Interfaces Usability for Monitoring Systems

R. A. Ribeiro
UNINOVA – CA3, Portugal

I. L. Nunes
Universidade Nova Lisboa, Portugal

INTRODUCTION

The objective of this article is to discuss the usability and suitability of having graphical visualization tools for decision support in Space monitoring systems. Operators dealing with specific Space missions are burdened with continuous real-time telemetry data about components' behavior and they have to take quick actions when some malfunction occurs. To have a decision support tool for monitoring what is happening is essential for ensuring the mission success.

In this work, for discussing interface usability concerns for decision support, we use a real case study, called MODI-Monitoring and Diagnosis for Mars Driller project (MODI, 2006), which was financed by the European Space Agency (ESA). The MODI objectives were the development of a fuzzy alarm fault detection system as well as a fuzzy terrain-hardness detection system, for the drill device included in the ExoMars rover (ExoMars, 2007).

Although a number of positive results have been achieved using different knowledge-based technologies for monitoring, diagnosis and control, for instance inference systems, expert systems, data mining, fuzzy logic, and so forth (Isermann, 1998; Ross, 2004), only recently attention on the usability and suitability of graphical visualization interfaces, acting as a decision support tool, is starting to be considered a relevant issue in software applications (Nunes, in press).

Fuzzy logic has been successfully applied in many different monitoring and diagnosis processes (Isermann, 1997, 1998; Ross, 2004). However, most applications are related with decision making (automatic control processes) and less with decision support (human control processes). In this work we focus in the latter, by combining Isermann's (1997) definition for monitoring and fault diagnosis: the task of checking measurable variables deviations and generation of alarms for the operator to take actions (i.e., decision support instead of decision making).

The main motivation behind this work is that Space monitoring applications require fast and intuitive visual interfaces to support the operator's real-time decision-making process. Further, International Organization for Standardization (ISO) standards for usability in the design of interfaces should be followed to ensure effective dialog tools. Moreover, this type of tool should also incorporate an explanation facility (Nunes, 2006; Turban & Aronson, 2001) to help the decision makers understand the reasoning and details about events occurred.

This article is organized as follows. First we present some background on fuzzy knowledge-based systems and interfaces usability. Second we present a Space monitoring case study to discuss the interface design. Third we discuss the case study interface usability results. Finally, we present the conclusions and future work.

Fuzzy Knowledge-Based Systems

Fuzzy logic models use sets represented by membership functions to describe and manipulate imprecise concepts and perform logical operations to achieve certain conclusions (Mendel, 2001; Ross, 2004). Fuzzy knowledge-based systems (FKBS), usually just called inference systems, rule-based systems, or expert systems (Kandel, 1992; Ross 2004), use input fuzzy linguistic variables, a rule-set with the relationships between the input variables, and an inference scheme, to provide logical conclusions about a specific phenomenon. As mentioned in the introduction, the focus here is on FKBS in decision support contexts, specifically for Space monitoring applications.

A general architecture for FKBS, in a decision support context, is shown in Figure 1 (adapted from Ribeiro, 2006 and Turban & Aronson, 2001)

As can be observed in Figure 1, FKBS are usually divided in five main modules:

Figure 1. FKBS architecture

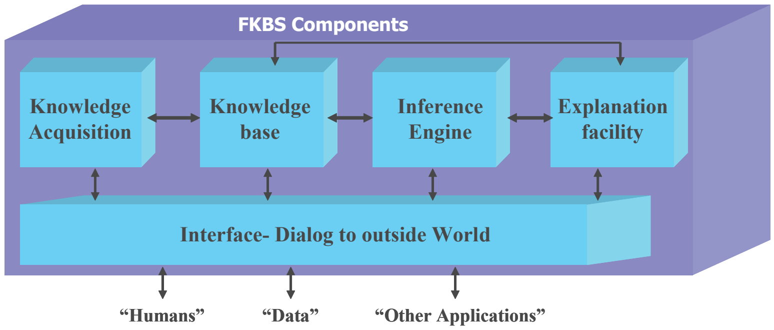
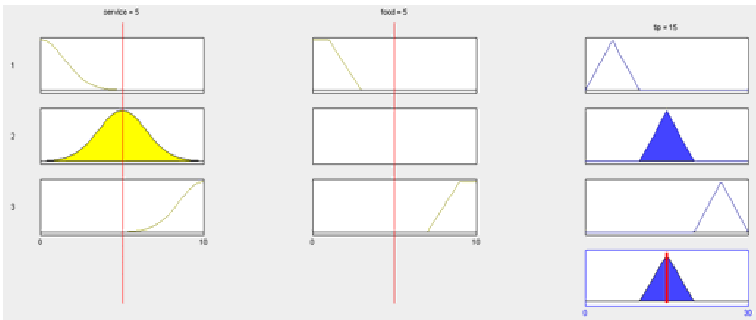


Figure 2. Example of inference system for restaurant tips



1. **Knowledge acquisition module:** Knowledge acquisition module performs the knowledge elicitation for the data and variables, their domains and respective relationships.
2. **Knowledge base module:** Knowledge base module contains the knowledge base with fuzzy sets, linguistic variables, the rule base, as well as other specifications;
3. **Inference engine module:** Inference engine module deals with the reasoning process. It includes the complete reasoning method/scheme for rule evaluation and aggregation to arrive at a conclusion.
4. **Explanation facility module:** Explanation facility module relates with the reasoning process taken to reach a result. Moreover, it increases confidence in the system by providing analysis of the reasoning path.
5. **Interface-dialog module:** Interface-dialog module deals with the problem of how the user will need to interact (dialog) with the system. The interface component defines the attributes that enable users to communicate with the inference system in an easy and efficient way.

In summary, FKBS have inputs and outputs. The inputs are represented by linguistic variables described by fuzzy sets, defined in the knowledge acquisition module and then stored in the knowledge base. The variables values and respective memberships are next passed to IF-THEN rules in the inference engine. Each fired rule is evaluated to obtain its respective strength (firing level) and then aggregated to obtain the final result. The final result can either be a singleton (crisp value) or a fuzzy area and in this case it must be defuzzified (Ross, 2004) to obtain a final crisp value. The interface establishes the complete dialog between users, data, and other applications (when required). In addition, in decision contexts, an explanation module is required to justify/explain the reasoning process and path (Turban & Aronson, 2001).

An illustrative example borrowed from Matlab (2001) is to define the appropriate tip to give in a restaurant, based on the quality of the service and food provided. The inputs of the system are service quality and food quality, both given on a scale of 0 to 10 and the output is the amount of tip to give in percentage, from 0 to 30. The system has three rules:

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