

# Fuzzy Thermal Alarm System for Venus Express

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## INTRODUCTION

In the aerospace field, where satellites and spacecraft contain numerous components that require constant, yet indirect, surveillance of large amounts of data, monitoring tools give the operators constant access to the state of the machinery, facilitating prompt and appropriate responses to any problems that may arise.

The objective of developing a Venus Express alarm system (Steel, 2006) is to monitor the thermal characteristics of each spacecraft face with respect to spacecraft altitude relative to the sun's position. A thermal alarm monitoring tool assumes particular importance in the Venus Express mission as the spacecraft will be subject to high levels of solar radiation due to its proximity to the sun.

In the space context, in particular for mission-control purposes, fuzzy inference systems provide a suitable technique to build this type of alarm system because the knowledge is imprecise or partial, going beyond the use of traditional, that is, crisp, methods (Ribeiro, 2006). Furthermore, the fuzzy linguistic approach used (Mendel, 2001; Ross, 2004) allows for an effective complement to human operators by creating systems that can support their actions in case of any fault detected.

In this article, we discuss the design and development of a fuzzy thermal alarm system for the Venus Express spacecraft using a new inference scheme, the Choquet-TSK (Marques Pereira, Ribeiro, & Serra, in press; Marques Pereira, Serra, & Ribeiro, 2006). The new inference scheme is based on the integration of the Choquet integral (Grabisch, 1995, 1996, 1997) in a fuzzy inference system of the Takagi-Sugeno-Kang (TSK) type (Sugeno & Kang, 1986; Takagi & Sugeno,

1985). This integration allows expressing synergies between rules, and the necessary combined weights are obtained by using correlation matrices (Marques Pereira & Bortot, 2004; Marques Pereira, Ribeiro, & Serra). The new Choquet-TSK inference scheme together with a defined fuzzy-rule base is the basis of the thermal alarm system for the Venus Express spacecraft, developed within the context of a European Space Agency (ESA) project (AO/1-4635/04/N/ML). The main motivation behind this work was to show that expressing synergies between rules could improve the reliability of space monitoring alarm systems.

## BACKGROUND

### Fuzzy Inference Systems

Fuzzy inference systems (FISs), sometimes also called fuzzy expert systems or fuzzy knowledge-based systems (see, for example, Zimmerman, 1996), express their knowledge through fuzzy linguistic variables (Mendel, 2001; Ross, 2004; Zadeh, 1987), whose role is to define the semantics of the problem. Then, by means of the fuzzy linguistic variables formulation, the linguistic variables are characterized and quantified. FISs also include a set of rules that define the way knowledge is structured and an inference scheme that constitutes the reasoning process toward the result.

A typical FIS (Mendel, 2001; Ross, 2004; Wang, 1997) includes the following steps: (a) "fuzzification" of the input variables, (b) definition of the output variables, (c) definition of the rule base, and (d) selection of the inference scheme (operators, implication method, and aggregation process). In some inference schemes,

for example, the Mamdani model (Mamdani, 1976), a “defuzzification” method is also required to transform the fuzzy output result into a crisp output. Here, because we follow the Takagi-Sugeno-Kang model (Sugeno & Kang, 1986; Takagi & Sugeno, 1985), which comprises fuzzy inputs but crisp outputs, we will not discuss defuzzification methods.

Fuzzification of the inputs implies their definition as fuzzy linguistic variables (Zadeh, 1987). Formally, 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, in which the linguistic variables  $X$  take values;  $U$  is the actual physical domain in which the linguistic variable  $X$  takes its crisp values;  $G$  is a syntactic rule that creates the terms in the term set; and  $M$  is a semantic rule that relates each label in  $T$  with a fuzzy set in  $U$ . For example,  $\text{height} = \{\text{short, average, tall}\}$  is a linguistic variable with three terms, where each label is represented by a fuzzy set. A fuzzy set represents the membership degree of objects of a specific term or set (Zadeh).

The definition of the outputs depends on the FIS model selected and can be divided in two main classes (Mendel, 2001): the Mamdani type, which uses fuzzy inputs and fuzzy outputs, and the Takagi-Sugeno-Kang type, which uses fuzzy inputs but crisp outputs. The Mamdani consequents are usually represented by linguistic variables, while the TSK consequents are usually a function of the inputs. In our application, we only use constants for the output functions (TSK model).

The developer and domain expert in close collaboration usually define the rules for the inference system application. The domain expert is essential for the definition of the rule set because rules represent existing relations between input variables and the desired conclusion, and they have knowledge about those relations. A fuzzy rule is usually defined as:

*IF  $X_1$  is  $A_1$  AND ... AND  $X_n$  is  $A_n$  THEN  $Y$ ,*

where  $X_k$  are the variables considered,  $A_k$  are the fuzzy terms of linguistic variables representing the variables considered, and  $Y$  is either a fuzzy term of a fuzzy output (Mamdani-type model) or a function (TSK-type model). For example, for a TSK model, the rule “IF Service is *excellent* THEN Tip=25” expresses that if the service in a restaurant is excellent (where excellent is defined by a fuzzy set), the tip should be

25% of the meal cost. For a Mamdani model, the rule “IF Service is *excellent* THEN Tip=*high*” expresses that if service is good, the tip should be high (where high is a fuzzy term of the linguistic output Tip).

The inference scheme process encompasses two phases for performing the inference (reasoning) of the application: the individual rule implication, which applies to all rules of the rule set, and the rule aggregation process, to reach a final result for a FIS. There are many implication operators to derive the conclusion for each rule (Lee, 1990; Wang, 1997; Zimmermann, 1996). However, the most used for FIS implication are, as mentioned before, the Mamdani one (minimum operator) and the TSK one (function of the inputs). The aggregation process, for all the rules implication values, depends, again, on the inference scheme selected. The Mamdani scheme proposes the max operator (many other operators could be used as can be seen in Wang; Zimmermann) while the TSK model uses a weighted average, where the weights are the normalized firing levels of each rule (Mendel, 2001; Ross, 2004).

## New Choquet-TSK Inference Scheme

The Choquet integral (Grabisch, 1995, 1997) is an operator capable of aggregating discrete sets of classifications for decision-making variables, taking into account the relations (synergies) that exist between those variables. It is an extension of the simple average weighting method (Grabisch, 1995). In a FIS, the relations between variables can assume three different forms: complementarity between rules, redundancy (or a certain degree of overlapping) between rules, and an intermediate case or independence. In the Choquet-TSK approach (Marques-Pereira, Ribeiro, & Serra, in press; Marques-Pereira, Serra, & Ribeiro, 2006), the individual weights correspond to the firing levels of each rule, and relations are represented by a fuzzy measure (Murofushi & Sugeno, 1991), acting as a structure of relative weights. The basic rationale is that if the firing levels for two rules are systematically similar, then those rules encode the same information and thus have a degree of redundancy; the joint weight that they have in the aggregation (their firing levels) should decrease. If, on the other hand, the firing levels for two rules are systematically opposite, then those rules encode complementary information and are thus important; the joint weight that they have in the ag-

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