Learning Style Recognition via FCM

by

D.Makry & D.A.Georgiou

Department of Electrical & Computers Engineering
School of Engineering
Democritus University of Thrace,
GR 671 00 Xanthi, Greece
dgeorg@ee.duth.gr

Abstract: Adaptive Educational Hypermedia Systems (AEHS) among the emerging technologies serves Knowledge and Learning Systems. Aiming to improve pervasiveness and efficiency of asynchronous e-learning has given emphasis to the development of tools which allow the machine to diagnose certain learner's characteristics to the purpose of providing learning material which can adapt to the learner's specific needs. This paper aims to contribute to this direction by introducing the Fuzzy Cognitive Maps technique, which modifies the learning style, i.e. the learner's qualitative characteristics, into appropriate quantitative characteristics. The importance of Fuzzy Cognitive Map's technique becomes even greater since this method takes into consideration the previously gained experience on learners' style diagnoses.

Keywords: Fuzzy Systems, Cognitive Maps, Adaptive Hypermedia, Learning Style Recognition

Biographical Notes: Despina Makry is a Ph.D. candidate at the Department of Electrical and Computer Engineering at Democritus University of Thrace in Greece. She is also a scholar of the Cultural and Educational Research Institute where she has participated in the "Multimine" and the "e-learning land" projects. These projects are supported partially by the Information Society. Her research areas include: Intelligent tutoring systems (ITS), Adaptive hypermedia and e-learning.

Dr. Demetrius Georgiou is Associate Professor at the Department of Electrical and Computer Engineering at Democritus University of Thrace in Greece, Head of Section of Physics and Applied Mathematics. He has coordinated several distance learning and e-learning projects, regarding secondary or vocational education in Greece. His research interests are on Applied Mathematical Analysis and on Adaptive Educational Hypermedia Systems. He coordinates the project ATTAIN (Aptitude Treatment Training in Adaptive Instruction) which develops an adaptive and interactive authoring tool.

1. INTRODUCTION

Adaptive Educational Hypermedia Systems (AEHS) are considered among emerging technologies which serves Knowledge and Learning Systems. Aiming to improve the efficiency of asynchronous e-learning AEHS takes advantage of knowledge gained in various scientific disciplines, and proposes more efficient e-learning systems. From the software engineering point of view, AEHS serves as a milestone in the roadmap of Knowledge and Learning implementing the daptive learning strategy (Lytras and Sicilia 2005).

Educational Sciences provide educators with deeper knowledge on various disciplines such as cognitive psychology, learning behaviourism, and teaching diagnostics. Educators face the need to conquer a wide range of knowledge to the purpose of improving their teaching behaviour. Educators are humans and as humans are flexible (or soft) systems. They can adapt to unfamiliar situations in class, and they are able to gather information in an efficient manner and disregard irrelevant details. The information, which is gathered, could be general, qualitative and vague because humans can reason, infer, and deduce new information. So educators exploit all the information concerning their students in order to teach in the best possible way. Educators have common sense. They can make good decisions on teaching strategy, and they can provide logical explanations for those decisions. They can learn, perceive, and improve their skills through experience. As they are humans, they can be creative, inventive, and innovative.

Educational Technology faces a very challenging task to seek to develop and to possess even a few of these simple human abilities. This challenge faced by researchers in the field of Adaptive Educational Hypermedia Systems (AEHS) mainly consider learner's preferences, interests, and browsing behaviours in providing personalized services. However, teachers have weaknesses too. They can be slow, inaccurate, forgetful, and emotional. In the presence of such characteristics their teaching behaviour becomes unstable.

Within the field of AEHS we seek to combine the advantages of a computer with some of the tutors intelligence characteristics to the purpose of making inferences, and taking decisions. Computers are fast, accurate, and have reliable memory. The idea is to implement human knowledge and experience in the computer in order to make it behave as the best possible tutor who adjusts teaching on the learner's characteristics and abilities. It is expected that this will result to the optimum gaining of knowledge.

Among many technologies based on artificial intelligence, fuzzy logic is now perhaps the most popular area, judging by the billions of dollars worth of sales and close to 6000 patents issued in Japan alone since the announcement of the first fuzzy chips in 1987. A wide variety of methodologies based on fuzzy sets, fuzzy relations and fuzzy control have appeared in literature. Certain methods can be applied on the diagnosis of mental disorders, language impairments or learning disabilities. Machine implemented diagnostic methods for the recognition of learner's cognitive characteristics would be greatly appreciated too, since such characteristics have been an important issue in Adaptive Educational Systems. Fuzzy Cognitive Map (FCM) is a soft computing modelling methodology that has been proposed and developed during the last decade. FCM has been proved a useful tool for the exploration of the impacts of different input states on fuzzy dynamical systems. A major advantage of FCMs is that they can handle even incomplete or conflicting information. This is considered to be of great importance because quite often pieces of information may be missing, or be unreliable, or difficult to integrate with information expressed differently. In this paper, we shall present the FCM methodology for the recognition of learner's cognitive characteristics. Additionally, we shall present an application to Learning Style (L.S.) recognition via FCM based on Kolb's classification. Some of the main objectives of the method we suggest are:

1. Contribution to AEHS introducing FCM methodology in L.S. recognition.
2. Allowing systems to take advantage of the experts' knowledge and previously gained experience on learner's cognitive characteristics .

The study presented in this paper contributes in the individualization of learning. We expect that knowledge society (Lytras et al ,2005), has individualization of learning as one of its major concerns. Learner's cognitive characteristics define the way he/she behaves within knowledge society. So it is crucial at engineering any knowledge and learning system to consider the identification of learner's cognitive characteristics as system's basic part.

2. L.S. AND ITS CHARACTERISTICS

Each individual responds differently to a given learning situation. This response will be influenced by the way the individual thinks, his past experience, the environment, and the current task. This approach is generally recognised as the individual's L.S.

In literature can found a number of L.S. classifications. In most cases the classifications have very little in common. To the best of the authors' knowledge, the Felders and Silverman classification, as appears in Felder et al.,(1988) is cited more times than any other paper referred on the same subject. Felder in his paper, which he originally formulated in collaboration with Linda Silverman, presents a model of learning styles and a parallel model of teaching styles that seems to apply better to students of technical disciplines. Kolb classified learning styles in a two-dimensional space, and proposed an easy diagnostic method for it. Several other methods for the recognition of individual's learning styles are also in use. Some of them have been already used in AEHS. Honey and Munford (1992), for example introduced a diagnostic method, which has been recently used by Papanikolaou et al. (2002).

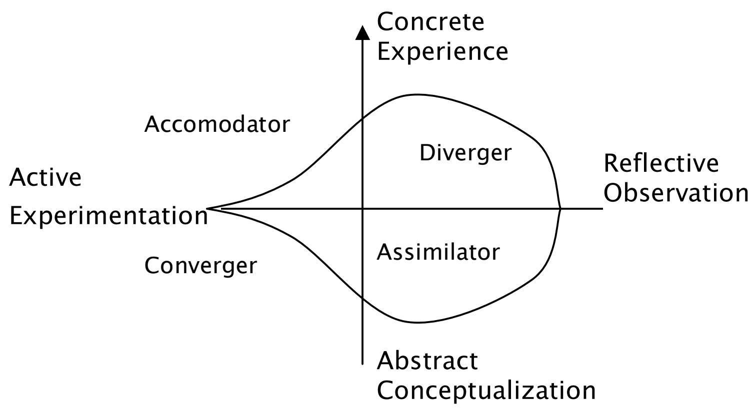


Figure 1

In this paper we introduce the FCM method as a tool for the diagnosis of learning styles. In order to do so we make use of the Kolb's L.S. theory. Clearly, the method is also adjustable to any L.S. classification and the choice of Kolb's theory is rather incidental. According to Kolb's classification, conception and elaboration of information are the two dimensions of learning process. Kolb 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 (CE)) and at the same time to analyze a driver's manual about the car's function (Abstract Conceptualization (AC)). 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 between Reflective Observation (RO) or Active Experimentation (AE). Such choices

Behavior	LS	Degree of causality
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
	Assimilator	**WEAK** (Less able)
Understanding symbols and abbreviation	Diverger	Needs concrete examples (rather poor)
	converger	Very good
	Accommodator	Good
	Assimilator	maximum
Boredom effectiveness /patience	Diverger	
	converger	
	Accommodator	**WEAK-** minimum
	Assimilator	**VERY STRONG-**maximum
Ability to get things done	Diverger	
	converger	**VERY STRONG-**Very good/apply
	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-
	converger	Good at self..-**ORDINARY**
	Accommodator	Needs guidance-**WEAK**
	Assimilator	Maximum – **EXTREMELY STRONG**
Collaborative learning	Diverger	**STRONG-** Prefers
	converger	***ORDINARY***
	Accommodator	**EXTREMELY STRONG –**Strongly
	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	

Table 1

determine the L.S. According to Kolb's model, there are four L.S. which are marked on the four quadrants of the two dimensional space (figure 1).

Educators are able to collect the information that is necessary and sufficient for the diagnosis of the L.S. by using an appropriate questionnaire (Boyatzis et al.,1993).

Kolb suggests a certain analysis of the collected data which results with a vector in the above mentioned two-dimensional space (figure 1). In order to design software that simulates the diagnostic method proposed by Kolb, one should establish a procedure based on collected data analysis. This procedure will enable the machine to recognise the user's L.S..

Table 1 shows some basic factors (Learning Activity Factors) that correspond to learner's behaviours. These factors are presented in a comparative way that shows the learning styles and certain behavioural characteristics.

3. 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. A FCM representation is as simple as an oriented and weighted compact graph. For example the simple FCM depicted in figure 2 consists of seven nodes which represent seven concepts. Concepts represent key factors and characteristics of the system and stand for its inputs, outputs, variables, states, events, actions goals and trends. Let us consider a system of N nodes. Each concept C_i (I=1, 2,…N) is represented by a numeric value $V(C_i)$ which indicates the quantitative measure of the concept's presence in the systems model. Each two distinct nodes are joined by one, at the most, weighted arc. The arcs represent the causal relationships between adjoint concepts. The causality degree from concept c_i to concept c_j is expressed by the value of the corresponding weight w_{ij}. Experts describe this degree by using linguistic variables to express the weights. Weights vary from -1 to 1.

There are three types of causal relationships expressing the type of influence among the concepts, as represented by the weights $w_{i,j}$. Weights can be positive, negative or zero. Positive weight means the increasing influence a concept has to its adjacent concept of the graph. On the other hand, negative weight means that as concept C_i increases, concept C_j decreases on the $w_{i,j}$ ratio. In case of absence of relation between C_i and C_j, the weight $w_{i,j}$ equals zero. FCMs converge either to a fixed point, or limit cycle or a strange attractor (Dickerson et al.,1997). In case the FCM is called to support decision making process, as the recognition of L.S., it is expected that FCM will result on a closed interval. The procedure starts assigning a value to each concept. The values of the concepts changed in the sequence as they are influenced by of the adjacent concepts and their corresponding weights, according to equation 1. $V^{n+1}(C_i) = f(k_1 \sum_{\substack{j=1 \\ i \neq j}}^{k} w_{ji} V^n(C_j) + k_2 V^n(C_i))$ (1)

where $V^{n+1}(C_i)$ is the value of the concept C_i at the discrete time step n+1 , $0 \leq k_1 \leq 1, and\ 0 \leq k_2 \leq 1.$ and f is a predefined threshold function. From now on unipolar sigmoid will be used as f.

The coefficient k_1 defines the concept's dependence on its interconnected

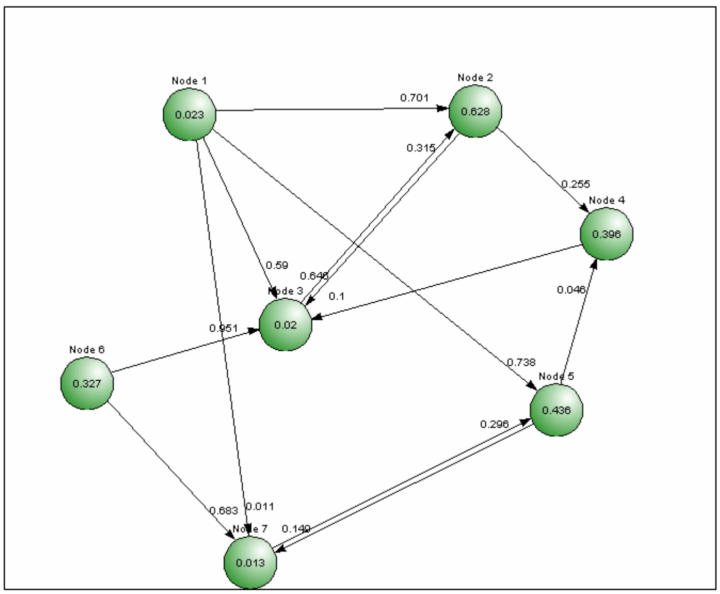


Figure 2

concepts, while the coefficient k_2 represent the proportion of contribution of the previous concept value in the computation of the next 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.

The function f is given by:

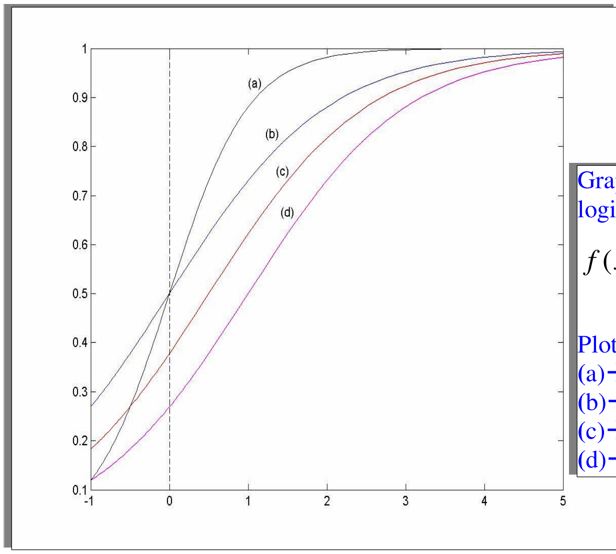
$$f(x) = \frac{1}{1+e^{-\lambda x}} \qquad (2)$$

where λ determines the steepness of the sigmoid with λ>0. Plots of the threshold function for various values of the constant λ are shown in the figure 3. For V(Ci)>0 and after some iterations, these values become greater than 1. Taking a look in plot (b) in figure 3 one can see that values greater than 1 converge towards value 1. Convergence towards 1 is not desirable since this way the output values do not lead to any decision. Increasing function's steepness makes things worse (plot (a) in figure 3). In order to avoid this convergence, we chose λ=1 and translated function's graph to the right. This resulted greater discreteness to the values of output concepts.

4: DESCRIPTION OF L.S. RECOGNITION MODEL

The proposed FCM model appears in figure 4. Each node of the graph represents a concept, which expresses explicitly or implicitly certain characteristics a learner has, or the main L.S.s characteristics according to Kolb (1984) 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. So, an integer of high value indicates the importance of the concept and an integer of low value indicates a concept of minor importance

There are two types of concepts: Learner Characteristics **(LC)** and Learning Activity Factors **(LAF)**. The four central concepts: Concrete Experience (CE), Abstract Conceptualization (AC), Active Experimentation (AE), Reflective Observation (RO), are of the Learner Characteristics type. They are considered to be the outcome of the L.S. Recognition Model. The concepts of the second type, that surround the four central concepts, are the LAFs. These are subjects measured by the system. Concepts of this type are for example: risk taking ability, collaborative learning preference e.t.c. (see table 1). 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 the positive or negative influence that LAFs can have to LCs. Thus weights assigned to these connections indicate the degree of influence. The influence degree can be negative or positive. Negative weight shows that while the value of the concept origin increases, the value of the concept target decreases. the value of the concept origin increases, the value of the concept target decreases.



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 3

The outputs of the FCM are the LCs. This is owed to the fact that it is desirable to maintain "competence" between output concepts. Such competence allows two at the most of the FCs be assigned by significally higher value than the rest. As a matter of fact this is the point of view of Kolb's model (Kolb, 1984).

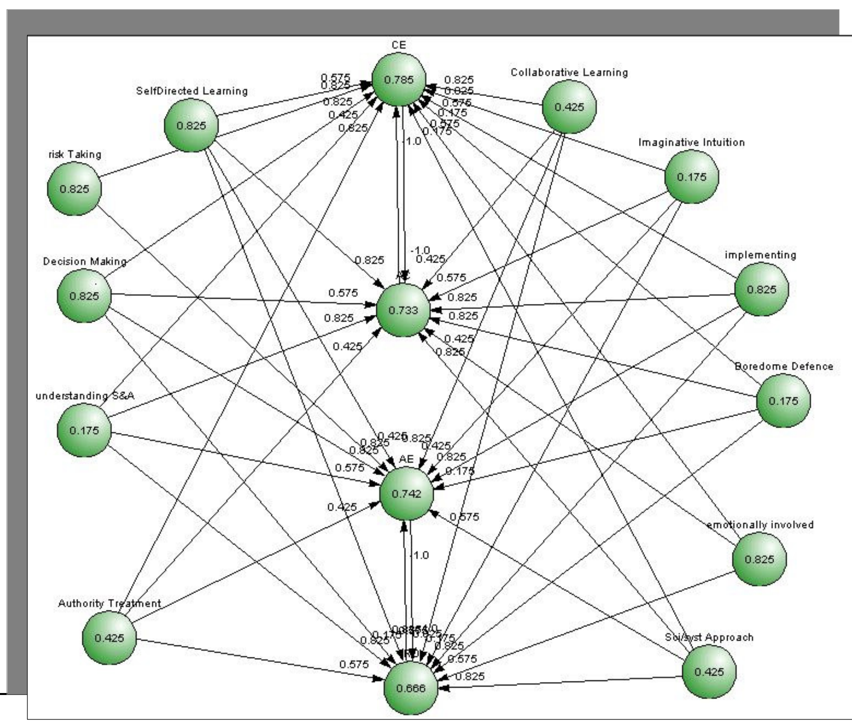


Figure 4.

According to this point of view Concrete Experience and Abstract Conceptualization are complementary concepts. This is also the case for the characteristics Active Experimentation and Reflective Observation. The desirable "competence" of the output concepts it is not valid for the L.S.s, as for example one can have both Diverger's and Assimilator's characteristics. So, we organize the central nodes in pairs: CE-AC and AE-RO, and we consider of interconnections among the members of the same pair at the lowest negative weight, which is –1. Connections between nodes of the two different pairs do not exist.

In order to formulate the algorithm we introduce the following notations:

1. Θ the set of concepts, $C_i \in \Theta$, where $\Theta=\{LAF\}\cup\{LC\}$;
2. **A**, a linguistic term of a linguistic variable (e.g. almost absolute cause) ;
3. X is a measurable numerical assignment compact interval and $X\in(-\infty,\infty)$;
4. $\mathbf{V}\in X$, a linguistic variable assigned to $C_i\in\Theta$;
5. $\mu_A(C_i)$, the membership value representing the degree of membership of θ_i to the set of elements determined by the 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 the case. As cognitive psychology experts describe mostly qualitative behavior by using linguistic variables, it is necessary to introduce a transforming algorithm to map the values of such linguistic variables into membership functions. Watanabe's (Watanabe,1979) 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 transformation which appears in Georopoulos et. Al. (2003). According to the suggested scheme, each fuzzy set corresponds to a membership function shown in the figure 5, where fuzzy sets describe the degree of causality corresponding to membership functions $\mu_A(C_i)$, A={w, o, s, vs}.

The proposed fuzzy sets and their corresponding membership functions are:

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

Domains of 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 (represented by the term $k_2V^n(C_i)$ in equation 1) and relationships between

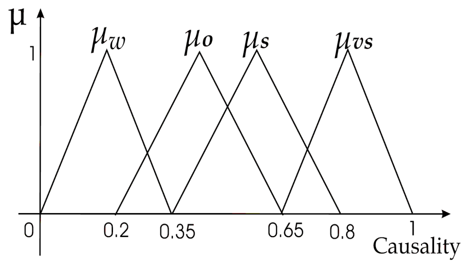


Figure 5

concepts (represented by the sum $k_1 \sum_{i \neq j}^{N} V(C_j)$ in equation 1). 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.

In table 1, appear the linguistic descriptions about the causality between LAFs and Kolb's L.S.s These linguistic descriptions have to be transformed to causality degrees towards LCs. Using the introduced membership functions we defuzzify the fuzzy degrees of LAF causalities towards L.S.s. This procedure relults to matrix W_1:

$$W_1 = \begin{bmatrix} 0.175 & 0.575 & 0.825 & 0.175 \\ 0.825 & 0.175 & 0.425 & 0.575 \\ 0.175 & 0.575 & 0.425 & 0.825 \\ 0 & 0 & 0.175 & 0.825 \\ 0 & 0.825 & 0.575 & 0.175 \\ 0.175 & 0.425 & 0.825 & 0.575 \\ 0.175 & 0.575 & 0.175 & 0.825 \\ 0.575 & 0.425 & 0.175 & 0.825 \\ 0.575 & 0.425 & 0.825 & 0.175 \\ 0.575 & 0 & 0 & 0.425 \\ 0 & 0 & 0.825 & 0 \end{bmatrix}$$

The matrix of relations between LCs and LSs is W_2.

$$W_2 = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

Elements of matrix W are the values which correspond to connections between LAFs and LCs concepts. The matrix W is constructed after the min-max synthesis of matrices W_1 and W_2. The values of the first four right columns of matrix W, correspond to weighted connections from all concepts towards the AE, RO, AC, CE concepts respectively. Also weight values –1 stands for competition between the output concepts. Diagonal elements are equal to 0.5 (see section 2). The rest of the elements are set to be 0, as it has been pre-supposed that there are no relations between LAFs. The question of taking into consideration experts opinions about relations among LAFs remains an open problem.

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

5. THE ALGORITHM WITH AN APPLICATION

The algorithm 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 while the learner responded to certain tests. Data have been stored as linguistic values A_i , and have been turned into 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 $w_{j,i}=0$ 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 $\underset{0\prec I\prec k}{MAX}\left|V^{n+1}(C_i)-V^n(C_i)\right|\prec\varepsilon,(\varepsilon\succ 0)$ then stop and store as result the learner's profile of the highest value $V^{n+1}(C_i)$

The above model is capable to identify student's learning preferences and to diagnose student's L.S. 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 hand when the Decision Making concept affects Active Experimentation with weight 0.875 it means that when one has Decision making strength it is a very strong cause/reason that he prefers Active Experimentation in Learning Cycle. Therefore, it is crucial that these weights are properly selected according to the experts' knowledge.

For the implementation of the proposed algorithm and the evaluation of the hypothetical test case, we used the "FCM-Analyst" which has been developed by M. Margaritis and it is discussed in Margaritis et al (2002).

The hypothetical case, which is used as described in table 2

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 2

Using the defuzzification method CoA (Dubois, 1980), and reserve zeroes for 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]

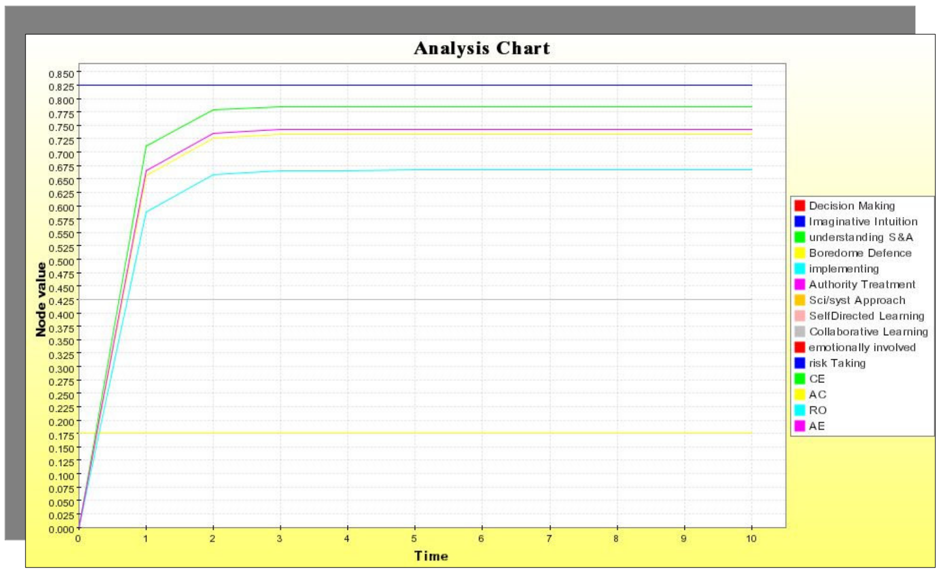


Figure 6

In figure 6 values of output nodes LCs appear . The values of LAF as one can see , remain stable . This is because in the initial model there are no interconnections LAFs. Finally the dominant values in our test case are : Concrete Experience and Active Experimentation . This results to the Accommodator L.S..

6. CONCLUSIONS AND FUTURE DIRECTIONS.

The above method has been developed to provide a fully computerized procedure able to diagnose the learner's profile. An Adaptive Educational Hypermedia platform, which supports asynchronous e-learning, will take fully advantage of the sugested algorithm, in order to "see" the learner and to tailor the learning material to his particular 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 (1991). The *Reverse rating* method takes a different approach when asking an expert to answer the following question ``Identify $\theta(V(\theta))$ 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 L.S. 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 proposed for FCM by Papageorgiou et al (2003) improves the efficiency and robustness of the system.

7. Acknowledgments

The development of this article has benefited by the kind offer of M. Margaritis and his co-authors in Margaritis et al., (2002) who generously offered the source code of FCM Analyst. Without this gentle offer our work presented here would be more time consuming.
The author also wishes to thank Institute of Cultural and Educational Technology for its support in this project.

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