User Modeling for Interactive Evolutionary Computation Applications Using Fuzzy Logic

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Abstract. Interactive evolutionary computation (IEC) is a branch of evolutionary computation where users are involved in the evolution process. In IEC systems the user generally evaluates subjective information of the population in large quantities. One of the problems in the IEC systems is not having friendly interfaces for the evaluation of mass information and this causes the user lose interest. These systems have quickly migrated to the Web by the large number of users that can be found on a voluntary basis. For these applications we can find users with different characteristics, for example, users with different level of knowledge about the application domain, different participation interest or experience in use of Web-Based IEC applications. In this paper we propose a user modeling for IEC to help tailor the user interface depending on the characteristics, preferences, interests, etc. of the user using fuzzy logic.

Keywords: User modeling, interactive evolutionary computation, IEC, Fuzzy logic.

1 Introduction

Interactive evolutionary computation (IEC) is a branch of evolutionary computation where users participate evaluating individuals in a population given by an application. It is based on subjective human evaluation [12].Users participate in such systems depending on their interest of the application domain and because of this several of these systems are Web-based. Literature tells us that in such systems there is a problem that has to do with the user interface, sometimes these user interfaces are not friendly for the user to interact with and this causes them to lose interest [12]. Because of this we proposed to use user-modeling techniques to personalize the user interface for a given application domain on interactive evolutionary computation. The proposed User model will provide us with the preference and needs according to the interface currently used by the user. With this information we can use fuzzy ruled based system to infer in what type of user is in a given time, then knowing the type of user we then can perform the interface adaptation.

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2 Interactive Evolutionary Computation

This technology is branch of evolutionary computation. Based on subjective human evaluation. Basically, this technique requires that the objective function is replaced by a person (user) [12]. In Fig 1 we show a general IEC system.

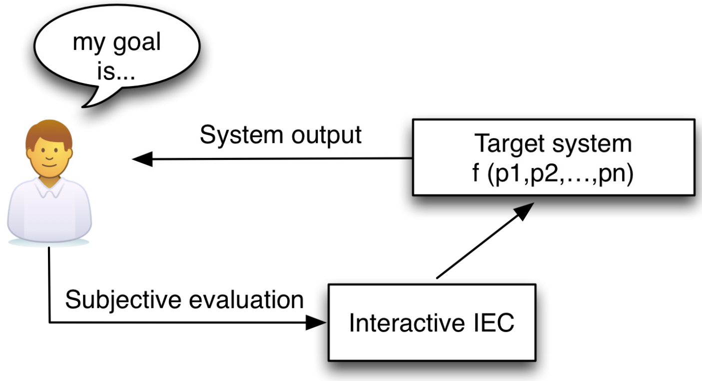

Fig. 1. General Interactive Evolutionary Computation system based on subjective evaluation. [12]

In this general IEC system we note that the user replaced the fitness function at the moment he or she interacts with the system. Logically the user needs a goal to know what is the evaluation he or she needs to perform. Finally the users receive an output and the process and start over again.

These techniques have been used in several areas of application, in particular:

- Music and sound.
- Digital Art.
- Design and editing documents
- Processing acoustic signals.
- Industrial design.
- Data mining and acquire knowledge.
- Face recognition.
- Robotics and control.

2.1 Problems and Limitations

In IEC there are some problems and limitations whereby the user is not comfortable to interact with these kinds of systems, Takagi identifies [12]:

- User fatigue: 20 to 30 iterations
- User memory: limits the maximum number of individuals per generation.
- User selection: Simple user interfaces.
- Stop condition: User dependent.
- Fluctuations in decisions: Changes in preferences.

This is why the user loses interest to participate in this kind of systems, in these paper we will focus in one of the problems, the user selection, we want to increase their participation in these applications by presenting a simple and usable interface considering their characteristics, preferences, interest, etc..

3 User Modeling

There is a reality that the World Wide Web is growing in an exponential way, which means the presence of more users in Web sites, Web systems are very varied, and we have users of any kind. These users follow different goals, for example make a reservation of a room in a five stars resort or just consulting their bank account or checking their status in Facebook. This variation of users represents a diversity of individuals, individuals with different abilities, interest, preferences, forms of learning, and knowledge, because of this they need different presentation of the information that they use to interact with the different variety of applications.

When we are dealing with users in systems that we want to personalize, we need to know some personal information about the users. This information is a collection of their needs, characteristics, feelings, etcetera to adapt something that we want in a system. This information is needed to represent knowledge about the user and all this is called user modeling (UM) [11].

A user modeling can be a simple profile system that represents some knowledge about them or can be a very complex representation of their characteristics, needs, and interest to understand a specific individual.

The main goal of a user modeling is to represent real world aspects of the users in an automatically autonomous form. There are several user models techniques, these UM techniques are the most frequently used:

- Rule based models.
- Ontologies based models.
- Stereotype based models.
- Hybrid models.

In next sections a brief description of these technique are presented.

3.1 Rule-Based Models

This type of user model is based on the experience of an expert in a given context, this means that rules can be made by that knowledge of the expert has, for example, an expert can make rules to represent that knowledge to a user model to infer in the personalization of a given application. In this way we can represent the user model [11].

3.2 Ontology-Based Models

Ontologies-based models are forms of representing knowledge starting by the idea of a well form semantic, "An ontology is a formal specification of shared specification"[7]. For example the semantic Web is based on ontologies that is an important part of this approach.

We can understand better an ontologies-based UM by the system architecture that Liana Razmerita [7] presented in her work, in Figure 2 we are present the mentioned architecture.

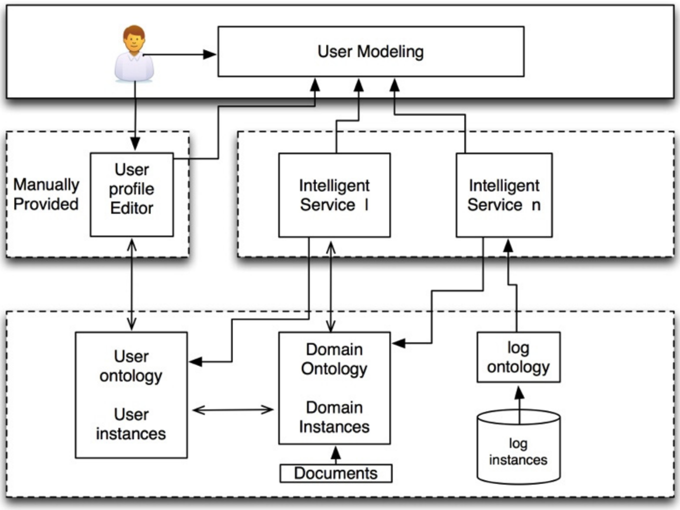

Fig. 2. An ontology-based user modeling system

Here in this architecture (Fig. 2) the ontology part is represented in three important aspects:

1. The User ontology structure represents distinct characteristics in their relationships.
2. The Domain ontology is defined by the context of the specific application and their relationships.
3. The log ontology represents the semantic of the user interaction with the system.

Monitoring the user interaction with the system generates the log data storage.

The intelligent services have two principal aspects in the system:

1. To maintain and update based of the data usage through the application by the number of heuristics.
2. To adapt service based on the needs of the user like skills, preferences, and knowledge.

3.3 Stereotype Based Models

This kind of user models is based on demographic statistics. This technique simply uses collections of facet-value combinations that describe groups of system users. The user is classified into common stereotypes. Using this technique the system can infer assumptions about the user if there might be no data about that particular context, because there is fact that demographic studies have shown that other users have the same characteristics given by the stereotype.

In figure 3 we present a Stereotype Hierarchy in GRUNDY [9].

This stereotype hierarchy representation adjusts the user model by an explicit representation of knowledge. The advantage of stereotype-based user model is with a small evidence about the user a system should infer a very decent model information.

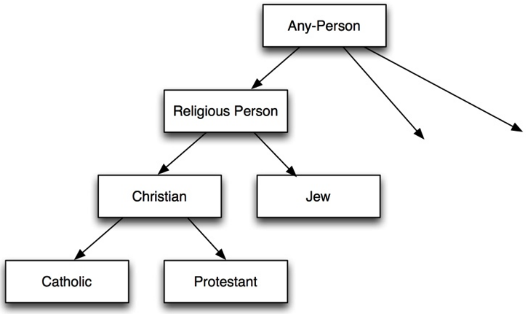

Fig. 3. Stereotype Hierarchy in GRUNDY[9]

The advantage of stereotype-based user model is with a small evidence about the user a system should infer an appropriate model information.

3.4 Hybrid Based Models

This kind of user models is just the combination of one or more techniques that we explained above. We can use this technique when we compare that the technique we used is better in particular cases so we produce the UM in a kind a switch state. For example if in the context of e-learning we have good results with rule-based technique and not too good in e-commerce we need to adjust in a particular context which technique we want to used. That is why we combine user-modeling techniques to gain better results [6].

4 Uncertanity in User Modeling

The current activities on the web have an increasing demand of preference discovery, on these days the user preferences information has become in a major tool for several areas as Marketing, eLearning and too many others. For example it is very common to find several applications to provide suggestions for some products based on recent purchases.

For that reason user preference provides multiple applications as an option for recommender systems in order to solve problems of personalized recommendations.

It's a quite of a challenge to deal with the description of user knowledge in order to recognize user's specific needs because these data involves imprecision and uncertain data.

Different from human interaction where we learn by explicit or implicit methods, it is necessary to design a user model to detect user preferences, profiles, choices, likes and dislikes [2].

In relation to this subject it is important to improve preference modeling for recommender systems to provide value added to the current web activities to succeed in an increasingly competitive world.

When a user interacts with systems, provides a high-grade uncertainty information, this is the main reason of the user modeling systems existence in order to control uncertainly data with certain degree [2].

These systems need to collect all the user information about their profiles, interaction history, choices and basic data with decision criteria.

In previous works we can find that the more information a user model has, the better the content and presentation will be personalized.

It is known that there exist different methods to manage uncertainty for user modeling, and is important to mention three general approaches:

- Rules with certainty factors
- Fuzzy Logic
- Bayes probability Networks

Fuzzy Logic goes more than a 0-1, truth or false ranges, it is based on many-valued logic and has the ability to handle partially answers with ambiguity. The general methodology of reasoning in fuzzy logic is by the IF…THEN rules [13].

Fuzzy Logic defines a framework in which the inherent ambiguity of real information can be captured, modeled and used to reason with uncertainty [13].

A traditional FL inference system is divided into three steps:

1. Fuzzification.
2. Fuzzy Inference.
3. Defuzzification.

Typically FL has been used in UM to implement applications that are based on a recommendation task. In these applications FL provides the ability of mixing different user preferences and profiles that are satisfied to a certain degree [4].

5 Proposed Method

Our proposed is to attract the users to participate in given IEC application and to improve their overall experience with the system. With the UM our expectations are user participation increases. We are going to explain in more detail with the architecture that we proposed in figure 4.

Is worth mention that we are focusing in the Web-based IEC application, in other words we want some how to adapt the interface of the IEC application to the user that is interacting with.

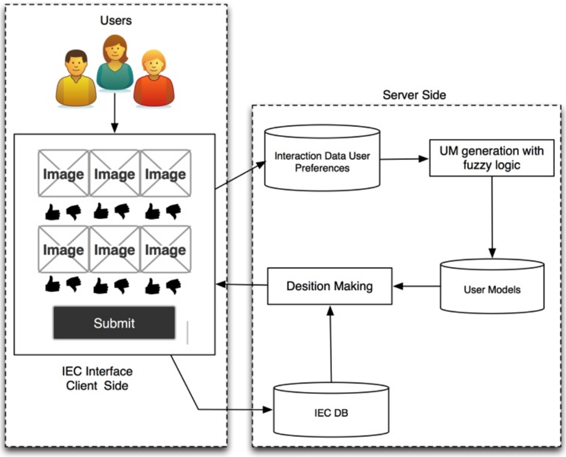

Fig. 4. Architecture for IEC using Fuzzy Logic

In Web-Based IEC applications we found that there are different types of users. For this reason we define three types of user for Web-Based IEC applications these are:

- Specialized users.
- Ordinary users.
- Anonymous users.

5.1 Specialized Users

These kinds of users are users that know all the functionality of the IEC application where they going to participate, in other words they know all the objectives of the IEC application and all the aspects of the goals that the particular application is going to, because of this they need all the functionality elements in the interface to interact with the IEC application.

5.2 Ordinary Users

These types of users are users that know certain knowledge about the goals and functionality of the IEC application where they going to participate, so they do not need all the functionality and elements of the interface to interact with, but these types of users are more attracted by the domain of the IEC application.

5.3 Anonymous Users

These classes of users are users that they feel some sort of empathy with the domain of IEC application but these classes of user have less degree of participation in the IEC application, for this reason the elements and functionality of the IEC application interface have to be very simple.

As you can see in the above architecture there is a user interface that represents the interactivity with the IEC application, that interface is the one we want to adapt to the different types of users previously defined.

5.4 Architecture for IEC Using Fuzzy Logic

Continuing with explanation of the UM architecture for IEC using fuzzy logic there is a data store mechanism that represent the preferences, interests of the users by the iterations in the IEC application. This mechanism is a monitoring of the IEC users in accordance to their different type of users.

Thanks to that mechanism we now have to store the preferences that we were provided by different types of users, now in the architecture there is a fuzzy UM generation process, where we propose to apply a fuzzy inference system (FIS) to perform the process of knowing what type of user is interacting with the IEC system. It is worth mentioning that there are several ways to accomplish this fuzzy inference system, we propose to develop according to the time the user spends using the IEC system and the difficulty of the task presented to the user. Under these conditions we can have an acceptable output in the fuzzy inference system, which represent the type of user. In Figure 5 we present is fuzzy inference system.

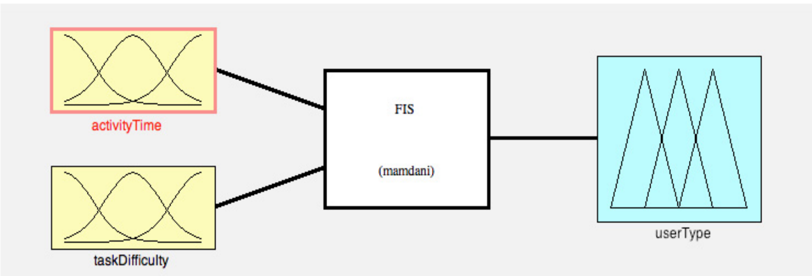

Fig. 5. IEC user interface Fuzzy Inference System

In this FIS we propose to use triangular membership functions in the input and also to the output. We also propose to use Mamdani type for simplicity. Where the ranges of activity could go from 0 to 30 that would represent the time of user activity in the IEC system, also the range of tasks (evaluations) in the sense of difficulty that could go from 0-100.In Fig 6 we present the inputs and the output that might be.

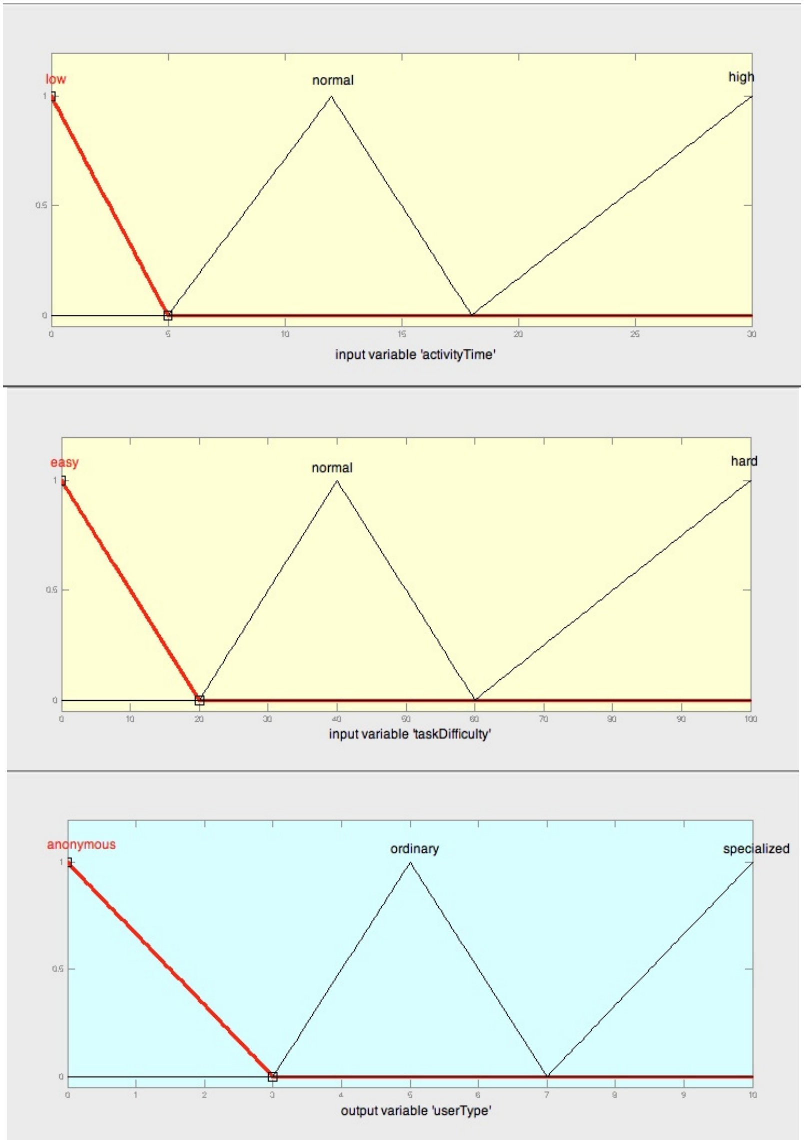

Fig. 6. Membership functions for the inputs and the output

Some of the fuzzy rules could be the following:

1. *if(activityTime is low) and (taskDifficulty is easy) then (userType is anonymous).*
2. *if (activityTime is normal) and (taskDifficulty is normal) then (userType is ordinary).*
3. *if (activityTime is high) and (taskDifficulty is hard) then (userType is specialized).*

Ones we have this rules we can proceed to store the inferences we obtain by FIS, then proceed to the process of the decision-making. In the decision-making we make the decisions based on the results of the FIS give, for example if we have an anonymous user, now we perform personalization for the interface on the IEC system, similarly when the user is ordinary we need to perform personalization on the interface elements, finally when the user is a specialized we will perform the personalization on the interface elements for IEC system.

6 Conclusion

We this method that we proposed we expect to increment the level of participation that the users have on interactive evolutionary computation applications. That means we reduce the non-friendly user interface that this kind of applications have.

Future work following this method is to tested in a real interactive evolutionary computation application. First phase by given the user a normal IEC application with a predetermined user interface and see what is the level of participation of the users. Then a second phase is to put this method on the IEC application and see if the level of participation of the users increases.

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