Fuzzy Logic Approach for Adaptive Systems Design

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Abstract. Adaptive system is a field in rapid development. Adaptation is an effective solution for reducing complexity when searching information. This article presents how to personalize user interface (UI) using fuzzy logic. Our approach is based on the definition of relations for selection of appropriate and not appropriate of UI components. These relations are based the degree of certainty about the meaning coincidence of metadata elements and user' preferences. The proposed approach has been validated by applying it in e-learning field.

Keywords: Adaptation, Adaptive Systems, Fuzzy logic, Evaluation, User Interface (UI).

1 Introduction

In past few years, there has been a widespread emergence of adaptive systems that go beyond the capabilities of traditional interactive systems. In fact, adaptation deals with the ability of a system to collect user information, to analyse this information, and to adapt the system to users' preferences [1]. In general, we can say that adaptation deals with the capacity of personalization of a user interface (UI) considering some information related to the context (i.e., platform, user and environment characteristics). The adaptation can take into account several aspects (e.g., navigation, structure, functionalities) and it can be performed basically on the UI containers presentation; i.e., layout, colors, sizes, and content; i.e., data, information [2] [3] [4]. Such systems can be used in many different domains; for example: e-learning [5], logistics and transport [6] are domains in which adaptation principles offer new perspectives. In fact, several research studies have been carried out about user modelling, design methods and tools for UI generation. However, the evaluation of such systems is neglected in the HCI (Human-Computer Interaction) literatures. To fill up this lack, it is necessary to envisage new evaluation methods taking into account the evaluation function for assessing the quality of adaptive system. This paper is structured as follows. Section II presents an approach for recommending UI adaptation based on the

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users' preferences. III concludes the paper, with illustrations concerning learning resources and futures perspectives.

2 User-Adaptive Systems

Adaptive system is a field in rapid development. Today, these systems are indispensable to those who want to retrieve appropriate information with less effort at any time and any where. Adaptation is an effective solution for reducing complexity when searching information. In this way, the user feels like the system was developed for him/her. Two categories of adaptation are often distinguished in the literature: adaptability and adaptivity.For [7] "Adaptability is used to refer to self-adaptation that is based on knowledge (regarding the user, the interaction environment, the context of use, etc.) that is available to (or is collected by) the system prior to the commencement of interaction, and leads to adaptations which also precede the commencement of interaction".

But, "Adaptivity refers to self-adaptation that is based on knowledge which is collected and / or maintained by the system during interaction sessions (either directly from the user, or through monitoring / inferencing techniques) and which leads to adaptations that take place while the user is interacting with the system". [8] defines adaptation as the process of modifying systems to work adequately in a given context, which means the system suits perfectly user expectation in a given context. In general, we can say that adaptation deals with the capacity of adaptation of a system considering some information related to the context of use (P: platform, U: user and E: environment). In general, we can say that adaptation deals with the capacity of adaptation of a system considering some information related to the context of use (P: platform, U: user and E: environment).

3 Approach Overview

For us, UI is depicted as a set of components or interactive objects. So, the personnalization of system requires adaptation of UI components presentation to a set user' preferences. Our approach is based on the definition of relations for selection of appropriate and not appropriate of UI components. These relations are based on fuzzy logic that represent the degree of certainty about the meaning coincidence of metadata elements and user' preferences. To understand better our contribution, we will start by giving the definitions of important concepts used in our proposed approach such as fuzzy rule-based systems and metadata for UI description.

3.1 Fuzzy Rule-Based Systems

Fuzzy logic may be viewed as an extension to classical logic systems for dealing with the problem of knowledge representation in an environement of uncertainly and impression. Fuzzy logic as it name suggests, is a form of logic whose underlying modes of reasoning are approximate rather than exact. Its importance arises from the fact that most modes of human reasoning are approximate reasoning [9]. Knowledge representation is enhanced with the use of linguistic variables and their linguistic values that are defined by context-dependent fuzzy sets whose meanings are specified by gradual membership functions. In our work, Fuzzy inference systems are developed for adaptive system using Mamdani-type.

3.2 Metadata for UI Description

Our approach is based on metadata which is commonly used for the reuse of UI components. This metadata is a set of data elements useful for the description of UI components. A metadata element has a name which might not be unique. For that reason a data element has a unique identifier. For the description of a UI components, the data element has to be associated with a specific value which characterizes the UI component. Formally, a metadata (useful to annotate UI components) is described as 5-tuple M= (I, N, IN, V, D) where:

- I: is a set of data elements Identifiers.
- N: is a set of data element Names.
- IN (data elements): is a relation from I to N.
- V: is a set of data element Values.
- D (Descriptive data element): is a relation from IN to V. D defines the value associated to each metadata element for describing UI components.

A user interface is a set of services represented by UI components. We assume that a service could be represented by more than one UI components. We assume also that each UI components is annotated with metadata. Formally, an interface is described as a 4-tuple C = (S, Ω, R, Ψ) where:

- S: is a set of services proposed by UI components.
- Ω : is a finite set of UI components, representing the services of UI.
- R : is a relation from S to Ω. R determines the UI components representing a service.
- Ψ : is a relation from Ω to $\mathcal{P}$ (D), $\mathcal{P}$ denotes the set of partitions. Ψ defines the set of metadata describing each UI component.

3.3 Semantic Relations between Values of Data Elements and Users' Preferences

Semantic relations represents the coincidence degree between descriptive data elements and users' preferences. Formally, SRVDL is described as 5-tuple R= (L, A, P, M, C) where:

- L: is a set of level values in natural language describing possible user' preferences in relation to adaptation attributs. For example novice and expert are possible values for experience attribut.
- A (adaptation attributs): is a set of dimensions which can be used for UI adaptation. Each adaptation attribut is related to a set of level values that describe possible user' preferences with respect to the adaptation attributs.
- P (users' preferences): is a relation from L to A. P defines the linguistic terms that are related to a particular adaptation attributs.
- M (Metadata element associated with users' preferences) is a relation from P(D) to P, where P denotes the set of partition.

- C (Coincidence Degree of Metadata elements with users' preferences) is a relation from M to [0..1]. C specifies the coincidence degree of metadata elements and users' preferences.

3.4 The Proposed Approach

The proposed method consists in recommending UI adaptation based on the users' preferences. By exploiting principles proposed by the inference engine of Mamdani fuzzy rule-based system, the principle of this proposed method will be based on fuzzy logic that represent the degree of certainty about the meaning coincidence of metadata elements and user' preferences. Our method has three phases (Fig. 1.): (1) Fuzzification interface. (2) An inference system. (3) A defuzzification interface. The proposed system use a rule base (RB) which stores the available knowledge about the problem in the form of fuzzy. A general model of a fuzzy inference system is shown in Fig. 1.

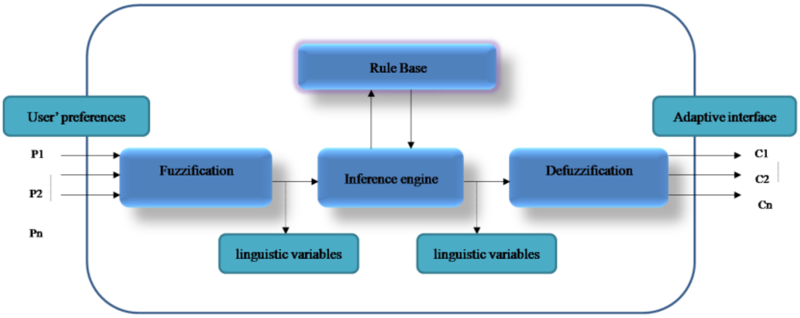

Fig. 1. A general model of a fuzzy inference system

- Fuzzification Interface: the fuzzifier maps input numbers (user' preferences) into corresponding fuzzy memberships. This is required in order to activate rules that are in terms of linguistic variables. A combination of all the input values defines a user profil. The fuzzifier takes input values and determines the degree to which they belong to each of the fuzzy sets via membership functions. The linguistic variable which represents the user' preference is described as a triplet T = (p, T(p), Up) where:

- p: is the name of preference or adaptation attribut for example level of knowledge
- $T(p) = \{E_1, E_2, ..., E_n\}$: is a set of values in natural language describing possible user' preferences levels for example {low, medium, high}.
- U_p: universe of discourse of p.

This phase is composed of three steps: (1) Determination of discourse universe for each user' preference, (2) Definition of fuzzy sets. (3) Definition of fuzzy membership functions.

- An Inference System: the inference engine defines mapping from input fuzzy sets into output fuzzy sets according to the information stored in the RB. Once the inputs are fuzzified, the corresponding input fuzzy sets are passed to the inference engine that processes current inputs using the rules retrieved from the rule base.

Each rule is in IF-THEN form:
IF X1 is A1 and ….and Xn is An THEN Y is B

With Xi and Y being imput and output linguistic variables, respectively and with Ai and B being linguistic labels with fuzzy sets associated defining their meaning.

- A Defuzzification Interface: the defuzzifier maps output fuzzy sets obtained from the inference process into a crisp action that constitutes the global output (adaptive interface). There are a number of methods of doing this, and the most common one among them is the centroid or centre of gravity method. The centre of gravity is simply the weighted average of the output membership function. The result is calculated using the formula:

$$\bar{X}(centroid) = \frac{\int_b^a x\mu(x)dx}{\int_b^a \mu(x)dx}$$

Where [a, b] is the interval of the aggregated membership function.

-Adapted Degree of UI Components to Users' Preferences. The idea is to select UI components to user' preferences. So, we define a relation for determining the degree of UI component appropriateness to a user' preferences and also a relation for determining the degree of not appropriateness ones to a users' preferences basing on the metadata (m). These relations are defined as follows:

- AdaptedDegree (Adapted degree of UI components (co) to users' preferences (p))
  AdaptedDegree : $P \times \Omega \rightarrow [0..1]$
  AdaptedDegree (p, co) = Max {C (m, p) / m : $\mathcal{P}$(D) and (co, m) $\in \Psi$}.
- NotAdaptedDegree (NotAdapted degree of UI components (co) to users' preferences (pr))
  NotAdaptedDegree : $P \times \Omega \rightarrow [0..1]$
  NotAdaptedDegree (p, co)= 1- AdaptedDegree (p, co)

The relations AppDegree and NotAppDegree are used to determine Adapted and Not Adapted UI components.

4 Case Study: Contextual Adaptation of Learning Resources

The use of information technology and communication has greatly improved the way we read and learn. These advances are revolutionizing our way of learning by adapting access to content and services. A large amount of educational resources is produced continuously on the Web. Given the cost of these resources and the expertise to produce them, it is essential to make them easily accessible, adaptable and reusable. The learner hope to have at his/her disposal only some information, just what he/she is directly interested in. The system offers him/her adaptive interface according to his/her preferences. To achieve this aim, we follow the classical phases of fuzzy logic system. The fuzzification interface takes as inputs the user' preferences, and generates as output an adaptive course with a set of personnlized services.

As an illustration, we consider a fuzzy inference system with two inputs and one output. Let the two inputs represent the number of years of education and the number of years of experience, and let the output of the system be difficulty which describes a complexity level of course. Let p_1 is the study level which indicates the number of years of education, $T_{study\ level}$ represent its term set {low, medium, high}, and the universe of discourse be [1-20]). Let p_2 indicate the number of years of experience, the universe of discourse be [0 -30], and the corresponding term set be {*low, medium, high*}. Similarly, c_1 is the difficulty of course which is an output variable characterizing the courses. In order to map input variables p_1 and p_2 to output c_1, it is necessary that we first define the corresponding fuzzy sets. The membership functions for the input and output variables are shown in Fig 2, 3 and 4.

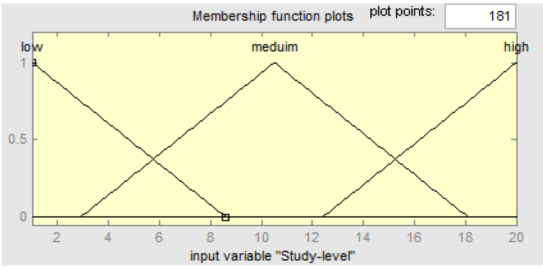

Fig. 2. Fuzzy membership functions for the study level

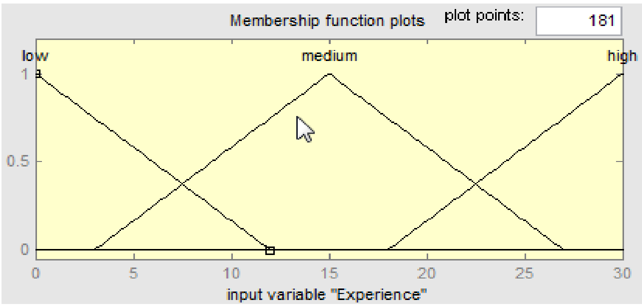

Fig. 3. Fuzzy membership functions for the expeience

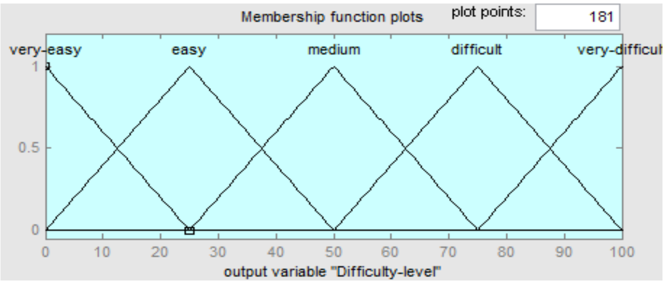

Fig. 4. Fuzzy membership functions for the experience

A fuzzy rule base contains a set of fuzzy rules R (r1, r2,…,rn). For the given example, the rules are stated as

1. If (Experience is low) and (Study-level is low) then (Difficulty-level is very-easy) (1)
2. If (Experience is low) and (Study-level is meduim) then (Difficulty-level is easy) (1)
3. If (Experience is low) and (Study-level is high) then (Difficulty-level is medium) (1)
4. If (Experience is medium) and (Study-level is low) then (Difficulty-level is easy) (1)
5. If (Experience is medium) and (Study-level is meduim) then (Difficulty-level is medium) (1)
6. If (Experience is medium) and (Study-level is high) then (Difficulty-level is difficult) (1)
7. If (Experience is high) and (Study-level is low) then (Difficulty-level is medium) (1)
8. If (Experience is high) and (Study-level is meduim) then (Difficulty-level is difficult) (1)
9. If (Experience is high) and (Study-level is high) then (Difficulty-level is very-difficult) (1)

Fig. 5. Examples of rules

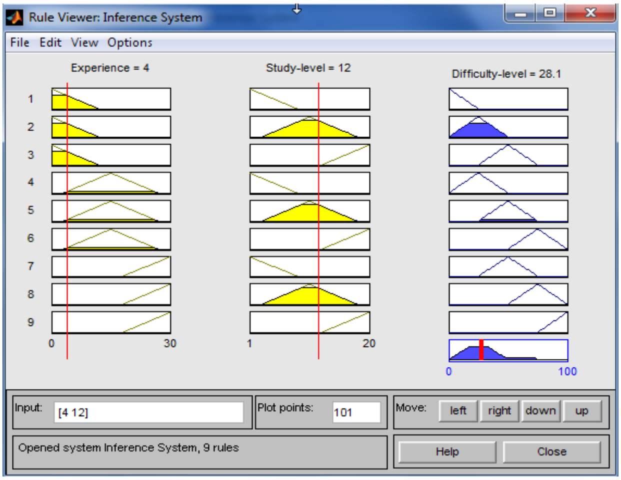

Fig. 6. Operation mode the inference system

The inference engine considered is the classical one employed by Mamdani which considers the minimum t-norm as conjunctive and implication operators and a mode A-FATI defuzzification interface where the aggregation operator G is modeled by the maximum t-conorm, whilst the defuzzification method is the centre of gravity.

The operation of the inference engine is graphically illustrated in Fig. 6 which depicts the membership functions resulting from the inference step.

Finally, the defuzzification interface aggregates the output fuzzy sets by means of the maximum. This process is graphically represented in Fig. 6 (right part).

5 Related Works

Several studies have recently focused on personalized e-learning using different techniques. [10] describes a data mining process based on Moodle Course Management System [11]. (e.g., the number of assignments done by a student, the number of quizzes failed, the number of quizzes passed, the total time spent on assignments, etc.). This approach is based on user activity data. However, this data is not analysed. A different viewpoint on educational data mining or data mining in e-learning is provided by [12], where the following categories are identified: prediction, including classification, regression and density estimation, clustering, relationship mining (including association rule mining, correlation mining, sequential pattern mining and causal data mining), distillation of data for human judgement, and discovery with models. In our approach, we propose an automatic analyse method which is based on the user background (history).

The majority of E-learning systems model the learner as an entity accompanied by a static predefined set of interests without modeling the learning resources. We can cite for example, Smart E-learning environment which is composed of two processes: teacher apprentice for authoring (TAA) and tutor apprentice for delivery (TAD) [13]. In our approach, we propose to define an interface as metadata for UI description that could be used during the adaptation process. In this way, the designer and the evaluator will use shared metadata to facilitate the personalization process.

Automatic learner modeling [14] is differing based on the queries attributes used previously. In automatic learner modeling approach, the learners profile is constructed using a conversion based on keyword mapping. There are different techniques used in learning modeling such as rule based methods, case based reasoning [15], Bayesian networks[16] [17], belief networks and decision trees[18]. To our best knowledge, our proposal is the first work that uses UI metadata to personalize interface using fuzzy logic principle.

Several studies have been carried out for the development of adaptive interface. Some of the most known studies are: TERESA [19], CAMELEON framework [20], SUPPLE [21], DMSL [22] [23]. These systems are based on user task and transformation rules. In our approach, we propose user model, UI metadata and fuzzy rules to personalize interface.

6 Conclusion

In this paper, we presented a rigor and generic approach based on fuzzy logic for the automatic prevision of UI adaptation. Mathematical notation is used for two reasons. First, mathematical notation enhances the rigor/precision of our approach. Second, the high abstract level of mathematical notation is used for defining the approach as a generic solution. The proposed approach exploits semantic relations between data elements and users' preferences to determine adapted UI components appropriate to users' characteristics. Future directions of this research will deal with extending the proposed approach and proposition of metrics for evaluation of adaptation strategies. Since we have tested our approach only in the e-learning context, it would be also interesting to generalize the approach with other fields of application (transport, logistics, etc).

References

1. Kobsa, A.: Personalized hypermedia presentation techniques for improving online customer relationships. The knowledge Engineering Review 16(2), 111–115 (2001)
2. Ledoux T.: Etat de l'art sur l'adaptabilité. Research Report RNTL ARCAD, number Livrable D1.1; Li, Y., Hong, J.I., Landay, J.A.: Design Challenges and Principles for Wizard of Oz Testing of Location-Enhanced Applications. IEEE PervasiveComputing 6, 70–75 (2001)
3. Zimmermann, A., Andreas, L.: LISTEN: a user-adaptive audioaugmented museum guide. In: User Modeling and User-Adapted Interaction, pp. 390–414 (2008)
4. Hervás, R., Bravo, J.: Towards the ubiquitous visualization: Adaptive user-interfaces based on the Semantic Web. Interacting with Computers 23, 40–56 (2011)
5. Essalmi, F., Jemni Ben Ayed, L., Jemni, M., Kinshuk, Graf, S: A fully personalization strategy of E-learning scenarios. International Journal of Computers in Human Behavior 26(4), 581–591(2010)
6. Huang, Y., Bian, L.: A Bayesian network and analytic hierarchy process based personalized recommendations for tourist attractions over the Internet. Expert Systems with Applications 36(1), 933–943 (2009)
7. Paramythis, A., Totter, A., & Stephanidis, C. A modular approach to the evaluation of adaptive user interfaces. Paper Presented at the Proceedings of Workshop at the Eighth International Conference on User Modeling, UM 2001, Freiburg, Germany (2001).
8. Ledoux T.: Etat de l'art sur l'adaptabilité. Research Report RNTL ARCAD, number Livrable D1.1; Li, Y., Hong, J.I., Landay, J.A.: Design Challenges and Principles for Wizard of Oz Testing of Location-Enhanced Applications. IEEE PervasiveComputing 6, 70–75 (2001)
9. Zadeh, L.A.: Fuzzy Sets. Information and Control 8, 338–352 (1965)
10. Amershi, S., Conati, C.: Combining Unsupervised and Supervised Classification to Build User Models for Exploratory Learning Environments. J. Educ. Data Min. 1(1), 18–71 (2009)
11. Moodle: Moodle.org: Open-source community-based tools for learning (2010), `http://www.moodle.org`
12. Koedinger, K., Baker, R., Cunningham, K., Skogsholm, A., Leber, B., Stamper, J.: A data repository for the EDM community: the PSLC datashop. In: Romero, C., Ventura, S., Pechenizkiy, M., Baker, R.S. (eds.) Handbook of Educational Data Mining. CRC Press, Boca Raton (2010)
13. Shehab, A., Gamalel, D.: Smart E-learning: A greater perspective; from the fourth to the fifth generation E-learning. Egyptian Informatics Journal Elsevier (accepted May 25, 2010)
14. Ebru, O., Gözde, B.: Automatic detection of learning styles for an E-learning system. Computers and Education, 355–367 (2009)

15. Ileh, M.T., Saleh, I.: Case Based Reasoning Approach of Tutoring in E-learning Platform. In: IEEE ICMCS 2009, Maroc, April 2-4 (2009)
16. Dan, Y., XinMeng, C.: Using Bayesian Networks to Implement Adaptivity in Mobile Learning. In: Proceedings of the Second International Conference on Semantics, Knowledge, and Grid, SKG 2006 (2006)
17. García, P., Amandi, A., Schiaffino, S., Campo, M.: Evaluating Bayesian networks' precision for detecting students' learning styles. Computers & Education 49, 794–808 (2007)
18. Ueno, M.: Animated Pedagogical Agent Based on Decision Tree for e-Learning. In: ICALT 2005, pp. 188–192 (2005)
19. Berti, S., Mori, G., Paternò, F., Santoro, C.: TERESA: A Transformation-Based Environment for Designing Multi-Device Interactive Applications. In: Proceedings of CHI 2004, Extended Abstracts on Human Factors in Computing Systems, pp. 793–794. ACM Press, Wien (2004)
20. Calvary, G., Coutaz, J., Thevenin, D., Limbourg, Q., Bouillon, L., Vanderdonckt, J.: A Unifying Reference Framework for Multi-Target User Interfaces. Interacting with Computers 15(3), 289–308 (2003)
21. Gajos, K., Weld, D., Wobbrock, J.: Automatically generating personalized user interfaces with Supple. Artificial Intelligence 174(12-13), 910–950 (2010)
22. Savidis, A., Antona, M., Stephanidis, C.: A Decision-Making Specification Language for Verifiable User-Interface Adaptation Logic. International Journal of Software Engineering and Knowledge Engineering 15(6), 1063–1094 (2005)
23. Antona, M., Savidis, A., Stephanidis, C.: A Process–Oriented Interactive Design Environment for Automatic User Interface Adaptation. International Journal of Human Computer Interaction 20(2), 79–116 (2006)