INTERNATIONAL JOURNAL OF ELECTRONICS; MECHANICAL and MECHATRONICS ENGINEERING Vol.4 Num 1 pp.(701 - 712)

Simulation of fuzzy adaptation of cognitive/learning styles to user navigation/presentation preferences by using MATLAB

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Abstract. *The purpose of this paper is to present a simulation methodology of a fuzzy adaptive interface in an environment of imperfect, multimodal, complex nonlinear hyper information space. A fuzzy adaptation of user's information navigation and presentation preferences to cognitive/learning styles is simulated by using MATLAB. To this end, fuzzy if-then rules in natural language expressions are utilized. The important implications of this approach is that uncertain and vague information is handled and the design of human computer interaction system is facilitated with high level intelligence capability*

Keywords: adaptive interface, fuzzy logic, cognitive/learning styles, navigation/presentation preferences, linguistic modelling.

1. INTRODUCTION

The power of hypermedia of web technology is in its capability to support non-linear navigation in hyperspace and multimedia presentation of the web content. Web Based Hypermedia adaptive Systems (WAHS) offers an alternative to the traditional "one-size-fits-all" hypermedia and Web systems by adapting to the goals, interests, and knowledge of individual users represented in the individual user models [1]. WAHS aims to minimize cognitive overload faced by users, to alleviate the disorientation problem of users, to enhance the usability and the utility of the system by applying intelligent information adaptation (personalization) techniques for user/system interactions that take into account individual differences of users [2]. Adaptation involves two key activities: (i) a user modelling activity to develop a user model and (ii) an adaptation activity that leverages a 'rich' user-model to personalize the information content, the information presentation style and the navigation path of the system to the user [3]. One of the ways to enhance the efficiency of WAHS is to build accurate user models. It can be achieved by taking into account human factors (or individual differences) that have significant effects on human computer interaction and on the learning process [4]. Research into individual differences suggests cognitive/learning styles have significant effects on student learning in hypermedia systems [5].

The purpose of this paper is to present a simulation methodology of an adaptive interface in an environment of imperfect, vague, multimodal, complex nonlinear hyper information space. To this end, a fuzzy adaptation strategy to cognitive/learning styles is simulated by using MATLAB. Fuzzy if-then rules are utilized to adaptively map cognitive/learning styles of users to their information navigation and presentation preferences through natural language expressions. The important implications of this approach is that uncertain and vague information is handled and the design of human computer interaction system is facilitated with high level intelligence capability

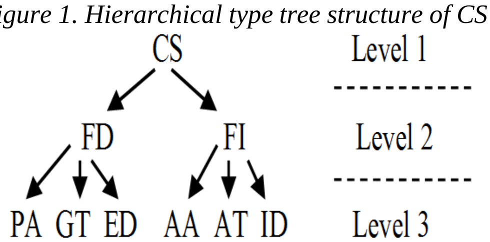
The paper is organized as follows. The description of cognitive and learning styles is given in Section 2. Navigation and presentation preferences of users are presented in Section 3. The adaptation process, examples of fuzzy granulation of input and output linguistic variables, and an inference mechanism of adaptation are presented in Section 4. Section 5 is devoted to description of a simulation example to illustrate the proposed approach. Finally, in Section 6 we present conclusions and future work.

2. COGNITIVE/LEARNING STYLES

The nature of cognitive styles (CL) is studied by cognitive psychology. CS deal with the form of cognitive activity (thinking, perceiving, remembering), not its content. Learning styles (LS), on the other hand, is seen as a broader construct, which includes cognitive along with affective and physiological styles. A key factor in determining cognitive styles with respect to learning is the field dependency factor. Field dependency refers to an individual's ability to perceive a local field as discrete form of its surrounding field. It is a single bi-polar dimension ranging from Field dependent (FD) individuals at one extreme to Field independent (FI) individuals at the other [6]. Characteristics of users in respect to CS are described in [5] and can be modelled by a hierarchy type tree structure given in Figure 1.

However, cognitive/learning styles (CLS) are disputable concepts that are not fully accepted by the whole community.

Figure 1. Hierarchical type tree structure of CS



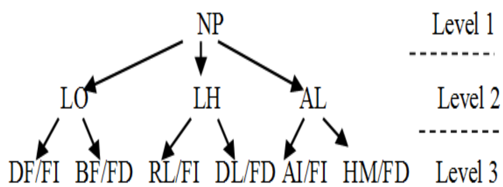
where FD – field dependent, PA – passive approach, GT – global tendency, ED – externally directed, FI – field independent, AA – active approach, AT – analytical tendency, ID – internally directed.

In most of the systems CLS is assessed through psychological questionnaires and psychometric tests or in the form of self-report. This kind of measures of CLS is based on subjective judgment users make about themselves. For that reason, CLS characteristics of users are intrinsically imprecise. Fuzzy logic and granulation methods are suggested in Section 4 to handle this imprecision.

1. NAVIGATION AND PRESENTATION PREFERENCES

Navigation preferences of users in respect to cognitive styles characteristics presented in [5] can be shown in the form:

Figure 2. Navigation preferences



where NP – navigation preference, LO – link ordering, LH – link hiding, AL – adaptive layout, DF – depth firth path, FI – field independent, BF – breadth-firth path, FD – field dependent, RL – rich links, DL – disabled links, AI – alphabetical index, HM – hierarchical map.

Presentation preferences are modes of delivering the content using a variety of multimedia techniques such as text, graphics, image, audio, video and etc.

1. Fuzzy adaptation cognitive/learning styles to navigation/presentation preferences

1.1.Fuzzy multilevel granulation of input linguistic variables

Let us introduce linguistic variables [7] CS, FD, PA, GT, ED, FI, AA, AT, ID, associated with the concepts CS, FD, PA, GT, ED, FI, AA, AT, ID, respectively, which are described in Figure 3. Initial membership functions of fuzzy sets of these linguistic variables are supposed to be in the trapezoidal form. The first level of granulation applied to the root CS of the tree yields [8]:

*Figure 3. Crisp sets for linguistic variable **CS***

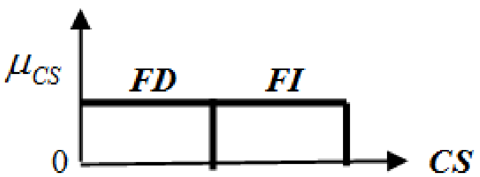
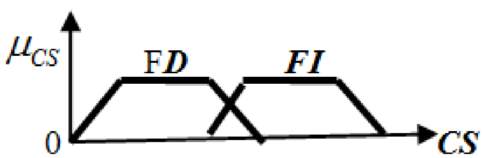


*Figure 4. Granulation of **CS***



The second level of granulation is applied to the nodes of the tree that are in the second level, for example, for ***FD*** we have:

*Figure 5. Crisp sets for **FD***

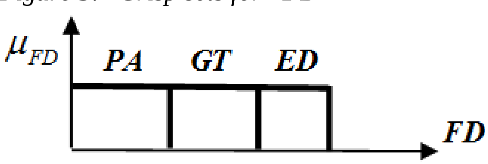
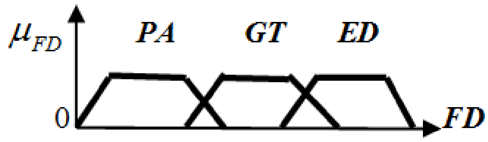
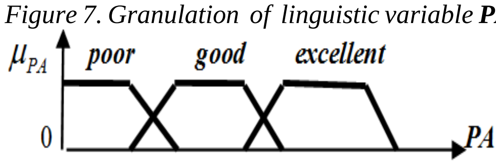


*Figure 6. Granulation of **FD***



Finally, we granulate the nodes from the third level through linguistic qualifiers poor, good, and excellent as follows:

*Figure 7. Granulation of linguistic variable **PA***



Next, we can use hedges for the next granularity level. Hedges are linguistic modifiers operated on membership functions. They are expressed by adjectives and/or adverbs such as very, somewhat, slightly, more or less, quite, extremely, fairly, below and etc. For example, hedge very applied to qualifier poor modifies its membership function as follows: $\mu_{verypoor} = (\mu_{poor})^2$

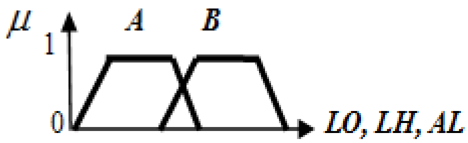
The visual/verbal dimension of LS modelled by linguistic variables VI/VB, respectively, can also be granulated in the similar way.

2.1.Fuzzy multilevel granulation of output linguistic variables

Based on Figure 4 we introduce output linguistic variables NP, LO, LH, AL, DF, BF, RL, DL, AI, and HM associated with the concepts NP, LO, LH, AL, DF, BF, RL, DL, AI, and HM, respectively. Applying multi level granulation method, similar to the one described above, we can form output membership functions for output linguistic variables LO, LH, and AL in the form shown in Figure 8, where for the linguistic variable LO - A stands for DF, B stands for BF; for the linguistic variable

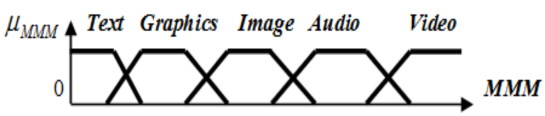
LH - A stands for RL, B stands for DL; and finally, for the linguistic variable AL - A stands for AI, B stands for HM.

*Figure 8. Granulation of linguistic variables **LO**, **LH,** and **AL** .*



Finally, we create one more output linguistic variable MMM associated with the concept presentation preferences and relate it with the input linguistic variables VI/VB. The multimedia mode of presentation includes text, image, audio, video, graphics, games, animation and any combination of these elements. One granulation option of linguistic variable MMM can be shown as follows:

*Figure 9.. Granulation of the linguistic variable **MMM***



Again, we can use linguistic qualifiers and modifiers, as we did with input linguistic variables, for the next granulation levels. The linguistic qualifiers low, medium, high are used for output linguistic variables and shown in Table 1.

1.1.Fuzzy inference

Fuzzy inference is a method that interprets the values in the input vector and, based on some set of if -then rules, assigns values to the output vector.The fuzzy predicates are associated with linguistic terms, and the proposed model is, in fact, a qualitative description of the system using rules like: IF input linguistic variable CLS is poor THEN output linguistic variable NPP is high. Such models are often called linguistic models [9].

More formally, let CLS and NPP are linguistic variables defined by fuzzy sets on the universes of discourse that contain granular values described in sections 4.1 and 4.2. Denote membership functions of linguistic variables CLS and NPP by μ_{CLS} and μ_{NPP}, respectively. Then the adaptation process can be characterized by a mapping $f : \mu_{CLS} \to \mu_{NPP}$. Granulation of function f is a fuzzy graph that is described as a collection of if-then rules. A fuzzy if-then rule can be defined as a binary fuzzy relation R considered as a fuzzy set with membership function: $\mu_R = f(\mu_{CLS}, \mu_{NPP})$. Using the compositional rule of inference, we can formulate the inference procedure in fuzzy reasoning in the form: $\text{NPP} = \text{CLS} \circ R$, where the sign $\circ$ denotes a fuzzy composition operator, consisting of a t-norm operator, followed by a t-conorm operator. The FIS for the adaptation of CLS to NPP is shown in Table 1. Some examples of rules at a variety of granulation level are presented below:

Level 1: IF CLS is FD, THEN NPP is DL; IF CLS is AA , THEN NPP is DF; IF CLS is poor, THEN NPP is high; IF CLS is very poor, THEN NPP is extremely high.

Level 2: IF FD is good, THEN DL is medium; IF FI is quite good, THEN AI is somewhat medium; IF VI is excellent, THEN MMM is video; IF VI is good and VB is good, THEN MMM is video and audio.

Level 3: IF PA is good and AA is good, THEN DF is medium and BF is medium; IF AA is very good, THEN AI is quite high.

Table1. FIS for adaptation cognitive/learning styles to navigation/presentation preferences with a variety of granulation levels

Input linguistic variables – Granular levels 1	2	3	terms	hedges	rules	hedges	terms	Output linguistic variables – Granular levels 3	2	1
CLS	*VI*		*poor*	*Very*	r1	*very*	*low*	*text*	*MMM*	*NPP*
				slightly	r2	*slightly*		*graphics*		
						somewhat		*image*		
				somewhat	-			*audio*		
	VB							*video*		
	FD	*PA*			-	*more or less*		*DF*	*LO*	
		GT	*good*				*medium*	*BF*		
		ED		*more or less*	-			*RL*		
	FI	*AA*						*DL*	*LH*	
		AT			-	*quite*		*AI*		
		ID		*quite*	rn			*HM*	*AL*	
			excellent	*extremely*		*extremely*	*high*			

5. Simulation example

To illustrate the proposed methodology, we consider constructing fuzzy linguistic models using MATLAB simulation software. Mamdani-type FIS [10] is used, which is well suited to human input, has widespread acceptance and is intuitive. Let us have a case study in the form:

Linguistic variables	Type	Terms	Range
Visual	Input	Poor Good Excellent	0 – 10
Verbal	Input		0 – 10
Cognitive style	Input	Poor Good Excellent	0 – 10
Multimodal	Output	FD Mixed FI	0 – 30
Link ordering	Output	Audio Mixed Video Depth-first Mixed Breadth-first	0 – 30

Sample knowledge rule base is:

1. IF (Visual is excellent) OR (Verbal is poor), THEN (Multimodal is video)
2. IF (Visual is good) OR (Verbal is good), THEN (Multimodal is mixed)
3. IF (Visual is poor) OR (Verbal is excellent), THEN (Multimodal is video)
4. IF (Cognitive style is FD), THEN (Link ordering is breadth-firth)
5. IF (Cognitive style is FI), THEN (Link ordering is depth-firth)
6. IF (Cognitive style is mixed), THEN (Link ordering is mixed)

Simulation of this case study in MATLAB generates the fuzzy linguistic model with the following characteristics. The FIS structure information obtained by getfis ( ) function from command line is as follows:

```
>> getfis (a)

   Name      = multimodal
 Type      = mamdani
   NumInputs = 3
   InLabels =
      Visual
      Verbal
      Cognitive style
   NumOutputs = 2
   OutLabels =
      Multimodal
      Link Ordering
   NumRules = 6
   AndMethod = min
   OrMethod = max
   ImpMethod = min
   AggMethod = max
   DefuzzMethod = centroid
```

The following screenshots are FIS information structure, membership functions of input/output linguistic variables, behaviour of the model by rule viewer, and interaction of variables of visual and verbal for surface view of variable of multimodal.

Figure 10. FIS structure information diagram

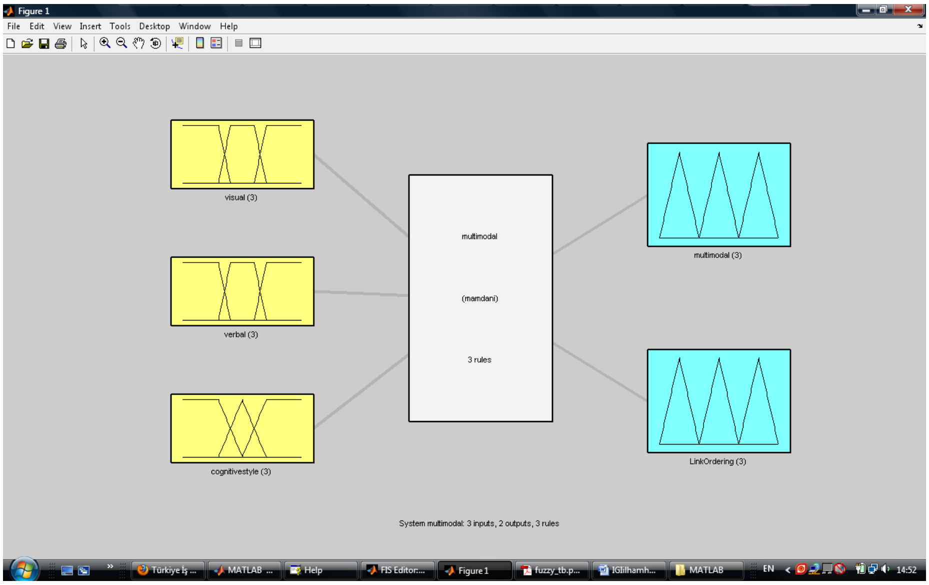


Figure 11. Membership function for linguistic variable visual

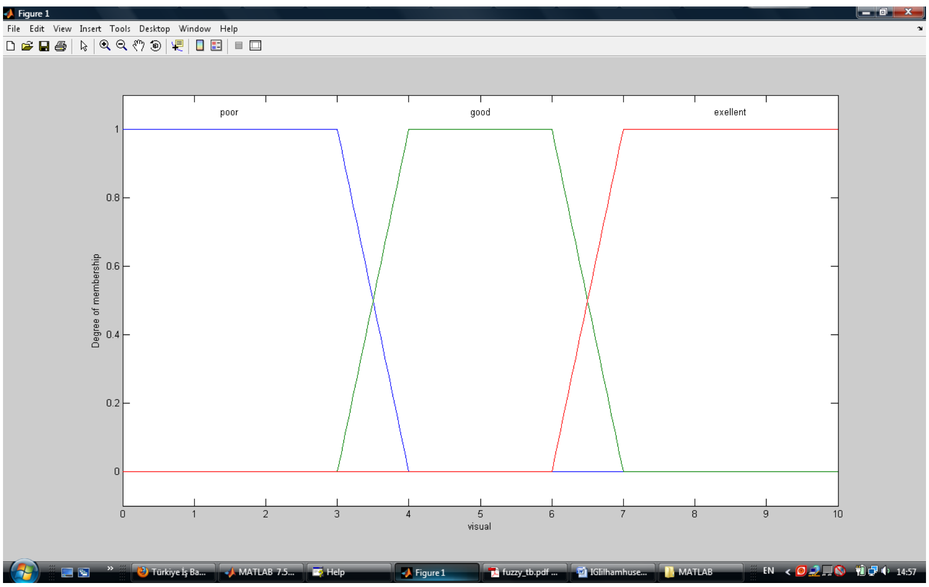


Figure 12. Membership function for linguistic variable verbal

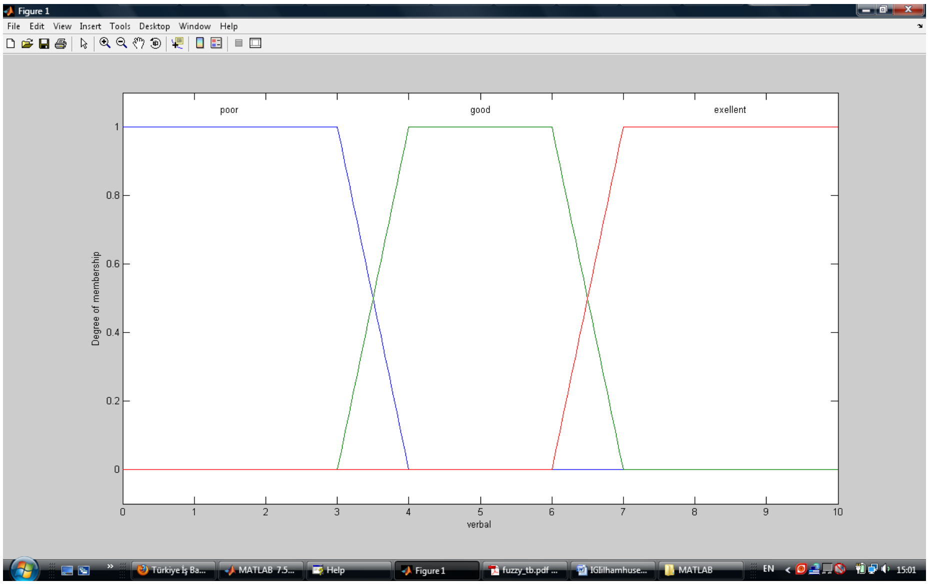


Figure 13. Membership function for linguistic variable cognitive style

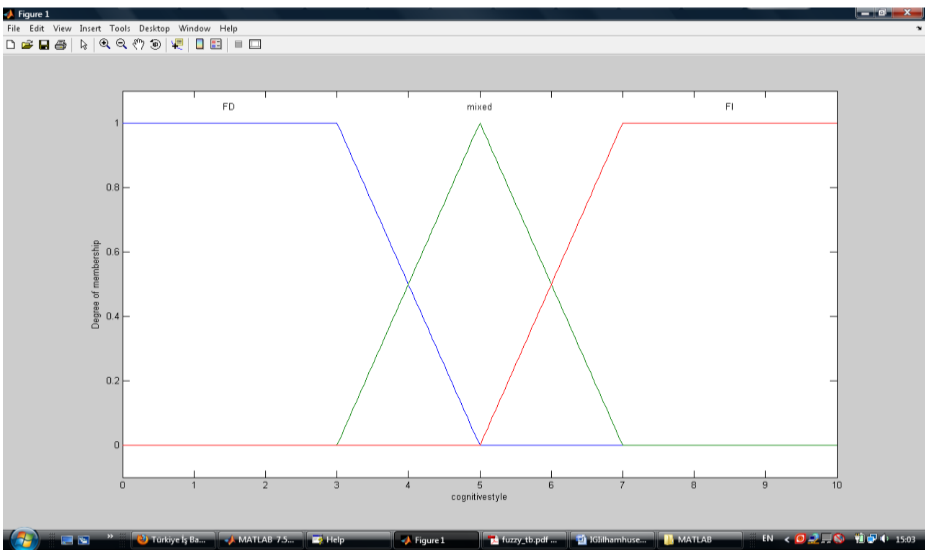


Figure 14. Membership function for linguistic variable multimodal

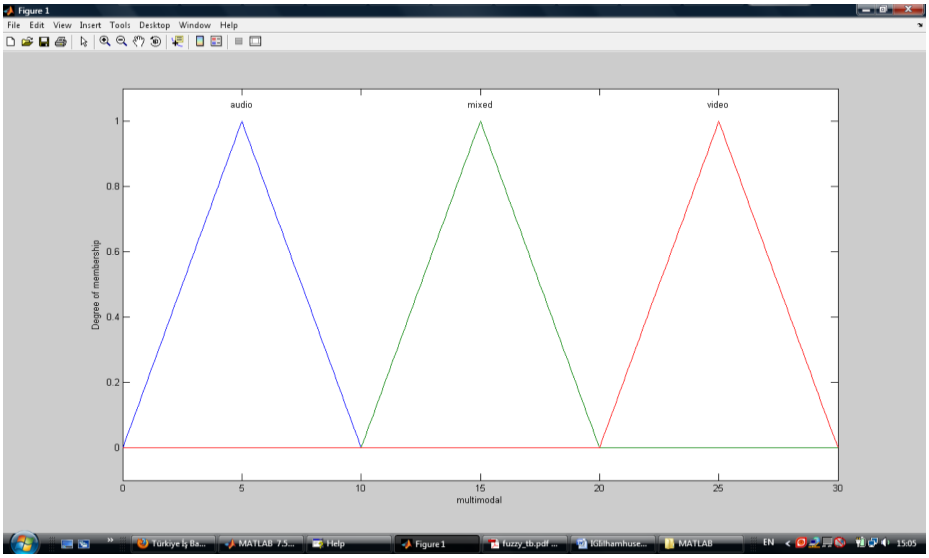


Figure 15. Membership function for linguistic variable link ordering

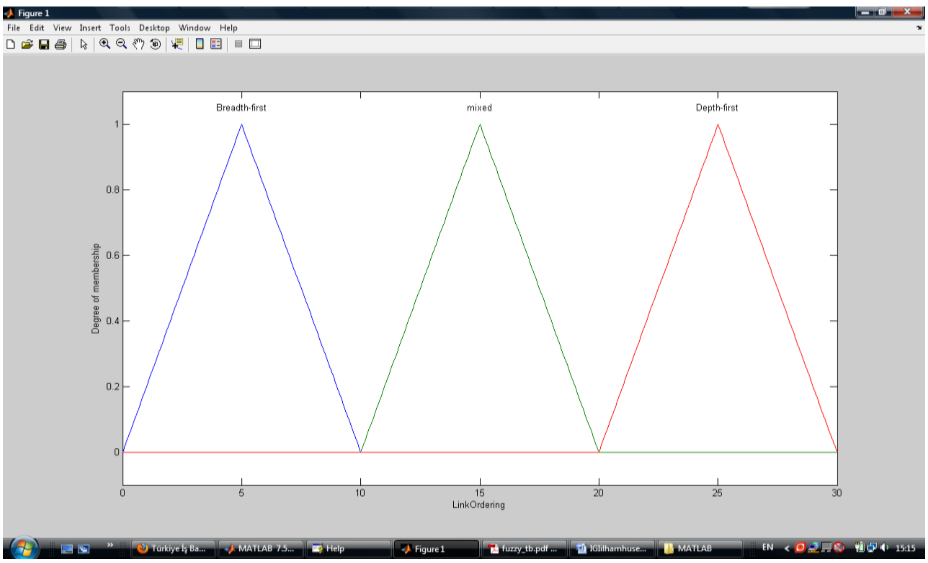


Figure 16. Behaviour of model with rule viewer

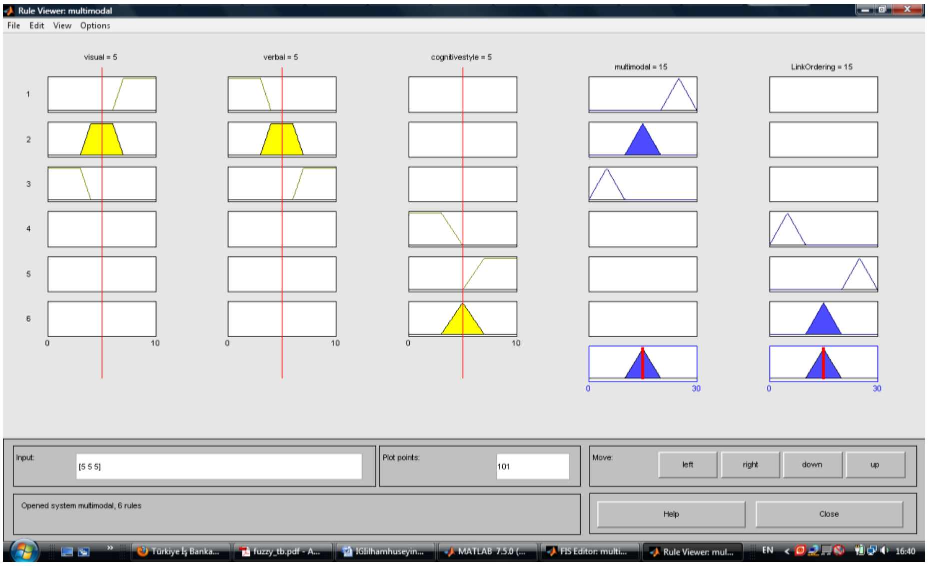
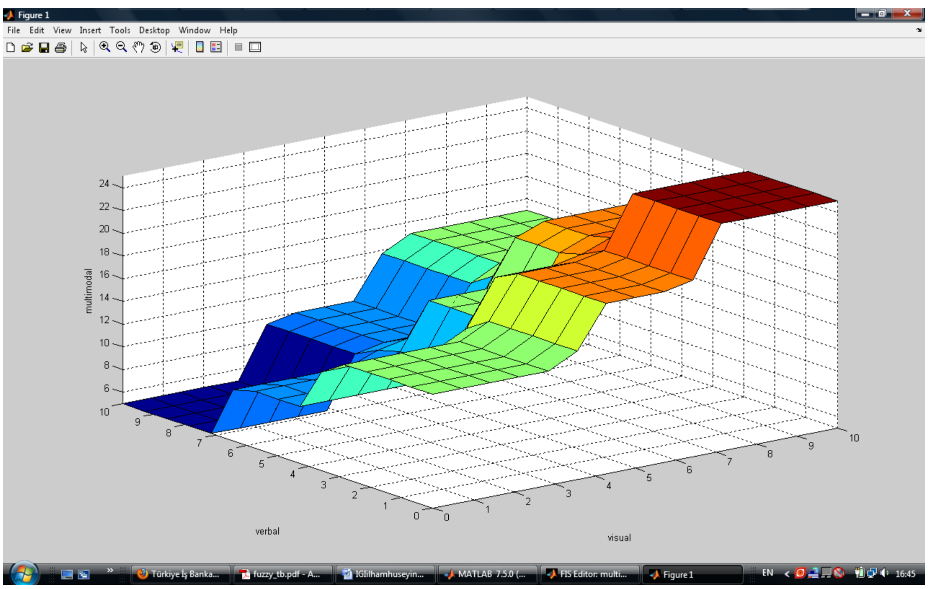


Figure 17. Interaction of visual and verbal for surface view multimodal



More complex models may incorporate a higher level of granularities, and yet the nature of the methodology does not change.

7. Results and conclusion

The Fuzzy Logic Toolbox in MATLAB is used to compute fuzzy adaptation of user's navigation/ presentation preferences to cognitive/learning styles The aim is to observe the behaviour of the proposed model and tune its parameters such as: input and output linguistic terms and their membership function shapes; relevance and weights of rules; the type of inference mechanism – Mamdani type max-min composition or Takagi-Sugeno type linear bounded-sum [11]; the type of defuzzification (centroid, middle of maximum, largest of maximum, and smallest of minimum). The Mamdani type FIS expects the membership functions of output linguistic variables to be fuzzy sets and requires the defuzzification step while Takagi-Sugeno type FIS expects output membership functions to be singletons. In this example, the Mamdani type FIS is choosen. As a future work, a prototype of the model shall be developed to validate the proposed linguistic model within the efficiency of user/system interactions in terms of the usability and the utility of the system.

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SIMULATION OF FUZZY ADAPTATION OF COGNITIVE/LEARNING STYLES TO USER NAVIGATION/PRESENTATION PREFERENCES BY USING MATLAB

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