Fuzzy Space Monitoring and Fault Detection Applications

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ABSTRACT. This paper addresses the suitability of fuzzy logic for space monitoring and fault detection applications as it relates to decision support in mission control processes. Specifically, a general architecture for building a fuzzy inference system is presented and a development process is proposed. To illustrate the suitability of the approach, two applications from projects developed by UNINOVA for the European Space Agency (ESA) are briefly presented.

Keywords: fuzzy inference systems, monitoring, fault detection, decision support.

1. Introduction

Fuzzy Logic may intuitively represent an attractive approach for solving certain problems. Nevertheless, the suitability of Fuzzy Logic (FL) is not universal and must firstly to be assessed in order to avoid trying the "wrong approach to the wrong problem". In general, there is a commonly accepted temptation to confront Fuzzy Logic with poorly known applications. A major issue is to identify if the lack of knowledge is essential or just circumstantial.

A major indicator of the suitability of FL for monitoring and fault detection problems is the way in which the parameters of the problem are defined. Models whose parameters have intrinsically imprecise properties are definitively well suited for fuzzy modeling. In this scenario, the major obstacle is the level of familiarization the developer has about the problem semantics (hence the importance of the cooperating dialog between the Domain Expert and the Software Engineer).

A Fuzzy Logic approach includes a model expressed in terms of a fuzzy vocabulary and where the underlying relationships, between the related fuzzy sets, are represented by rules. Usually, these systems are commonly called fuzzy inference systems (FIS) (Mendel 2001) and this is the nomenclature we will use in this paper. The effective model design proceeds from changes in the number, shape and overlapping between fuzzy sets rather than solely from changes in the production rules. All these are fundamental hints in terms of model representation that should be supported by a specific methodology, like the one we propose in this paper, in order to appropriately encode system knowledge.

In a Fuzzy Inference Systems (FIS), sometimes also called fuzzy expert systems or fuzzy knowledge based systems (see for example (Zimmermann 1996)), we express the dynamics of the system as a series of set-level inferences held in a series of conditional and unconditional fuzzy rules. Basically, the fuzzy sets vocabulary defines the "semantics" (the knowledge) of the problem. The rules manipulating fuzzy sets define the way the knowledge is applied.

Fuzzy Inference Systems (FIS) have the capacity to capture highly non-linear systems in its models. This is only one consequence (a major one – of course) of fuzzy logic's inherent approximate reasoning ability. The approximate reasoning capability tries to mimic human decision making processes and this is the reason why it can be used either to support the decision maker or to "substitute" him/her. Approximate reasoning also helps to fix criteria for the identification of possible candidate applications:

- Applications in systems for which no (or no reasonable) mathematical model exists;

- Applications in systems that exhibit very complex and non-linear behaviours;
- Applications in systems where a complete understanding of the system process is not available.

Moreover, the nature of fuzzy rules and the way relationships between fuzzy sets of different shapes are coded do provide a powerful capability for incrementally modelling a system whose complexity makes traditional expert system, classical mathematical and statistical approaches very difficult.

It should be clarified that fuzzy logic application in monitoring and fault detection problems may be applied in two different contexts - either as a decision making tool (substituting the human decision maker) or as a decision support tool (supporting the decision making process). In this work we concentrate in the latter, by following Isermann´s (Isermann 1997) definition for “monitoring”: the task of checking measurable variables deviations and generation of alarms for the operator (i.e. decision support instead of decision making). In summary, we focus on space monitoring applications designed for supporting human operators.

Fuzzy Logic has been successfully applied in many different fault detection and diagnosis technical processes (summaries can be found in (Isermann 1997) (Isermann et al 1997) (Iserman 1998)). However, most of these applications are related with decision making (automatic control processes) and not with decision support (human control processes). Further, as reported in (Donati 2000) there is very little work on the application of fuzzy inference tools in space monitoring problems to assist human operators in the task of mission control processes.

Considering that the use of fuzzy decision support tools in space monitoring applications has been rare, we focus on the experience gained by our research group with developing fuzzy monitoring and fault detection tools for the European Space Agency (ESA) (see for example (Pereira, Moura-Pires et al. 2002; Pires, Ribeiro et al. 2002) (Pantoquilho, Joaquim Neto et al. 2004)). Hence, we propose a step-by-step development process for monitoring and fault detection FIS and then we briefly describe two space applications to illustrate the approach.

In summary, Fuzzy Inference Systems appear to be well suited for space monitoring systems, particularly in mission control processes, because:

- It is almost impossible to define a general mathematical model;
- The knowledge about the parameters is usually imprecise;
- The complexity of parameters behaviour is quite large;
- Sometimes the variables boundaries are soft and not crisp (i.e. they are not precisely defined);
- The knowledge is only partially detained by domain experts and includes human judgment.

- Operators need decision support tools to help them make timely decisions to avoid costly and potentially dangerous hazards.

This paper is structured as follows. In this introduction we address the applicability of a fuzzy logic approach to monitoring and fault detection problems. In section 2 we present the main underlying concepts of Fuzzy Set theory that are at the core the of Fuzzy Inference Systems. In section 3 we provide an overview of Fuzzy Inference Systems (FIS) in the perspective of decision support to end-users. In section 4 we propose a step-by-step development process of FIS and then we briefly present two applications of monitoring and fault detection in space projects. In section 5 we present the conclusions.

2. Fuzzy logic overview

Zadeh first proposed Fuzzy Set Theory (commonly named fuzzy logic) in 1965 (Zadeh 1965). In 1973, Zadeh wrote another seminal paper where he introduced the concept of linguistic variable and proposed the use of IF-THEN rules to represent human knowledge (Zadeh 1973). Based on those two seminal papers, in this section we will discuss the main concepts of fuzzy set theory for fuzzy inference systems. Fuzzy sets are mostly used to represent imprecise or incomplete information, within a mathematical framework (Wang 1997).

A fuzzy set A of generic elements *x*, in a universe of discourse U is characterized by a membership function $\mu_A(x)$ that takes values in the interval [0,1], and may be represented as a set of ordered pairs:

$$A = \{(x, \mu_A(x)) \mid x \in U\} \qquad [1]$$

where U can be either continuous or discrete.

For example, the fuzzy set *small* numbers (in a continuous domain) can be defined by (using the notation $\mu_A(x)/x$):

$$small(x) = \left[1 + \left(x/10\right)^2\right]^{-1} / x \quad x \, \varepsilon \, U \qquad [2]$$

The basic operations on Fuzzy Sets are complement, union, and intersection. The complement of *A* is a fuzzy set $\overline{A}$ in U whose membership function can be defined as,

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x) \quad [3]$$

The union of A and B is a fuzzy set in U, whose membership is defined as,

$$\mu_{A \oplus B}(x) = \oplus\left[\mu_A(x), \mu_B(x)\right] \quad [4]$$

where $\oplus$ is any t-conorm operator.

The intersection of A and B is a fuzzy set in U, whose membership is defined as,

$$\mu_{A \otimes B}(x) = \otimes\left[\mu_A(x), \mu_B(x)\right] \quad [5]$$

where $\otimes$ is any t-norm operator.

There are many operators proposed in the literature to perform the operations of intersection, union and complement. The most common are the classes of t-norms for intersection and t-conorms for union and the classical negation for complement (Wang 1997). Another important class of operators that will not be discussed in this work are the averaging operators (Wang 1997). For details about classes of operators see, for instance (Zimmermann 1996). Moreover, in the section about fuzzy inference systems we will return to the subject of operators because they play a fundamental role in rule-based systems.

Another important concept for fuzzy logic is the existence, or not, of relations between fuzzy sets. A fuzzy relation, defined in the Cartesian product of the crisp sets $U_1, U_2, \ldots, U_n$, is a fuzzy set R such that

$$R = \left\{((u_1, \ldots, u_n), \mu_R(u_1, \ldots, u_n) \mid (u_1, \ldots, u_n) \in U_1 \times \ldots \times U_n\right\} \quad [6]$$

where $\mu_R : U_1 \times U_2 \times \ldots \times U_n \rightarrow [0,1]$

An example could be the fuzzy relation “more or less close” between two sets of cities, U={Lisbon, Paris} and V={Paris, London} with the fuzzy set R={0.4/(Lisbon, Paris)+ 0.2/(Lisbon,London)+ 1/(Paris, Paris)+ 0.8/(Paris, London).

The extension of fuzzy relations in the same space to different Cartesian product spaces (a concept essential for fuzzy knowledge-based system) is performed by the compositional rule of inference (Zadeh 1987-a). Hence, the composition rule of fuzzy relations P(U,V) and Q(V,W) denoted by $P \circ Q$ is defined as a fuzzy relation in $U \times W$ whose membership function is,

$$\mu_{P\circ Q}(x,z)=\max_{y\in V} t\left[\mu_P(x,y),\mu_Q(y,z)\right] \quad [7]$$

where the operator t can refer to a max-min composition or a max-product composition (Wang 1997). An easy way to compute the compositional rule of inference (7) is to use the multiplication principle of matrices (Mendel 2001), i.e. multiplying lines per columns with columns per lines, by using max for addition and min for multiplication (in the case of the max-min composition) and max and product for the max-product composition.

Another important concept for fuzzy logic, particularly for fuzzy inference systems, is the concept of linguistic variable (Zadeh 1987-b). The objective of defining linguistic variables is to enable expressing imprecise semantic concepts using a consistent mathematical formulation and then enable to perform approximate reasoning. In general, if a variable can take words in natural language as its values, it is called a linguistic variable, where the words (usually called terms) are characterized by fuzzy sets in the same domain as the linguistic variable. More formally (Zadeh 1987-b), (Wang 1997), a linguistic variable is characterized by the five-tuple (X,T,U,G,M) where: X is the name of the linguistic variable; T is the set of linguistic terms, values that X can have; U is the actual physical domain in which the linguistic variable X takes its crisp values; G is a syntactic rule which creates the terms in the term-set; M is a semantic rule that relates each label in T with a fuzzy set in U. For example, Temperature={cold, pleasant, hot} is a linguistic variable with three terms, where each label is represented by a fuzzy set. Figure 1 illustrates this example of linguistic variable.

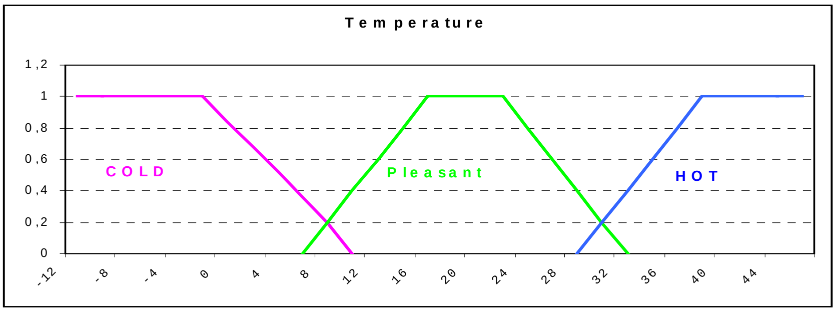

Figure 1. *Linguistic variable Temperature*

Now we provide a brief overview of fuzzy rules and approximate reasoning, two important aspects of fuzzy logic and fuzzy inference systems. Recall that intersection operators are usually associated with the logical AND in rules, such as “IF A *AND* B THEN C”, while the union operators are usually associated with the logical OR, such as “IF A *OR* B THEN C” or even with rule aggregation.

A fuzzy IF-THEN rule is a conditional statement that can be expressed as:

$$\text{IF} < \text{fuzzy proposition} > \text{THEN} < \text{fuzzy proposition} >$$

From the above rule we need to clarify what is meant by a < fuzzy proposition>. Fuzzy propositions can be of two types: atomic fuzzy propositions and compound fuzzy propositions. Atomic fuzzy propositions are statements like, *x is A*, where x is a linguistic variable and A is a linguistic value of x. A compound fuzzy proposition is a composition of atomic fuzzy propositions using the connective operators “and”, “or” or “not”. These operators correspond, respectively, to “fuzzy intersection”, “fuzzy union” and “fuzzy complement” (Ross 2004) (Wang 1997). An example of a compound fuzzy proposition can be “(x is *slow* and x is not *fast*) or x is *medium*”, where slow, medium and fast are labels (they can also be called granules) of the linguistic variable “speed”.

Usually, compound propositions have more than one linguistic variable, such as this example for intersection,

“x is A and y is B”.

Therefore, compound propositions should be understood as fuzzy relations, either in the $U \times U$ domain, for (x, x), or in a $U \times V$ domain, for (x, y). The question is now (Wang 1997): How to determine the membership functions of these fuzzy relations? Lets consider the above intersection compound proposition, where x, y are the variables in the domain *U* and *V* and A and B are fuzzy sets in *U* and *V*, respectively. Hence we can interpret the proposition as a fuzzy relation, with membership function,

$$\mu_{A \cap B}(x, y) = t[\mu_A(x), \mu_B(y)] \qquad [8]$$

where $t : [0,1] \times [0,1] \to [0,1]$ is any t-norm.

The same interpretation can be made for union but with t being a t-conorm and for the complement we should use $\overline{A}$ (not A).

Now we can describe the interpretation for the IF-THEN rules (also called production rules), i.e. how should we interpret the rules? In classical propositional calculus, the expression “IF *p* THEN *q*” is written as $p \to q$ with the implication, $\to$, being a connective defined by a truth-table, where the values of *p* and *q* are either true or false. There are many implication operators proposed in the literature for fuzzy logic systems (Klir and Folger 1988; Wang 1997), but the most used are:

Kleene-Dienes implication => $\mu_{KD}(x,y) = \max[1-\mu_A(x), \mu_B(y)]$ *[9]*

Lukasiewicz implication => $\mu_L(x,y) = \min[1, 1-\mu_A(x)+\mu_B(y)]$ *[10]*

Zadeh implication=> $\mu_Z(x,y) = \max[\min(\mu_A(x), \mu_B(y)), 1-\mu_A(x)]$ *[11]*

Mamdani implication => $\mu_M(x,y) = \min[\mu_A(x), \mu_B(y)]$ *[12]*

Mamdani implication (Ross 2004), which is equivalent to cross product of fuzzy sets, is the most widely known in FIS because of its interpretability, computational simplicity (Mendel 2001) (Ross 2004) and capability of handling systems with multiple outputs (called alternatives in multicriteria problems). The latter property will be discussed in more detail in the FIS section.

The most important aspect when performing inference in a fuzzy environment is what is called approximate reasoning. Approximate reasoning refers to the deduction of imprecise conclusions (fuzzy propositions) from a collection of imprecise premises (fuzzy propositions) (Wang 1997). Inference rules (also called tautologies or production rules) are used to make the deductive inferences to obtain the conclusions.

The most common inference schemes in classical logic are the Modus Ponens and Modus Tollens. Since the main goal of Fuzzy Logic is to provide the foundations for Approximate Reasoning, these schemes were generalized to accept fuzzy propositions and the determination of their membership functions is done by the compositional rule of inference (Wang 1997; Mendel 2001).

3. Fuzzy Inference Systems (FIS)

Classical Inference Systems (non-fuzzy) are computerized systems that employ human knowledge on a given domain, captured in software, to solve problems from that specific domain. From a functional point of view, it can be said that their main goals are to capture, store, reason and explain knowledge (Turban, Aronson et al. 2004). When we extend the classical inference to the fuzzy logic domain we have the added value of being able to represent imprecision and to perform approximate reasoning within a fuzzy environment.

As mentioned before, Fuzzy Logic is a good approach to represent and manipulate imprecise data. FL models use fuzzy sets to describe and manipulate imprecise concepts and then perform logic operations to achieve conclusions (Mendel 2001). Fuzzy inference systems (FIS), require the development of a knowledge base, which will contain the set of rules using fuzzy sets. Rules are at the core of a FIS and are usually provided by experts or they can be extracted directly from numerical data (Mendel 2001). FIS are primarily used in control but they can have a broader interpretation by considering their possible actions: monitoring and fault detection, suggestion, conclusion, evaluation, selection and forecasting. As mentioned before, here we follow (Isermann 1997) general interpretation of “monitoring” as a decision support task for users and, consequently, the architecture described includes an explanation facility to support the human decision making process.

Furthermore, we should distinguish between MISO (Multiple Inputs Single Output) and MIMO (Multiple Inputs Multiple Outputs) inference systems (Mendel 2001). Usually classification systems like monitoring systems are MIMO. Even though we can transform any MIMO into several MISO inference systems (Mendel 2001) the selection of the type of model to use is important because Mamdani-type of FIS is appropriate to deal with MIMO systems while Sugeno-Takagi FIS should only be used for MISO, because it encompasses a weighted average, for the rule aggregation, and there is no sense in mixing outputs from different domains. Hence, if we want to develop a MIMO system and not divide it into multiple MISO we have to select a Mamdani-type inference model. In the case of monitoring problems, because they are really classification problems, i.e. the outputs are alternatives in the sense of multicriteria problems; they should be defined as MIMO systems. Hence it is common to select the Mamdani-type inference model for monitoring problems, as will be shown in the illustrative examples.

3.1. FIS architecture

In general, we can say that FIS for monitoring and fault detection will include characteristics from classical decision support systems (e.g. explanation module) and characteristics from a common FIS. Hence, a possible architecture for a monitoring FIS is depicted in Figure 2 (adapted from (Mendel, 2001) (Hopgood 2001) (Turban, Aronson et al. 2004)).

The architecture depicted in Figure 2 shows the links between each component. The knowledge acquisition module is mainly used to construct the knowledge module and for this purpose, this component needs to communicate with the experts and developers. The explanation module is linked with the knowledge base as well as the inference engine in order to explain **why** and **how** a conclusion is reached. These pieces of information are then passed to the users by the dialog module. The knowledge base and the inference engine are connected to allow the reasoning process to take place using facts and rules from the Knowledge Base. The dialog module is connected to the knowledge module and the explanation module to allow the dialog between the outside world and the system. Next we present the main characteristics of each module in Figure 2.

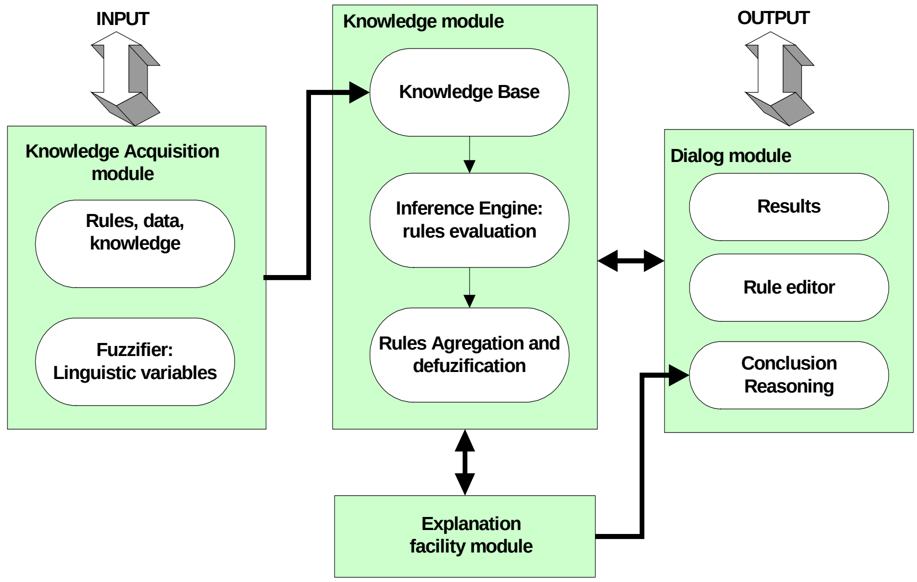

Figure 2. *Fuzzy Inference System for Monitoring*

Knowledge acquisition module

One important bottleneck of inference systems is the knowledge acquisition process. Most knowledge is elicited from experts and their expertise must be converted, for example, into a set of rules to include in the knowledge base. Another possibility is to get the knowledge directly from experimental data, if there is enough data (in terms of quantity and quality) in order to infer the knowledge (e.g. neural networks; decision trees induction) (Hopgood 2001).

Explanation module

This module aims at clarifying the reasoning, actions or recommendations given by the FIS. Most explanation facilities provide two basic types of explanation answering to:

why? and **how**?

The purpose of the explanation module (Turban, Aronson et al. 2004) is to make the system more intelligible to the user, to explain the reasoning process taken to achieve a result and, when applicable, to conduct sensitivity analysis. Moreover confidence in the system, as well as inference validations, is obtained through the analysis of the reasoning path.

Dialog Module

A major issue when reasoning on a FIS is the consideration of how the user will need to interact (dialog) with the system.

The interface (dialog) component refers to the attributes that enable both users and developers to access and use the information and the programming languages. In FIS an important component of the interface is the inclusion of a rule-editor that will allow the system to evolve according to the necessities of the users.

The architecture depicted in Figure 2 shows the three main elements that this module should have: an interface with the results, shown according to the user's preferences; the rule-editor and how the conclusions were reached.

Knowledge Module

This module is composed of three elements: knowledge base, inference engine and the aggregation/defuzzification component.

The knowledge base can include a rich environment with knowledge stated in different formats; in general, it can be assumed that the Knowledge Base consists of <u>Rules</u> and <u>Facts</u>. Rules may become pretty complex and Facts may include sequences, structured entities, attributes and relationships between themselves.

In general it is assumed that a Knowledge Base is divided into five (5) layers (Turban, Aronson et al. 2004):

- Consultation level (sometimes called working memory) – which is composed by instantiated facts, rules, conclusions reached etc.
- Simple rule level – Goals and simple facts and rules.
- Structured rule level - complex facts and rules organized into a context tree.
- Object level – objects, agents and relationships.
- Meta level – rules that examine other rules in the knowledge base.

It should also be noted that the five layers are usually based in the knowledge representation technique called propositional logic (in this paper fuzzy propositional logic).

Inference Engine

Inference engines vary according to the type, formalisation and complexity of knowledge with which they deal. The inference engine should be understood as the interpreter of the knowledge stored in the knowledge base. The most common strategies used in the inference engine are (Hopgood 2001):

- Data-driven (forward chaining)
- Goal-driven (backward chaining).

The data-driven approach is more appropriate for problems of interpretation and diagnostics, while the goal-driven is more appropriate for problems that, on the basis of a starting statement, shall provide proof or negation. Both strategies largely depend on the search algorithm chosen for the implementation. In monitoring and fault detection problems obviously the data-driven strategy is more appropriate because it deals with detection of deviations from nominal behaviour and triggering alarms for warning the operator.

Recall that we can have compound fuzzy propositions in the rules, i.e. rules with more that one antecedent, then we will now discuss the inference process for a fuzzy inference system. To simplify the explanation we will only use compound propositions with the intersection operator "AND" (note that rules with "OR" antecedents can be transformed into "AND" ones) (Wang 1997).

Let us consider a set of rules of the form IF *x is A'* AND *y is B'*… THEN *z is C'*. The three steps we must follow to obtain the output of the set of rules are (Mendel 2001):

A. Strength or firing level. This is obtained by using composition conjunction, i.e. by intersecting the fuzzy propositions of the antecedent (compound statements), such that,

$$\alpha_i = \otimes(\mu_{A'}(x), \mu_{B'}(y)) \qquad [13]$$

where $\otimes$ is any t-norm operator.

B. Rule evaluation. This step refers to the actual inference (deduction) to obtain the conclusion of a fired rule. The formulation is then,

$$\mu_{\alpha \to C'}(z_i) = *(\alpha_i, \mu_{C'}(z_i)) \qquad [14]$$

where $*$ refers to any implication operator.

C. Rules aggregation. To decide which action to take (output of the fuzzy inference system) we need to aggregate all the rules that were fired. The most common aggregation operator is *max* (union of rules), but others could have been used (Wang 1997; Mendel 2001). Formally,

$$\mu_{output'}(z) = \cup \mu_{\alpha \to C'}(z_i) \qquad [15]$$

where $\cup$ refers to an aggregation operator.

After performing the aggregation of rules to achieve a conclusion we have two cases to consider, either we have a Sugeno-Takagi type of System or a Mamdani-type System (Mendel 2001). In the first case we do not need defuzzification because the aggregation is performed with a weighted average and provides the final crisp result. In the second case (Mamdani type) we need to decode the output obtained in order to produce a single value *z* representative of the membership function obtained from step C. This process is known as Defuzzification. There are many proposals in the literature for defuzification methods such as: center of the area (COA); mean of maximum (MM), height defuzzification method and so forth. Here, we will not discuss defuzzification methods in detail, for good overviews see (Wang 1997; Mendel 2001).

3.2. Development process

In general the choices to be made in the development of a FIS for an operator decision support, in monitoring and fault detection problems, are (adapted from (Mendel 2001) and (Ross 2004)):

- At the input level, define the linguistic variables and the shapes of the membership functions.
- Construct the knowledge-base either using rules provided by the experts or extracted from numerical data.
- Choose the t-norm to be used for the firing level of the rule antecedent.
- Choose the implication operator to be used for the evaluation of rules.
- Choose the combination operator to aggregate all rules fired and obtain the final output membership function.
- Choose the defuzzification method to obtain the single crisp value for the action to take, which represents the final output membership function.

From the experience acquired with the development of human-controlled Space monitoring applications, we propose the following extension to the above steps:

1. Identify the input variables (problem understanding)
2. Define the System in terms of an Input-Process-Output model
3. Address Model variables (input and output)
   - Decide on a Level of Granularity
   - Determine Domain of Model Variables
   - Understand Degree of Uncertainty in the Data (either from experts or from data extraction processes).
4. Define Fuzzy linguistic variables and respective Fuzzy Sets (Fuzzification process)
   - Choose surface Morphology for Fuzzy Sets
   - Elicit a Fuzzy Set Shape
   - Select an Appropriate Degree of Overlap
   - Ensure Sets are Conformably Mapped
5. Rule Construction
   - Define Ordinary Conditional Rules
   - Define Eventual Unconditional Rules

  - Add Hedges, if necessary
  - Select operators to use for intersection, union and rule firing level (implication).
  - Select the type of Inference scheme to use: Mamdani-type FIS or Sugeno-Takagi-type FIS.
6. Inference process definition
  - Select the operator to be used for rules aggregation (reasoning to reach a conclusion). It will depend on type of inference scheme.
  - Define the necessary Metaknowledge
  - Create explanations/justifier for the resulting inferences ("why"?)
7. If output is fuzzy (e.g. Mamdani FIS) select a defuzzification method (e.g. center-of-mass). If output is crisp (e.g. Sugeno-Takagi FIS) stop.

This development process, in combination with the architecture depicted in Figure 2, has proved quite successful in developing fuzzy monitoring inference systems, as can be seen by the illustrative cases discussed in the following section.

4. Illustrative FIS for space monitoring problems

In this section we will briefly describe two space related applications that have been, and are being, developed for the European Space Agency (ESA) by the UNINOVA/CA3 research team (www.uninova.pt/ca3). The first project is described in more detail because it is already completed.

ESA project "Fuzzy Logic for Mission Control Processes"(FL-MCP)

A Fuzzy Inference tool was developed for monitoring and fault detection of the ENVISAT satellite gyroscopes (Pereira et al 2002). The ENVISAT gyroscopes monitor and fault detection tool was jointly developed by GTD (Spanish company) and UNINOVA (Portuguese R&D Institute) for the European Space Agency (ESA) project "Fuzzy Logic for Mission Control Processes"-AO/1-3874/01/D/HK.

The rational for using a FIS for this monitoring and fault detection tool were: (1) the number of gyroscope failures in the past was quite limited; (2) no data was available to automatically induce new rules; (3) no detailed mathematical model existed to describe the gyroscope degradation on the long-run; (4) there was experience from the experts on the domain.

The fuzzy inference tool development focused on two important points: one was the knowledge extraction from experts; the second was the design of FIS using the proposed architecture and development process (as close as possible).

The complete tool developed included three FIS. Since we are dealing with MISO and MIMO systems we selected the Mamdani-type of model and we used the operators: min for intersection; maxmin for implication and max for rules aggregation. The deffuzzification method selected was center-of-mass. Moreover, the three FIS provide explanation for the faults detected ("why" characteristic). Briefly the three FIS are:

1. Detection of faulty deviations from gyroscopes nominal values (defined by the gyroscope manufacturers); see (Pereira, Moura-Pires et al. 2002). This FIS is a MIMO with 11 input variables, 4 output variables and 4 complex composite rules (i.e. including "and" and "or"). All the 11 input variables are repeated 4 times, one per gyroscope; hence, in reality the system has 44 input variables. Below is an example of one of the rules for monitoring the gyroscopes (note that this rule is repeated for each of the existing 4 gyroscopes):

IF
HuntingFrequencyAxis1 is "*Exist*" **and** HuntingFrequencyAxis2 is "*Exist*" **and** DeviationHuntingAxis1 is "*Tolerable*" **and** DeviationHuntingAxis2 is "*Tolerable*" **and** AmplitudePSDHuntingAxis1 is "*Tolerable*" **and** AmplitudePSDHuntingAxis2 is "*Tolerable*" **and** EnergybandAxis1 is "*Tolerable*" **and** EnergybandAxis2 is "*Tolerable*"
and (RandomNoiseFirstBandAxis1 is "*Not tolerable*"
or RandomNoiseSecondBandAxis1 is "*Not tolerable*"
or RandomNoiseThirdBandAxis1 is "*Not tolerable*"
or RandomNoiseFirstBandAxis2 is "*Not tolerable*"
or RandomNoiseSecondBandAxis2 is "*Not tolerable*"
or RandomNoiseThirdBandAxis2 is "*Not tolerable*")
THEN Alarm is "*GyroNoiseAlert*".

The linguistic variables used in this rule Existence={*Exist*, *Not-Exist*} and Deviations={*Tolerable*, *Not-tolerable*} were all represented by two labels and trapezoidal functions.

For example, Figure 3 depicts the membership function for the term *Tolerable* of the hunting frequency variable, DeviationHuntingAxis1. The construction of this term assumed a plateau interval (interval with membership value 1) of 5% for each side of the variable nominal value (experts supplied the nominal value) and the deviations allowed (with memberships from 1 to zero) were 10% for each side. The label *Not- tolerable* was represented by the negation of *tolerable*.

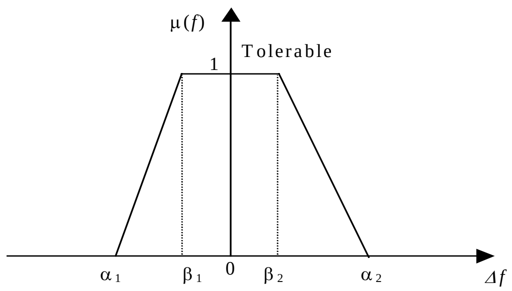

Figure 3 *Deviation of hunting frequency*

2. Alarm system for the general system level (ENVISAT satellite). This FIS is a MISO, but to maintain the consistency within the complete tool we used again the Mamdani- type model. This FIS generates alarms with different degrees of criticality and a severity level of the alarm itself, instead of a simple presence/absence of the alarm. The FIS includes 11 input variables (see Table 1), 6 output variables and 73 rules. Figure 4 depicts graphically the knowledge module for this FIS.

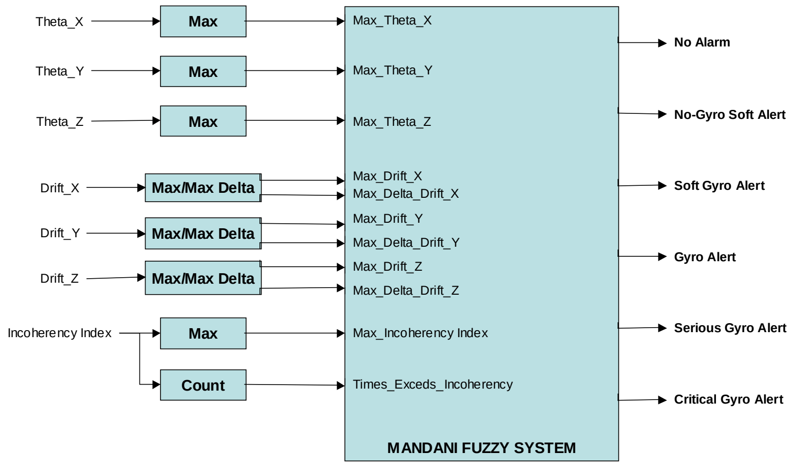

Figure 4. *General System Level Model*

INPUT Variables	**Description**
Max_Theta_X/Y/Z	For each three satellite axes X/Y/Z is the maximum (absolute) value of the estimated Attitude (Theta).
Max_Drift_X/Y/Z	For each three satellite axes X/Y/Z is the maximum value of the estimated Drift.
Max_Delta_Drift_X/Y/Z	For each three satellite axes X/Y/Z is the difference between maximum and minimum value of the estimated Drift.
Max_Coherency_Index	The maximum value of coherency index.
Coherency_Index_Trigger	The number of times when the coherency index exceeds a given (user configurable) threshold.

Table 1. *Short description of the input variables*

Below we describe an example of one of the rules of this FIS. Note that the fuzzy label Not-Tolerable was used again, because the degree of uncertainty is measured in terms of deviations from nominal values.

IF MaxThetaX is *Not-Tolerable* **and** MaxIncoherencyIndex is *Not-Tolerable* **and** IncoherencyIndexTrigger is *Not-Tolerable*
THEN SystemLevelAlarm is *SeriousGyrosAlert*

3. The objective of the last FIS in this project is to measure the quality of the telemetry data due to gaps in the telemetry signal arriving to Earth. Details can be found in (Pires, Ribeiro et al. 2002).

Briefly, this FIS is a MISO with 2 inputs and 1 output and only 2 rules (repeated for the gyroscopes 2 axis=2x2). The two input variables are: NoMissing - percentage of the total number of missing points by the total number of points; MaxGap - percentage of the maximum number of continuous missing points (i.e. the largest gap) by the total number of points. Below find the two rules used in this FIS.
IF NoMissing is *Good* **or** MaxGap is *Good*
THEN Quality is *Good*
IF NoMissing is *Bad* **or** MaxGap is *Bad*
THEN Quality is *Bad*

The benefits of the fuzzy logic approach used in this project are related with the nature of the gyroscopes. With our fuzzy logic approach, we can express statements such as "The deviation of the current status from the nominal situation is not tolerable" and obtain a measure of how true such a statement is.

The main achievements of the tool, as pointed by ESA (Donati 2003), were: (a) early detection of a slight noise increase affecting gyroscope #1 measurements, despite the fact that noise levels were still well within the specifications; (b) implemented Fuzzy Logic model demonstrated reliable in performing correct early anomaly detection; (c) independent capability of assessing hardware status of back-up gyroscopes, in quasi real-time, was verified.

ESA project - "Simulation of Knowledge Enabled Monitoring and Diagnosis Tool for Mars Lander Payloads" (MODI)

The MODI project is an ESA initiative with the objective to develop a monitoring and diagnosis tool for a Drill and Sampling System. The project consortium includes UNINOVA and DEIMOS (Spain). Galileo Avonica (Italy) is the external consultant providing data for the drill, selected for the case study in the project.

The MODI project is considered in the context of the ExoMars mission: search for signs of past and / or present life on Mars (ExoMars09 2002). To accomplish this ambitious mission a scientific package must be developed in order to analyze the organic and inorganic composition of Martian samples (deposits) with possible exobiological remaining. This package is called Pasteur payload and includes a component that is the focus of the monitoring and fault detection tool: the drill and sampling device for the rover that will acquire samples from the Mars sub-surface.

The project will also identify the advantages and limitations of using a Rule Base System based on Fuzzy Logic following the proposed development procedure.

At this stage we already performed the four first steps: 1. Identify the input variables (see Table 2); 2. Definition of the System in terms of an Input-Process-Output model; 3. Address input and output model variables; 4. Fuzzification of variables: linguistic variables and respective fuzzy sets.

INPUT VARIABLES (3 examples out of 11 input variables identified)	**Range**
RPM speed (rpm) – indicates the current rotational speed	0 - 200
Feed Rate speed (mm/min) – indicates the current translational speed	0 – 1.5
Motor Current (A) – Indicates the current that is being used by the Motor	0 – 3

Table 2. *Defined input variables examples*

The identified output variables are the types of terrain where the drill is drilling and 3 levels for alarms representing the deviations from the required nominal values. For example, the linguistic variable for the terrain hardness includes five terms {very-weak, weak, medium, strong, very-strong}.

The input-process-output model will be based on the following 6 scenarios: a) Drill profile while not drilling; b) Drill profile in Gas-Concrete; c) Drill profile in Travertine; d) Drill profile in Concrete; e) Drill profile in Tuff; f) Drill profile in Marble.

The fuzzification of the variables was based on the identified ranges and considering nominal values that were automatically generated using data mining algorithms and experimental data given by the external consultant for the 6 scenarios described above. For example, the RPM speed is defined as a linguistic variable with 3 labels {low, medium, high} where each label is represented by a triangular fuzzy set, defined by a nominal value and acceptable deviations from that central value.

Since this project is still on-going we are now starting to address step 5 (Rule construction). Two examples of rules that the monitoring FIS will have are:

IF RPM Speed is Low **and** Feed Rate Speed is Low
THEN Very Strong Terrain.
IF RPM Speed is Medium **and** Feed Rate Speed is Medium
THEN Weak Terrain.

After constructing the rules and selecting the type of inference schema (in our case it will probably be Mamdani-type) we will address steps 6 and 7 of the proposed development process.

5. Conclusion

This paper discussed the suitability of fuzzy logic to deal with monitoring and fault detection problems in space applications, when certain knowledge is imprecise.

To highlight this suitability, we provided a general architecture for fuzzy inference systems (FIS) and proposed a simple step-by-step development process. Then, we briefly presented two illustrative space applications that used this approach, one already finished and one still under development.

From the illustrative examples presented we conclude that a Fuzzy Logic approach is clearly appropriate, for space related monitoring and fault detection problems, when knowledge is imprecise and the complexity and non-linear behaviour of the system cannot be expressed with a mathematical model.

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