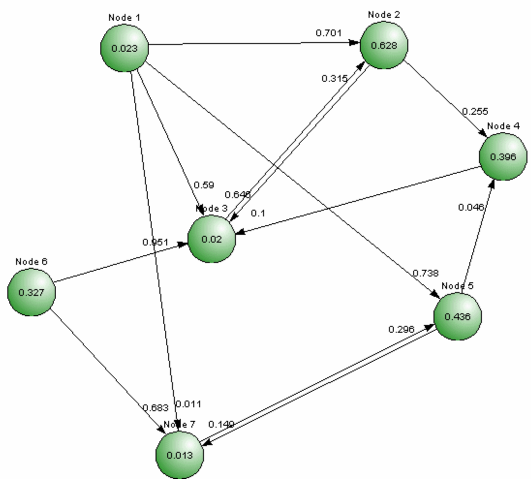

Figure 1

the concepts, as they represented by the weights $w_{i,j}$. Weights can be positive, negative or can also be zero. Positive weight means the increasing influence a concept implies to its adjacent concept of the graph as on the other hand, negative weight means that as concept C_i increases, concept C_j decreases on the wi,j ratio. In absence of relation between C_i and C_j, the weight $w_{i,j}$ equals zero.

Since there is a vast and sometimes controversial variety of expert's opinion on the weight with which a concept influences another concept, it is worth full to introduce a suitable algorithm for the adjustment of the set of weights in FCM. As it has been already mentioned, the numerical values of weights have to lay in the interval [-1,1], as the FMC will converge either to a fixed point , or limit cycle or a strange attractor Dickerson and Kosko [2]. In the case in hands, where the FCM is called to support decision making process, as the recognition of learner's style is, it will better to converge to a certain region which is suitable for the selection of a single decision.

Initially, every concept gets a hypothetic value and as the time proceeds, the values of the concepts change as they are under the influence of the adjacent concepts and their corresponding weights.

At the step n the value $V^n(C_i)$ of the concept C_i is determined by the relation

$$V^{n+1}(C_i) = f\left(\sum_{\substack{j=1 \\ i \neq j}}^{k} w_{ji} V^n(C_j)\right) \qquad (1)$$

where $V^{n+1}(C_i)$ is the value of the concept C_i at the discrete time step n+1.
For this research we use the more general formulation which is proposed in [depy2]

$$V^{n+1}(C_i) = f\left(k_1 \sum_{\substack{j=1 \\ i \neq j}}^{k} w_{ji} V^n(C_j) + k_2 V^n(C_i)\right) \qquad (2)$$

Where 0□ k_1□1, 0□k_2□1.
The coefficient k_1 defines the concept's dependence of on its interconnected concepts, while the coefficient k_2 represent the proportion of contribution of the previous value of the concept in the computation of the new value. We selected $k_1=k_2=0.5$ as this results in smoother variation of the values of the concepts after each recalculation and more discrete final values.
Function f is predefined threshold function. Generally two kinds are used in the FCM framework . f(x)=tanh(x) is used for the transformation of the content of the function in the interval [-1,1]. We used the unipolar sigmoid as we want to ensure values of concepts between 0 and 1. The function is given by:

$$f(x) = \frac{1}{1+e^{-\lambda x}} \qquad (3)$$

where $\lambda>0$ determines the steepness of the sigmoid. Plots of the threshold function for various values of the constant λ are shown in the figure [1]. As $V(C_i)>0$, after some iterations easily these values become greater than 1. Taking a look at plot (b) in figure []we can easily understand that values greater than 1 are squashed towards value 1. This leads to discreteness loss that is needed in order to have a safe decision of user's LS. Increasing functions steepness makes things worse (plot (a) in figure []). Choosing $\lambda=1$ we tried out translating function's graph to the right, which , as we will see later, gave greater discreteness to the values of output concepts.

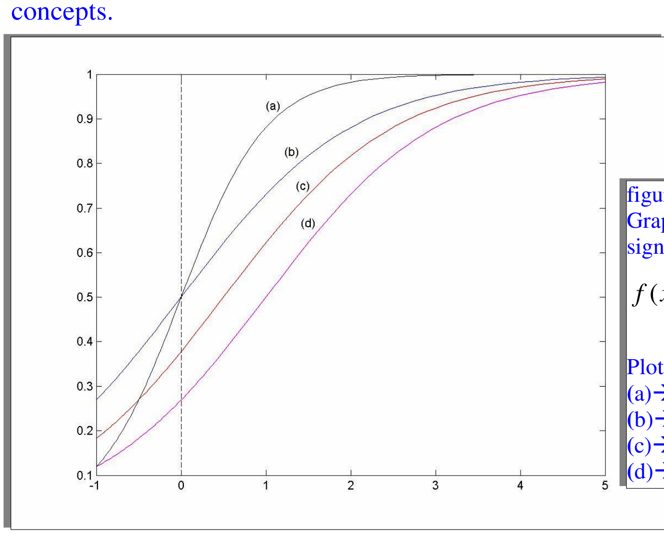

figure []:
Graphical representation of logistic signal function:

$$f(x) = \frac{1}{1+e^{-\lambda x}}$$

Plots for the cases:
(a)→ f(2x)
(b)→ f(x)
(c)→ f(x-0.5)
(d)→ f(x-1)

Figure 2

SECTION 3: Description of Learner Style Recognition Model

The proposed FCM model is depicted in figure [2]. Each vertex of the graph represents a concept, which express explicitly or implicitly certain characteristics a learner has, or the main learner styles characteristics according to Kolb [5] classification. The vertices of the graph connect pairs of the user characteristics if and only if there is a certain relationship among them. Each concept is characterized by an integer indicating the significance of the characteristic in the model. So, an integer of great value indicates the importance of the concept, as an integer of low value indicates a concept of minor meaning. In order to transform these values of concept significance into the scale of [0,1], which is in use by the fuzzy logic methods, we introduce an appropriate simple linear transformation. As a matter of fact, the labels that stand for the weights of the graph's oriented edges should also be defuzzified and transformed to values in [-1,1]. The final graph is designed in a way that easily its observer can see the significance of a concept and the influence each concept has on another. As of the simplicity of its structure, an expert can easily add more vertices and edges in case new concepts should be introduced or more experts are asked to be represented in the model.

The concepts of the proposed FCM are of two different types. The four central concepts : Concrete Experience (CE) , Abstract Conceptualization (AC), Active Experimentation (AE), Reflective Observation (RO). The values of these concepts are the **Learner's Characteristics (LC)** according to Table 1 and are considered to be the outcome of the Learner Style Recognition Model. The concepts of the second type , which consist the outer layer of the proposed FCM , are the measurable **learning activity factors (LAF)** which are subjects to be diagnosed by the machine. Such factors influence directly the learner's characteristics. The oriented connections between concepts – vertices of the graph are represented by arrows. The connections may show positive or negative influence LAF can have to LCs. A negative connection reduces the probability to diagnose a certain LP in case of strong presence of a connected LAF.

LC are selected to be the outputs of the Learner Style Recognition Model instead of the learning styles according to table 1. The reason for this is that it is desirable for the output nodes to "compete" each other in order one or two of them to have dominating values, so we can have correct identification of user's learner style with the highest probability. In the dimension of information conception within the learning process, as we have aforementioned, one cannot simultaneously use Concrete Experience and Abstract Conceptualization. The same is truth for the dimension of information elaboration within learning process and the choices Active Experimentation and Reflective Observation. The desirable "competence" of the output concepts it is not valid for the learner styles, as for example one can have both Diverger's and Assimilator's characteristics. So organizing the central nodes in pairs: CE-AC and AE-RO, we consider of interconnections among the members of the same pair that should have very high negative weight, even –1. This implies that the higher the value of the one node leads to lowering the value of the other. No interconnections exist between the nodes belonging to two different pairs.

To explain these approaches the following related definitions are required.

1. the set of elements $C_i \in \Theta$, where $\Theta = \{LAF\} \cup \{LC\}$;
2. **A**, a linguistic term of a linguistic variable (e.g. almost absolute cause) ;
3. A measurable numerical assignment compact interval $X \in (-\infty, \infty)$;
4. $\mathbf{V} \in X$, a linguistic variable which is a label for $C_i \in \Theta$;

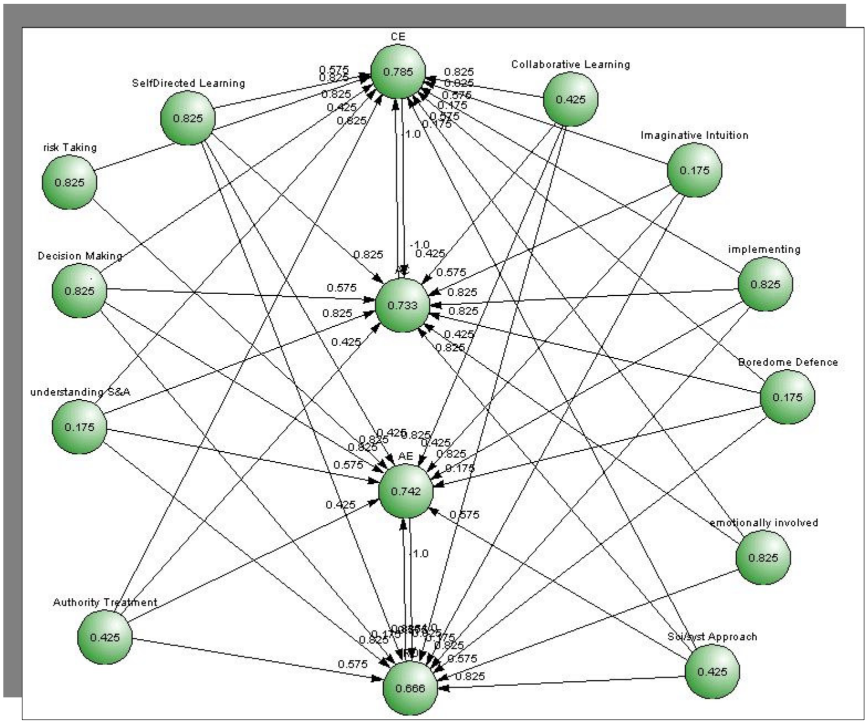

Figure 2

5. $\mu_A(C_i)$, the membership value representing the degree of membership of θ_i to the set of elements determined by linguistic term **A**.

Since we do not expect that all LAFs have the same degree of effectiveness and causality on their adjacent LCs, weights must determined in order to express the degree of effectiveness and causality in case. As cognitive psychology experts mostly describe qualitative behavior using linguistic variables, it is necessary to introduce a transforming algorithm to map the values of such linguistic variables into membership functions. Watanabe's [9] membership functions direct estimation methods take an approach by asking experts to grade an event on a scale. Using such grading, we make use of the transform which appears in Georopoulos et. Al. [3]. According to the proposed scheme, each fuzzy set corresponds to a membership function shown in the figure 2, where fuzzy sets describe the degree of causality corresponding to membership functions $\mu_A(C_i)$, A={w, o, s, vs}.

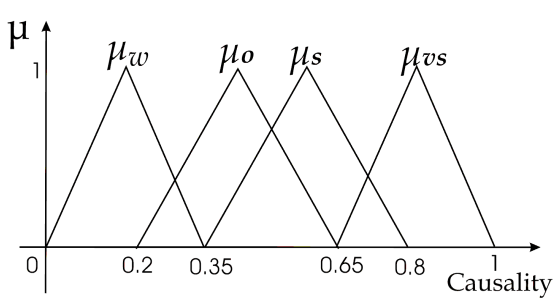

Figure 3

The proposed fuzzy sets and their corresponding membership functions are:

- M_w(weak cause) the fuzzy set for causality around 17.5 % with membership function μ_{wc}.
- M_o(ordinary cause) the fuzzy set for causality around 42.5 % with membership function μ_{oc}.
- M_s(strong cause) the fuzzy set for causality around 57.5 % with membership function μ_{strc}.
- M_{vs}(very strong cause) the fuzzy set for causality around 82.5 % with membership function μ_{esc}.

The membership functions are not of the same size since it is desirable to have finer distinction between grades in the edges of the influence scale.

FCM have the ability to describe systems where there are feedback relationships and relationships between concepts. The interrelation of the concepts and the feedback relation is described by the matrix W. Weights in Feedback relation are the values of the diagonal matrix elements, while the rest of the matrix elements are the weights of concepts interrelations. More analytically: W_{ij} means that concept C_i affects concept C_j with weight W_{ij}.

According to table 2, which has been constructed based on the relevant literacy. we have linguistic descriptions about the causality of each one of the LAF to Kolb's Learning styles. As we have decided to use LC as output concepts , these linguistic descriptions had to be translated appropriately to causality degrees towards LC. Using the above membership functions we defuzzify the fuzzy degrees of LAF causalities towards Learning styles. We put the crisp numerical values we obtained to the matrix below:

$$\begin{bmatrix} 0.175 & 0.575 & 0.825 & 0.175 \\ 0.825 & 0.175 & 0.425 & 0.575 \\ 0.175 & 0.575 & 0.425 & 0.825 \\ 0 & 0 & 0.175 & 0.825 \\ 0 & 0.825 & 0.575 & 0.175 \\ 0.175 & 0.425 & 0.825 & 0.575 \\ 0.175 & 0.575 & 0.175 & 0.825 \\ 0.575 & 0.425 & 0.175 & 0.825 \\ 0.575 & 0.425 & 0.825 & 0.175 \\ 0.575 & 0 & 0 & 0.425 \\ 0 & 0 & 0.825 & 0 \end{bmatrix}$$

The corresponding to Table 1 matrix is :

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

The matrix W for the values corresponding to connections between LAF and LC concepts is depicted in figure 4 and it is constructed after the min-max synthesis of the above matrices. The values of the first , the second , the third and the forth column of this matrix correspond to weighted connections from all concepts towards the AE ,RO ,AC ,CE concepts respectively. Also included in this matrix are the –1 weight values for competition between these concepts (the output concepts). The diagonal elements are set to 0.5 value, reason for this has been explained in section 2. The rest elements are set to 0 , as initially we suppose that there are no interrelations between LAF . One of the future improvements will be to take into consideration expert's opinions about interrelations among LAF.

$$\begin{bmatrix}
0.5 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0.5 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.825 & 0 & 0 & 0.825 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.575 & 0.425 & 0.575 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.825 & 0.575 & 0.425 & 0.825 & 0 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.425 & 0.825 & 0.825 & 0.575 & 0 & 0 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.575 & 0.825 & 0.825 & 0.175 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.425 & 0.575 & 0.425 & 0.825 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 \\
0.825 & 0.175 & 0.825 & 0.575 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0 & 0 & 0 \\
0.175 & 0.825 & 0.825 & 0.175 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0 & 0 \\
0.575 & 0.825 & 0.825 & 0.425 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0 \\
0.425 & 0.825 & 0.575 & 0.825 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 \\
0.825 & 0.175 & 0.575 & 0.825 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5
\end{bmatrix}$$

SECTION 4: THE ALGORITHM AND A TEST CASE

The algorithm that is used is as follows:

Let N be the number of concepts in the FCM

- Set the number k of learners
- Set initial values n=0, $V^0(C_i)$ for i = 1, 2, … , N from the learner's profile database. Data have been stored as the learner responded to certain tests. Data have been stored as linguistic values A_i , and have been turn to fuzzy degrees $V^0(C_i)$ for all concepts except those in LP. Concepts in LP are set equal to 0 for n = 0.
- Set the initial values for $w_{j,k}$ according to given information.
- For n=n+1, apply the relation (1) and set values $V^{n+1}(C_i)$. Update learner's profile database. Following the defuzzification the weights at the edges of the graph are presented as elements of the adjacent matrix W_n.
- Set $\mathbf{V}^{n+1}=W_n\mathbf{V}^n$, where
- If a C_i does not be influenced by any C_j , $j\neq i$ then $w_{j,i}=1$ at present n
- If a $V^n(C_i)=$ **m** $[V^n(C_j)]^{-1}$, for a given measure of competence $0<\mathbf{m}\leq 1$, then set $w_{i,j}= -\mathbf{m}$
- Use the unipolar sigmoid function to transform the coordinates of V^{n+1} into the interval [0,1].
- If $\max_{0<i<k}|V^{n+1}(C_i)- V^n(C_i)| < \varepsilon$, $(\varepsilon>0)$ then stop and store as result the learner's profile which has the highest value $V^{n+1}(C_i)$

The above model is capable to identify student's learning preferences and diagnose student's learning style. The validity of the model is based on the weights that are the elements of the above-mentioned matrix W. For instance -as it is figured out by the matrix, "Boredom tolerance/patience" concept affects "Active Experimentation" concept with weight 0.175. This means that having great patience /boredom tolerance is rather a weak cause that one prefers Active Experimentation in learning cycle. On the other side Decision Making concept affects

Active Experimentation with weight 0.875 means that the fact that one has Decision making strength is a very strong cause that he prefers Active Experimentation in Learning Cycle. Therefore it is crucial that these weights are properly selecting according to experts knowledge.

To testify the above model we used a hypothetical case as it is depicted in table 3

LAF	Linguistic value of weight
risk taking	very strong
emotionally involved	very strong
collaborative learning	ordinary
self directed learning	very strong
scientific/systematic approach	ordinary
authority treatment	ordianary
implementing	very strong
boredom tolerance	weak
understanding symbols& abbreviations	weak
imaginative intuition	weak
decision making	very strong

Table 3

Using the defuzzification method CoA , and reserve as zeroes the values of the output concepts , we have the following initial vector:

V^0=[0, 0, 0, 0, 0.825, 0.825, 0.425, 0.825, 0.425, 0.425, 0.825, 0.175, 0.175, 0.175, 0.825]

For the implementation of the proposed algorithm and the evaluation of the hypothetical test case, we used “FCM-Analyst” which has been developed by Meletis Margaritis and it is discussed in [reference 10]. In figure 4 we have the values of output nodes LC. The values of LAF as we can see ,are not changed during iterations. This is because in our initial model we do not have interconnections among them. The dominant values , for our test case are : Concrete Experience and Active Experimentation . This results to a Accommodator Learning Style.

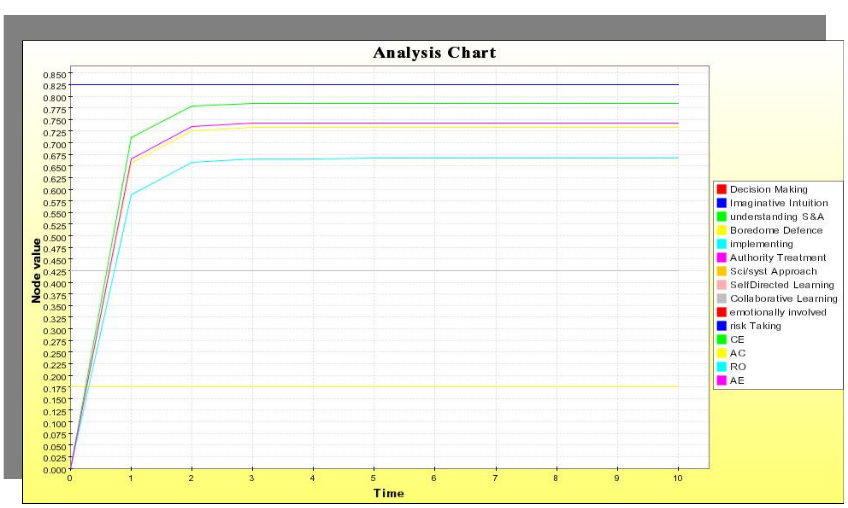

Figure 4

SECTION 5:CONCLUSIONS AND FUTURE DIRECTIONS.

The above method has been developed to provide a fully computerized procedure which will be able to diagnose the learner's profile. An Adaptive Educational Hypermedia platform, which supports asynchronous e-learning, will take fully advantage of the proposed algorithm, in order to "see" the learner and to tailor the learning material to his special needs. This study is considered to be part of the project for the developing of the ATTAIN (Aptitute Treatment Training in Adaptive Instructions) platform.

Alternatively to Watanebe's Direct Esimation Methods, one can apply the Reverse Rating method, introduced by Turksen [8]. As the *Reverse rating* method takes a different approach by asking an expert to answer the following question ``Identify θ(V(θ)) that has the y-th degree of membership in fuzzy set **A**." This technique allows a direct use of machine applicable diagnostic tests, which produce certain degree of membership in fuzzy sets, to the purpose of learner's style and characteristics recognition.

Another possible approach to the recognition of learner's profile could be the application of learning methods. Such approach overcomes deficiencies caused by the dependence on human experts and the learner's responses. The introduction of Hebbian algorithm as it has been proposed for FCM by Papageorgiou, Stylios and Groumbos [7], improves the efficiency and robustness of the system.

Table 1: Learner's style and characteristics

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