Adaptation based on Psychological Factors using Fuzzy Logic

Ilham N. Huseynov¹, Akin Cellatoglu²,
¹Computer Engineering Department, European University of Lefke, Gemikonagi-Lefke, Mersin 10, Turkey
²Computer Engineering Department, European University of Lefke, Gemikonagi-Lefke, Mersin 10, Turkey

Abstract - Hypermedia and multimedia capability of web supports the new constructivist way of active learning. However, it may lead to cognitive overload and resulting in ‘disorientation’ or ‘lost in hyperspace’ problem. To reduce this cognitive overload the content should be tailored to individual differences of users. Psychological factor is one of many factors that influence characteristics of individual users and their learning process. Adaptation based on psychological preferences of users becomes an important research issue. However, instruments measuring psychological preferences use subjective judgments of users, experts or ambiguous questions resulting in incomplete, imprecise, uncertain information. This paper proposes fuzzy logic approach to represent psychological features. An algorithm for adaptation to psychological features in web-based hypermedia learning systems is proposed to find the optimal learning object that best fits the psychological requirements of the targeted user.

Keywords: adaptation, psychological factors, psychological model, representation, fuzzy sets

1 Introduction

The Internet provides a powerful educational infrastructure for teaching, learning, sharing and collaboration by offering web-based learning tools and environments. Some benefits of web-based education are its geographic, temporal, platform independences, cost-effectiveness, it multimedia ability, learner centred, access freedom and flexibility. Hypermedia and multimedia capability of web supports the new constructivist way of active learning. The hypermedia-based learning may contribute to enhance learning and promote cognitive flexibility when it is tailored to individual user needs. Two main problems with web-based learning are: (1) cognitive overload of users, and (2) the same content is delivered to all users. In the former, users have a lot of freedom in hyperspace that may lead to ‘disorientation’ or ‘lost in hyperspace’, in the latter, individual differences of users are not taken into account by system. [1]. One approach to overcoming these problems is to adapt the content and links to individual differences of users [2]. Such learning systems are called adaptive hypermedia systems (AHS).

Psychological factor is one of many factors that influence characteristics of individual users and their learning process. However, the instruments measuring psychological preferences use subjective judgments of users, experts or ambiguous questions resulting in incomplete, imprecise, uncertain information. This paper deals with this fuzziness information and proposes fuzzy logic approach to handle it. The representation model of psychological features is presented. An algorithm of adaptation to psychological features in web-based hypermedia learning systems is proposed to find the optimal learning object that best fits the psychological requirements of the targeted user.

2 Adaptive hypermedia systems

The AHS can be defined as the technology that allows personalization for each individual user of hypermedia application. The process of personalization customizes the content and structure of a web site to meet the specific needs of individual users, without requiring them to ask for it explicitly [3]. For example, in educational AHS, personalization allows to dynamically adapt the instructional sequence to the individual user knowledge level, goals, preferences and etc.

A typical architecture of AHS is shown in Fig.1. It consists of two parts: client side and server side. The client side provides interface to user/system interactions. Certain parameters of the user interface can be adjusted either by users manually or by the system automatically. In the first case, the user interface is said to be adaptable, in the second case, it is said to be adaptive. The degree of user/system control of interface parameters of the system depends on the level of user’s experience and skills, learning styles and cognitive styles. Server side is composed of three modules: the user module, the domain module and the adaptation module. A brief description of each module is given below.
2.1 User module

The user module builds user model through a User Modelling process. This process is divided into two subprocesses: acquisition information about the user and representation of this information. The user model is a key source of information for the adaptation module. It contains basic features of an individual user such as, user’s goals, state of knowledge about the subject, background, hyperspace experience and preferences [4]. This data can be collected explicitly from the user by querying, tests, during registration process with the system, or can be inferred implicitly by the system recording user interactions with the system. An accurate user model would include all features of the user behaviour and knowledge that affect his/her learning process, performance and efficiency. Recent research studies [5, 6, 7, and 8] suggested that it is desirable to incorporate psychological factors into the User Model that can significantly enhance the efficiency and usability of the AHS. For example, cognitive styles, learning styles, cognitive control are basic important psychological factors. Human behaviour is dynamic and complex. As a result, the information contained in User Model changes with time and therefore, it has to be continuously refined by updating its content. The initial user model can be generated by default values based on information submitted by the user. Then it can be updated monitoring the learning process.

2.2 Domain module

The Domain Model represents the knowledge about a subject that is to be taught to a user. It is a network of concepts that compose a course material. In the web-based AHS each concept can be described or explained by one or more than one web pages. The number of web pages depends on the complexity of the concept, on details of the explanation and on the user characteristics. Web pages are normally constructed from smaller pieces of knowledge units called learning objects (LOs). LOs describe any chunk of decontextualized learning information, digital or non-digital, such as, multimedia content (an image, text, video, education game, sound files), instructional content, learning objectivities, instructional software tools, even persons, organizers [5]. LOs can be reused in multiple contexts. They can be shared over the Internet between instruction designers. A LO is described by its metadata specification. This specification can be extended by instructional designers to enhance LO’s functions. For example, it is suggested to add PFs to the metadata of LO in [5].

2.3 Adaptation module

Two types of adaptation are distinguished in the AHS, namely adaptive presentation support and adaptive navigation support. The aim of adaptive navigation is to support users to find their learning paths in hyperspace by editing links [4]. For example, a link can be added, removed, or edited to change its format and presentation. The adaptive presentation supports users in selecting the content (or a LO) of the current node of course structure and the content presentation style or mode. The basic sources of the adaptation information are the User Model and the Domain model.

3 Psychological factors

Psychological factors (PFs) include motivation, emotion, cognitive styles, cognitive control and learning strategy, learning modality and skills. Incorporating PFs to the AHS is studied in [1, 6, 7, and 8]. The nature of PF is studied by cognitive psychology. The most referenced PFs are shown in Fig.2. Cognitive styles deal with the form of cognitive activity (thinking, perceiving, remembering), not its content. Learning styles, on the other hand, is seen as a broader construct, which includes cognitive along with affective and physiological styles [8, 9].
We present brief characteristics of psychological attributes (PAs) – leaves of the tree given in Fig.2 [1, 5]. Holists are global in interpretations of their environment, while serialists focus on the details of the environment. Users with a visual style prefer to get more pictorial information, whereas users with a verbal style prefer to get a more textual description (which can be provided through written text or spoken audio). Kinaesthetic users prefer to process information through interactive media. Users with reflector style respond by reviewing and reflection, pragmatists are well equipped for planning, users with theorist preferences are well equipped for concluding and finally, activist users are well equipped for experiencing. Field dependent individuals perceive objects as a whole while field independent users focus on parts of the object. Finally, cognitive flexibility determines a student’s ability to ignore distractions from his environment while he is focusing on some relevant information at hand. An individual high in flexibility would not be as easily distracted as someone who is classified as a constructor.

4 Adaptation based on psychological features

4.1 Problem Description

PF is a disputable concept that is not fully accepted by the whole community. In most of the systems the PF is assessed through psychological questionnaires and psychometric tests or in the form of self-report. This kind of measures is based on subjective judgment users make about themselves. Furthermore, not all characteristics they measure are stable and invariable across different subject domains [10]. It is often the case when the mixed result for the same person is obtained, that is a student may have preference for one particular style, preference for more than one style and different levels of preferences for the different styles. For example, a learner may be attributed to the visual style at the high level, but also to verbal style up to a certain extent, at the medium level. To deal with this fuzziness fuzzy logic methods will be used. Fuzzy logic provides a conceptual and computational framework for representation and handling uncertainty knowledge. The concept linguistic variable of fuzzy logic makes it closer to human natural language, facilitates the understanding of the inference process and easy implementation in computer. As Lotfi Zadeh, who is considered to be the father of fuzzy logic, once remarked “In almost every case you can build the same product without fuzzy logic, but fuzzy is faster and cheaper.” [11, 12]. Within the fuzzy inference system framework the problem of adaptation based on PF can be depicted by the following schema.

![Fig.2 Hierarchical type tree structure of PFs](image)

![Fig.3 Schema of adaptation based on PF](image)
As seen from Fig.3 the problem of adaptation to PF is reduced to the problem of selection of the relevant LO whose PF best matches the psychological model of the targeted user.

More formally, given the targeted user $u_t$ with psychological profile $P$ and a repository of LOs $L = \{l_1, l_2, ..., l_m\}$, with psychological profiles $P_{l_1}, P_{l_2}, ..., P_{l_m}$, respectively, it is required to choose such a $l_j \in L$ that the similarity measure value is maximum, that is

$$S(P, P_{l_j}) \rightarrow \text{max},$$

(1)

where $S$ is a similarity function.

### 4.2 Representation of psychological features

Let the set $X$ be a nonempty set, $X \neq \emptyset$. A fuzzy set $A$ in $X$ is characterized by its membership function $\mu_A : X \rightarrow [0, 1]$ and $\mu_A(x)$ is interpreted as the degree of membership of element $x$ in fuzzy set $A$ for each $x \in X$, the closer the value of $\mu_A(x)$ is to 1, the more degree $x$ belongs to $A$. $A$ is completely determined by the set of pair $A = \{(x, \mu_A(x)) \mid x \in X\}$.

If $X = \{x_1, x_2, ..., x_n\}$ is a finite set and $A$ is a fuzzy set in $X$, then we often use the notation $A = \mu_1[x_1, ..., \mu_n|x_n]$, where the term $\mu_i[x_i, i = 1, ..., n$ means that $\mu_i$ is the degree of membership of $x_i$ in $A$.

Typical functions that can be used to represent a fuzzy set are sigmoid, Gaussian and pi. However, these functions increase the time of computation. Therefore, in practice, most applications use linear fit functions. In practice, simple, easy computed linear fit functions are used such as, trapezoidal and triangular forms. The trapezoidal membership function is shown in Fig.4.

![Fig.4. Membership function of the trapezoidal form](image)

For the representation $PA$ we introduce linguistic variables associated with psychological attributes. Assume five levels for linguistic variables: level 1 for 'low', level 2 for 'more than low', level 3 for 'medium', level 4 for 'more than medium' and finally level 5 for 'high'. The fuzzy membership functions corresponding to these five levels are shown in Fig.5.

![Fig.5. Fuzzy membership functions of the five levels](image)

### 4.3 Inference

To make any inference about the selection of a learning object the most matches psychological model of the user one must evaluate PF of user and LOs we have in our DB. The hierarchical type tree structure of PF shown in Fig.2. allows us to use multi-attribute theory methods for PF evaluation [12]. According to this theory, the overall evaluation of PFs is defined as an aggregation of its evaluation in respect to its relevant value dimensions. Applying to the structure given in Fig.2. we have

**Evaluation (PFs) =** Aggregation [Evaluation (CognitiveStyles), Evaluation (CognitiveControl), Evaluation (Learning Styles)].
The evaluation of these dimensions can be decomposed by their subdimensions which are then further decomposed until we reach attributes that are leaves of the tree. Since the targeted user’s psychological preferences are expressed through these attributes then starting at the bottom of the tree with leaves we can back up the tree using an aggregation operator. When we reach the root of the tree we stop and this will be the evaluated value of PF. To illustrate this let us describe the tree through symbols:

![Tree Diagram]

Then we have:

\[
\text{Evaluation } (P) = \text{Aggregation } \left( \text{Evaluation } (P_1), \text{Evaluation } (P_2) \right);
\]

\[
\text{Evaluation } (P_1) = \text{Aggregation } \left( \text{Evaluation } (P_{11}), \text{Evaluation } (P_{12}) \right);
\]

\[
\text{Evaluation } (P_2) = \text{Aggregation } \left( \text{rating } (P_{21}), \text{rating } (P_{22}), \text{rating } (P_{23}), \text{rating } (P_{24}) \right);
\]

\[
\text{Evaluation } (P_3) = \text{Aggregation } \left( \text{rating } (P_{31}), \text{rating } (P_{32}), \text{rating } (P_{33}), \text{rating } (P_{34}) \right);
\]

\[
\text{Evaluation } (P_{11}) = \text{Aggregation } \left( \text{rating } (P_{111}), \text{rating } (P_{112}) \right);
\]

\[
\text{Evaluation } (P_{12}) = \text{Aggregation } \left( \text{rating } (P_{121}), \text{rating } (P_{122}) \right).
\]

Here ratings for attributes (leaves of the tree) and selection of aggregation operators are assumed to be chosen by domain experts. For example, as an aggregation operator the weighted -sum operator [12], or the ordered weighted averaging operator (OWA) [13] can be chosen. Let us describe OWA from [13]. The OWA operator \( F \) of dimension \( n \) is a mapping OWA: \( R^n \to R \) characterized by an \( n \) -dimensional vector \( W \), called the weighting vector, such that its components

\[
w_j \in [0,1] \sum_{j=1}^n w_j = 1, j = 1, \text{ that is}
\]

\[
\text{OWA} (a_1, a_2, \ldots, a_n) = \sum_{j=1}^n w_j b_j,
\]

where \( b_j \) is the \( j \)th largest of the \( a_i \).

Selecting of vector \( W \) using linguistic quantifiers - Low, Low than medium, Medium, More than medium, High – we can emphasize different dimensions, subdimensions of hierarchy.

Now in order to compute expression (1) a similarity function should be chosen. Some similarity functions with fuzzy sets are given in [14]. The following is the similarity function introduced in [15].

\[
S(\mu_1(x), \mu_2(x)) = \frac{\sum_{j} \min \{ \mu_1(x_j), \mu_2(x_j) \}}{\sum_{j} \max \{ \mu_1(x_j), \mu_2(x_j) \}}
\]

where \( j = 1, \ldots, n, x \in X = R^n \).

Using equation (2), the matching values between PF for the targeted user and PF for each LO can be calculated. According to these values LO are ranked to show their capability to match the PF of the targeted user.
4.4 Algorithm of adaptation based PF

Summarizing the steps given in the previous section, we present the following algorithm of adaptation to PF:

Step1. Measure the PF of the targeted user and assign the relative importance weights to them.

Step2. The domain experts rate the PF for LOs and assign the relative importance weights to them.

Step3. Represent the PF both for the targeted user and for LOs.

Step4. Evaluate the PF both for the targeted user and LOs.

Step5. Calculate the similarity measure between the PF for the targeted user and the PF of each LO.

Step5. Rank LOs in accordance to similarity measure values.

Step6. Select or recommend a LO the similarity measure value of which is the most.

Step6. If there are two or more LOs with maximum matching value then the psychological model is tuned on certain attributes until the optimal LO will be found that best fits the targeted user psychological requirements.

5 Conclusion

In this paper we have considered the problem of adaptation to psychological factors. We adopted the learning object based adaptation based on psychological model of the targeted user. Using fuzzy set theory, we presented the representation model for both PF of LOs and PF of the targeted user. Then the evaluation mechanism for the PFs and similarity operator is introduced. An algorithm for adaptation based on PFs is proposed to find the optimal learning object that best fits the psychological requirements of the targeted user. Future study can be focused on the experimental research issues: what is the appropriate shape of membership functions, the type of the aggregation operator and the type of similarity operator.

6 References


