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Dynamically Tracking A User's Progression along Novice-Expert Continuum

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Abstract

Representing the dynamics of dialogue behavior is one of the most critical capabilities of an intelligent interface. When an intelligent interface monitors a user's strategies for solving a complex problem or accomplishing a goal, a discernible pattern of user interaction behavior emerges. This paper introduces and discusses a methodology to identify user's task-specific expertise dynamically for adaptive user interfaces.

Introduction

There are several ways that a system can infer a user's expertise of a particular domain. The system can observe a user's dialog such as the usage of command language at the syntactic or lexical level regionally; or the system can analyze the interaction sequence globally. Conventional expert systems seem inappropriate to support these kinds of tasks. These reasons are from several aspects: [1]

0 Expertise cannot be demonstrate or explained
0 Problems characteristics are poorly structured;
0 Inferences involve incomplete, ambiguous, and conflicting circumstances; and
0 Many production rules incur system overhead and increase difficulty of maintenance.

The objective of this paper is to further explore those issues addressed above. Neural network, fuzzy cognitive map, and fuzzy compositional rule of inference techniques are investigated for tackling these problems. As depicted in Figure 1, a system architecture is proposed and aimed to support constructing a user model that accurately captures user progression along the novice-expert continuum.

![System Architecture Diagram](image)

**Figure 1. System Architecture**

Using the following scheme, three major reasoning modules -- a fuzzy cognitive map, a neural network, and the compositional rule of inference can be used to deduce a user's expertise.

0 **Fuzzy Cognitive Map (FCM):** A fuzzy cognitive map [2] is usually used for problems that involves a casual relationship between process entities and inherent 'fuzziness' reasoning. The methodology explored here uses FCM for inferring user implicit knowledge.

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based upon the casual links between different concepts.

Neural Networks: Several studies suggest using neural networks for detecting human-computer dialog behavior. Neural network in this paper is used to identify the dialog behavior into pre-defined performance pattern.

Compositional Rule of Inference: Compositional rule of inference is one of the methods used to resolve fuzzy association [3]. Based on the output generated by neural pattern recognition, a user can be classified into different pre-defined categories with respective grades of membership receptively. In order to collapse these fuzzy values into a single crisp value, a set of linguistic production rules (based on the compositional rule of inference) is used to refine this direct observation. Finally, this crisp value signifies a user's that affects the subsequent system interaction strategies.

As noted above, neural network is used to classify the user's dialogue behavior into the pre-defined categories. It can be trained with the stereotypical user navigation pattern to classify similar patterns. This neural network is trained with the stereotypical user navigation pattern which is from the output of iterative propagation with fuzzy cognitive map. These patterns are collection of several consecutive dialog sequences. The ordinal characteristics of these dialog sequences thereby indicate a discernible performance pattern that can be identified by neural network. Also, based upon the assumption that when the user issues a command then the user's mastery of this command is concluded. Therefore, FCM can further infer all the possible related procedure the user might know and the average knowledge index (AKI) is calculated based on the inferred information.

Details of Design

Let \( \mu_{\text{OPP}}, \mu_{\text{AKI}}, \) and \( \mu_{\text{UKL}} \) express the degree of membership of a user's knowledge level to ONP (Observed_Performance_Pattern), AKI (Average_Knowledge_Index), UKL (User_Knowledge_Level) respectively. These fuzzy sets are characterized by the their membership functions as described below:

\[
\mu_{\text{OPP}} = f_{\text{OPP}}(x_j); \quad \text{where } x_j \text{ is the } j\text{th consecutive association indices at the } j\text{th dialog session}
\]

\[
\mu_{\text{AKI}} = f_{\text{AKI}}(y_j);
\]

where \( y_j \) is the average knowledge index at the \( j\text{th} \) dialog session

\[
\mu_{\text{UKL}} = f_{\text{UKL}}(z_j);
\]

where \( z_j \) is the user knowledge level concluded at the \( j\text{th} \) dialog session

\[
j = 1, 2, \ldots, r, \quad r \text{ is the total number of sessions being monitored.}
\]

And \( f_{\text{OPP}} \) is defined as neural network function transforming the 5 consecutive association indices into the value between 0 and 1 for each performance categories shown in Table 2. Both \( f_{\text{AKI}} \) and \( f_{\text{UKL}} \) can be constructed by experience domain expert or by iterative modification of initial setup.

For instance, a fuzzy subset \( A' \) generated from NEURAL_NET and FKA, is represented as

\[
A' = \{\mu_{\text{OPP}}(x), \mu_{\text{AKI}}(y), \mu_{\text{UKL}}(z)\}
\]

where \( x \in X \) (Space of all possible combination of association indices);

\( y \in Y \) (Space of knowledge index); and

\( z \in Z \) (Space of user knowledge level).

Then the user's knowledge level can be inferred via the following type of fuzzy production rule:

If Observed_Performance_Pattern (OPP) is (VS, LS, US, LU, VM) and Average_Knowledge_Index (AKI) is (LO, MD, HG) then User_Knowledge_Level (UKL) should be (NV, NN, NI, IM, NE, EP)

where

the linguistic fuzzy sets are defined as following:

for the input variable OPP

VS: very-likely stable
LS: likely stable
US: unstable
LU: likely misunderstood
VM: very-likely misunderstood

for the input variable AKI

LO: low
MD: medium
HG: high

for the output variable UKL

NV: novice
NN: near_novice
NI: near_intermediate
IM: intermediate
NE: near_expert
EP: expert

Next, by applying the compositional rule of inference as the internal inference mechanism the input \( A' \) can be transformed into the corresponding output value User_Knowledge_Level (UKL'). The algorithm is described as follows:
\[ R = \bigcup R_i \]

\[ = \max \min \left[ \mu_{\text{OPP}}(x), \mu_{\text{AKI}}(y), \mu_{\text{UKL}}(z) \right]; \]

for \( i = 1, 2, \ldots, n \)

where \( R_i \) is the \( i \)th rule in the overall production rules set.

On the other hand, to derive a crisp output value, a defuzzification process is required for collapsing all the fuzzy values (generated from each rule) into a single crisp value \( v_i \). By using the centroid method, the final solution can be derived via the following algorithm:

\[
v_{\text{UKL}} = \frac{\sum_{i=1}^{n} z_i \mu_{\text{UKL}}(z_i)}{\sum_{i=1}^{n} \mu_{\text{UKL}}(z_i)} \quad \text{for } z_i \in Z
\]

where \( v_i \in V \) (User_Knowledge_Level space); \( n \) is the total number of fuzzy production rules.

**Example**

The following is a more detailed explanation of how the information from the NEURAL_NET and PFA are used by the fuzzy production rules and how the fuzzy values generated from individual rule is integrated into a single crisp value of user's knowledge level. The following is a two-rule set of IF-THEN statement:

(Rule 1) If Observed_Performance_Pattern (OPP) is LS and Average_Knowledge_Index (AKI) is HG then User_Knowledge_Level (UKL) should be EP;

Else

(Rule 2) If Observed_Performance_Pattern (OPP) is VS and Average_Knowledge_Index (AKI) is MD then User_Knowledge_Level (UKL) should be NE;

Finally, the Max-Min process is used to refine the outputs of the neural networks so that outlying values do not significantly affect the classification result.

**Conclusion**

Currently a simulation experiment is conducted for evaluating a user's proficiency of using UNIX commands set. Base on the statistical deviation analysis, a preliminary result indicates that the inferred user expertise presents a smooth and gradual change rather than discrete and sudden shifts that are inferred by non-fuzzy approaches. Further experiments are also being conducted in integrating these modules with other inference components that are able to adapt the interface in other application modules such as teaching module, learning module, and those applications that involve complicated commands or menu driven environments.

**References**

