Fuzzy-based System for Intelligent Diagnosis of Motion Problems on Ground Robots

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Abstract

This work describes the application of a fuzzy system using expert and induced knowledge, applied to the detection of motion problems in ground robots. Appropriate characterization of the robot behaviour becomes a key issue in order to identify the variables that should be used so as to detect the fact that the vehicle has collided against an undetected obstacle, and that the obstacle is currently being dragged by the vehicle. Under those circumstances, vehicle consumption will be greater than necessary leading to an undesired situation that should be detected and corrected by an appropriate intelligent system.

1 Introduction

It is widely admitted that autonomous robots, independently of their application, must have efficient locomotion systems (low power consumption subsystems, highly precise sensors, and large autonomy batteries are the essential key points), reliable navigation and operational systems, and be able to work safely in their environment. Thus, the technology required to realize robust, reliable and safe robots is given considerable attention worldwide. As a consequence, the use of autonomous or semi-autonomous robots in real applications is only possible when those robots exhibit a certain level of intelligence, being able of fulfilling the previous requirements.

Soft computing techniques have been considered as a way of adding that level of intelligence from different points of view. The most common approach integrating soft computing techniques in robotics is that of applying it for navigation [1] and control [4]. Some other approaches have considered these techniques at the level of processing sensor information (ultrasounds, vision, ...) applied to localization [3], path following (corridors, walls) or obstacle avoidance.

The use of fuzzy techniques in diagnosis problems has been considered [8] but mostly in the field of automation, without considering autonomous robots. In the area of autonomous or semi-autonomous robots the effort is quite reduced and only a few applications have been proposed considering model based diagnosis, mostly using artificial neural networks, and centered on the diagnosis of actuator problems.

In order to focus on this problem, a general architecture for integrating fault diagnosis and recovery modules into autonomous robots is being developed in the framework of the European research project ADVOCATE II [10]. As pieces of this architecture, different Artificial Intelligence based modules (Neuro symbolic systems, Bayesian belief networks, and Fuzzy systems) devoted to diagnosis and recovery are developed and integrated into different robotic platforms.

The present paper describes one of the application problems of the ADVOCATE II project: diagnosis of collision with undetected obstacles of a ground robot, with the aim to provide recovery actions. The diagnosis module is made up of a fuzzy system that is mainly based on expert knowledge, but integrates data sample information.

The paper only analyses a fuzzy logic based intelligent module, assuming that the rest of the architecture operates properly and provides it with the required information (alarms, commanded and measured actuation, sensor information, . . .)

2 Problem analysis

To represent the diagnosis problem that will be introduced in this section, we choose the fuzzy logic formalism [11] for its well known linguistic concept modeling ability. The fuzzy rule expression is close to expert natural language. On the other hand, as they are universal approximators, fuzzy inference systems can be used for knowledge induction processes. The problem under consideration in this paper requires the integration of both, expert and induced knowledge, since none of these sources of information seems to offer a complete view of the problem. The cooperation between expert knowledge and induced knowledge highly depends on induced rule interpretability.

The robot under consideration integrates some obstacle avoidance capabilities based on the use of the information provided by an ultrasound ring. Under some circunstances, an obstacle may by undetected and the robot will collide with it. The objective of the fuzzy logic module is to provide one of the following diagnosis when the vehicle piloting module sends an alarm. This alarm is provided whenever there is a suspicion that a collision has occurred and it has not been detected by the ultrasound ring.

- Normal: it means that a false alarm was launched by the Robot Piloting Module, as no real collision has occurred.
- Vehicle_drags_obstacle: the vehicle has collided against an obstacle not heavy enough to block vehicle movement. Thus, after a transient interval the vehicle controller (adaptive) regains the commanded velocity and keeps on moving by dragging the obstacle on its way.
- Vehicle_stalled: in this case the obstacle is heavy enough to impede the vehicle from moving. Upon these circumstances, there are two different possibilities: wheels start to slip without producing any vehicle movement or the vehicle wheels could get trapped by the obstacle.
- Test_needed: it may happen that no accurate diagnosis can be issued based on the information provided by the variables involved in the process. In this case, a test is recommended in order to gather further data so as to launch a more precise diagnosis.

The fuzzy system design involves expert knowledge and its cooperation with data samples. The following sections will analyse those sources of knowledge.

3 Expert knowledge

To deal with complex problems such as robot motion, expert knowledge is of prime importance. The expert knows the main influential variables and is able to describe their behavior. From our experience, expert reasoning uses linguistic terms and is based on prototypes.

The expert knowledge extraction process can be kept at a 'high' abstraction level. The process can be limited at the expert domain, without considering implementation details which are not part of expert knowledge. For example the expert can only indicate the number of linguistic terms he needs for a given variable without defining the corresponding fuzzy sets.

The first step is then to define the number and nature of variables that are involved in the diagnosis process according to the domain expert experience. Considering the problem of detecting abnormal dynamics due to obstacles dragging or even stalling, the problem stated in previous section, the next variables are proposed after appropriate preprocessing provided by the Robot Piloting Module.

- Linear and angular velocities. Both commanded and measured velocities are included.
  - *Measured_linear_velocity*.
  - *Commanded_linear_velocity*.
  - *Measured_angular_velocity*.

– *Commanded_angular_velocity*.

As will be graphically demonstrated latter in this section (Figure 1), a fast but deep undershoot in vehicle velocity takes place upon collision with an obstacle, until the velocity controller regains the commanded reference. This constitutes the key hint to properly provide a diagnosis on it.

- Depth and width of velocity undershoot (*Undershoot_depth* and *Undershoot_width*) produced upon collision. These variables are crucial for determining whether the vehicle has really collided with an obstacle that is being dragged, or on the contrary, whether the undershoot is due to measurement noise. The depth and width of the velocity undershoot are tightly related to the commanded vehicle velocity as deep peaks occur at high velocity while small ones take place at low speed.

- *Difference_of_battery_voltage*. It provides a differential measurement of the decrease suffered by the battery voltage when colliding against an obstacle. This decrement is directly linked to the vehicle consumption, that should increase upon collision, subsequently producing the battery voltage to go slightly down. Under specific circumstances, the contribution of some subsystems of the robot to energy consumption should be also considered. As in previous case, this variable needs some preprocessing made by comparison of the mean value of battery voltage over an interval before and after peak (minimum) value of velocity.

- A ring of 16 ultrasound based sensors is used to provide range measurements around the robot. The variable *Range_measurements* and its derivative, *Derivative_of_range_measurements*, are useful to provide information concerning robot movement with respect to its environment.

Based on the above mentioned variables, experts can state different pieces of knowledge to describe certain situations relating some symptoms with a certain diagnosis.

As a first example, let's consider the use or range measurements to get information about a possible situation of robot stalled. To gain further knowledge on how expert rules are stated, let's determine whether the vehicle is moving or not. The next options are possible.

- The value of variable *Range_measurements* is different from null (something is detected within the detection range) and its derivative is different from zero. It could mean that the robot is moving in a static environment, that the robot is moving in a dynamic environment, or that the robot is not moving but the environment is dynamically changing (due to some moving obstacle). Consequently, no deterministic diagnosis could be provided under these circumstances.

- The value of variable *Range_measurements* is null (nothing is detected within the detection range). In this case there is no information at all about the environment, and thus, no diagnosis could be either issued.

- The value of variable *Range_measurements* is different from null (something is detected within the detection range) and its derivative is zero. This means that the vehicle is not moving.

According to the three previous possibilities an expert rule could be constructed by following the next reasoning. If range measurements are different from null and their derivative is zero then the environment surrounding the robot is not changing. If on these circumstances the vehicle odometry system measures a velocity different from zero, it can be deduced that the vehicle is stalled and its wheels are slipping. The rule can be formalized as follows:

IF *Range_measurements* is *not(null)* **AND** *Derivative_of_range_measurements* is *zero* **AND** *Measured_linear_velocity* is *not(zero)* **THEN** *Vehicle_stalled*

This piece of knowledge contains a couple of fuzzy propositions that are affected by one of the main questions considered when designing fuzzy systems: the use of negation. This paper will not analyze this situation in deep, but there are two possible interpretations of the fuzzy proposition

Measured_linear_velocity is *not(zero)*

where *not* can be interpreted at the level of membership functions or at the level of terms. In the first case, the membership function will be computed by applying the negation operator to the membership function of the linguistic term *zero*, where negation operator is generally defined as $\mu_{not(zero)}(x) = 1 - \mu_{zero}(x)$. In the second case, *not(zero)* will be computed as the union of the membership degrees to the remaining linguistic terms, what in this case represents *negative_big or negative_small or positive_small or positive_big*. In some cases, both values could be numerically equivalent, as in the case of considering strong fuzzy partitions (to define the membership functions) and bounded sum (as the t-conorm defining the or operator), but that is not the most common situation. The inference engine used in this application does not use the negation operator, and consequently the proposition will be interpreted as

Measured_linear_velocity is (*negative_big or negative_small or positive_small or positive_big*)

The semantics of the linguistic terms considered in these rules, as well as the method to define it, will be described in the next section.

Another example of expert rule can be produced for the collision and drag case according to the situation illustrated by Figure 1. Raw data has to be processed to be put in the form of the variable used by the expert. In this case we use Kalman and FIR (Finite-input response) filtering to define a clearer *velocity undershoot* produced by the collision. The rule is provided as follows:

IF *Undershoot_depth* is *medium* **AND** *Measured_linear_velocity* is *low* **AND** *Difference_of_battey_voltage negative_small* **THEN** *Vehicle_drags_obstacle*

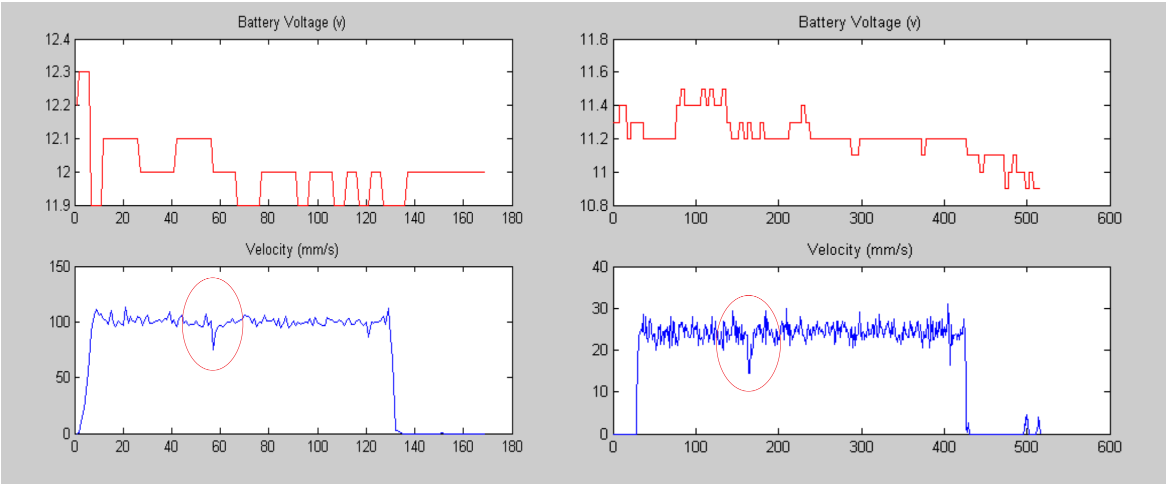
This rule is complemented by a complete set of rules analyzing other combinations of terms relating different values of the three considered variables, as the one considered in Section 5.

Previous paragraphs illustrate situations where the vehicle is stalled or the vehicle drags an obstacle. It becomes necessary to identify and assess those situations that require the execution of a test in order to gather further information concerning the vehicle state so as to issue an accurate diagnosis. Thus, if the original diagnosis provided by the fuzzy logic based intelligent module is not reliable enough, a test could be the key element to improve the decision by performing an additional predetermined manoeuvre. After peer consideration of practical cases, the two situations described in the following paragraphs have been identified.

The first situation is when an alarm has been raised by the Robot Piloting Module, but the amplitude of the velocity undershoot is much lower than expected compared to the average measured velocity of the vehicle. On the other hand, the width of the velocity fluctuation is short enough so as to consider that it has been caused by an obstacle that is being dragged by the vehicle. In such a case, a test is needed. During the test, the vehicle should execute a back-and-forth manoeuvre in order to check the variation of velocity. If the same velocity fluctuation is measured then the obstacle being dragged diagnosis gets confirmed and a liberation manoeuvre should be performed afterwards. If not so, the vehicle continues the mission unvaried.

The second situtaion is when an alarm has been raised by the Robot Piloting Module, but the amplitude of the velocity undershoot is much higher than expected compared to the average measured velocity of the vehicle, or the velocity goes to zero for a short time. After that, the vehicle velocity gets back rapidly to its commanded value. This situation could be caused by a heavy obstacle that is blocking the vehicle. In such a case, it's very likely that the vehicle stops for a while (due to the collision) and then enters into slippery mode. A test is needed to clear up what's going on. For this purpose, the vehicle should perform an odometry independent velocity measurement based on visual optical flow. If the measured velocity is similar to zero, then the slippery mode is confirmed and a liberation recovery manoeuvre should be launched. On the contrary, if the measured velocity is similar to the commanded velocity, the vehicle continues the mission unvaried.

Once analysed the expert rules extraction process



(a) *Test 1. Commanded linear velocity: 100 mm/s.*

(b) *Test 2. Commanded linear velocity: 25 mm/s*

Figure 1: Vehicle Battery Voltage and Linear Velocity during a collision-and-drag case.

we will briefly consider knowledge induction.

4 Induced knowledge

In complement with expert knowledge, data are likely to give a good image of variable interaction.

In order to induce complementary pieces of knowledge, some real experiments have been performed so as to collect data concerning the vehicle battery voltage and linear velocity. Thus, in a first trial a small but heavy obstacle was deliberately introduced in the environment in order to interrupt the vehicle trajectory during autonomous operation. Due to its small size, the obstacle can not be detected by the ultrasound-based obstacle detection module onboard the vehicle. Accordingly, the vehicle collides with the obstacle, yielding a temporary decrease in its linear velocity. Upon collision, the velocity controller adapts to this situation by increasing the actuators torque so as to rapidly attain the commanded reference velocity. This causes the vehicle to drag the obstacle along its way by increasing the battery current consumption, and consequently, the battery voltage goes slightly down.

Let us concentrate on this example to illustrate the knowledge extraction process, including its cooperation with expert knowledge.

This behavior, for two different commanded linear velocities, is shown in Figure 1, where the vehicle battery voltage and linear velocity are depicted for a real collision-and-drag case. The undershoot in the left Figure has a depth of 25% of velocity, i.e. 25 mm/s, while in the right one has a depth of 44%, i.e. 11 mm/s. These two values, according to the partition that will be generated in the next step, can be considered as medium and small undershoots, respectively.

We now use the results of a set of experiments producing this kind of preprocessed data, to define variable fuzzy partitions.

As expert rules use linguistic terms, it is of prime concern to design highly interpretable fuzzy partitions. The necessary conditions for interpretable fuzzy partitions have been widely studied [2].

We implement the main constraints of fuzzy partitions as follows:

$$\begin{cases} \forall x \displaystyle\sum_{f=1,2,\dots,m} \mu^f(x) = 1 \\ \forall f \; \exists \, x \; \mu^f(x) = 1 \end{cases} \tag{1}$$

where m is the number of fuzzy sets in the partition and $\mu^f(x)$ is the membership degree of x to the fth fuzzy set. Equation 1 means that any point belongs at most to two fuzzy sets when the fuzzy sets are convex.

Due to their specific properties [9] we choose all fuzzy sets of triangular shape, except at the domain edges, where they are semi trapezoidal.

Conditions from equation 1 are implemented by choosing fuzzy set breakpoints as shown in Figure 2.

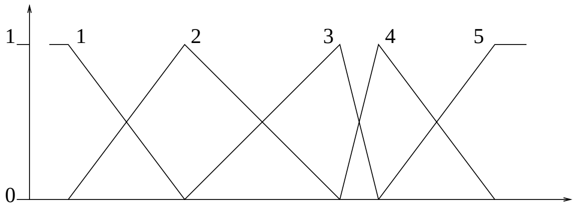


Figure 2: A standardized fuzzy partition

As a part of the ADVOCATE II project, a knowledge extraction tool has been developed. This tool offers, among others, capability to induce fuzzy partitions from data. The tool integrates different methods, as the hierarchical fuzzy partitioning (HFP), described in [5, 6], or the k-means algorithm [7].

Figure **??** illustrates that point by showing one of the screens of the extraction tool.

Analysis by the experts of the fuzzy partitions determines the best suited according to expert criteria. As an example, in the case of the varianble undershoot depth, the preferred partition is that obtained by HFP with four fuzzy sets, but adding a fifth term, corresponding to the label *null*, to include the case of no collision that was not represented in the experimental data.

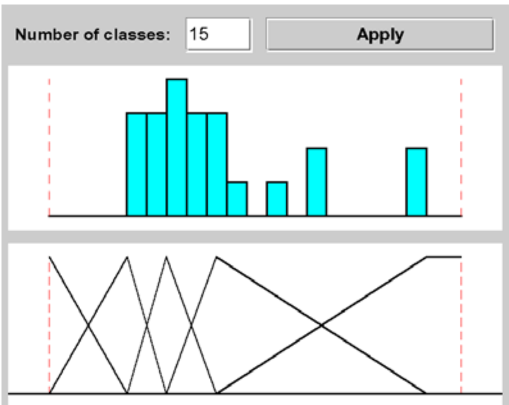


Figure 4: Expert selected fuzzy partition.

The final result is shown in Figure 4. As expected, the partition is highly interpretable while being designed according to the data. The five fuzzy sets correspond to the linguistic terms {*null*, *small*, *medium*, *large*, *very_large*}. The five anchor points in the partition are located at {0, 15, 22, 32, 73} mm/s

The knowledge extraction tool provides also functionalities for rule induction, but its use have been limited, in this paper, to partition design.

5 Results and discussion

For performance analysis of our system several motion trials using BART prototype have been carried out in the way previously explained. The comparison of the diagnoses given by the fuzzy system and the expert shows that the fuzzy diagnosis was correct in most of the trials.

Next, we are going to present a trial example for illustrating the overall process. In this case, the robot (which mass is 12 kg) is moving straight ahead with a linear velocity of 150 mm/s. The robot collides with a heavy obstacle (two batteries which overall mass is 5 kg) deliberately introduced in its trajectory and then the vehicle drags the obstacle. The preprocessed variables involved in this experiment are depicted in figures 5 and 6.

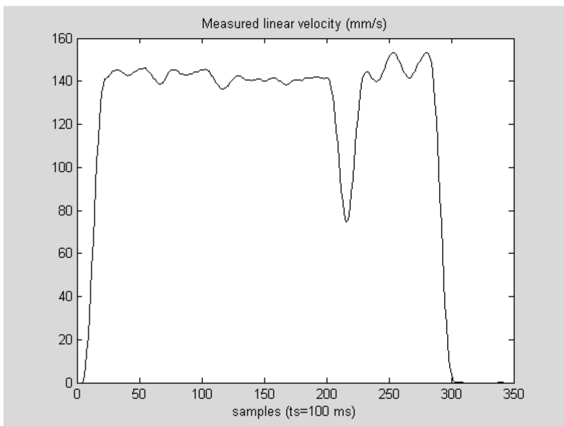


Figure 5: Vehicle velocity upon heavy obstacle collision.

The values of the variables to be considered are:

- *Undershoot_depth* = 67 mm. Being $\mu_{very\_large}(\triangle v) = 0.85$ and $\mu_{large}(\triangle v) = 0.15$.
- *Measured_linear_velocity* = 143 mm/s. Being $\mu_{high}(v) = 0.86$ and $\mu_{medium}(v) = 0.14$.

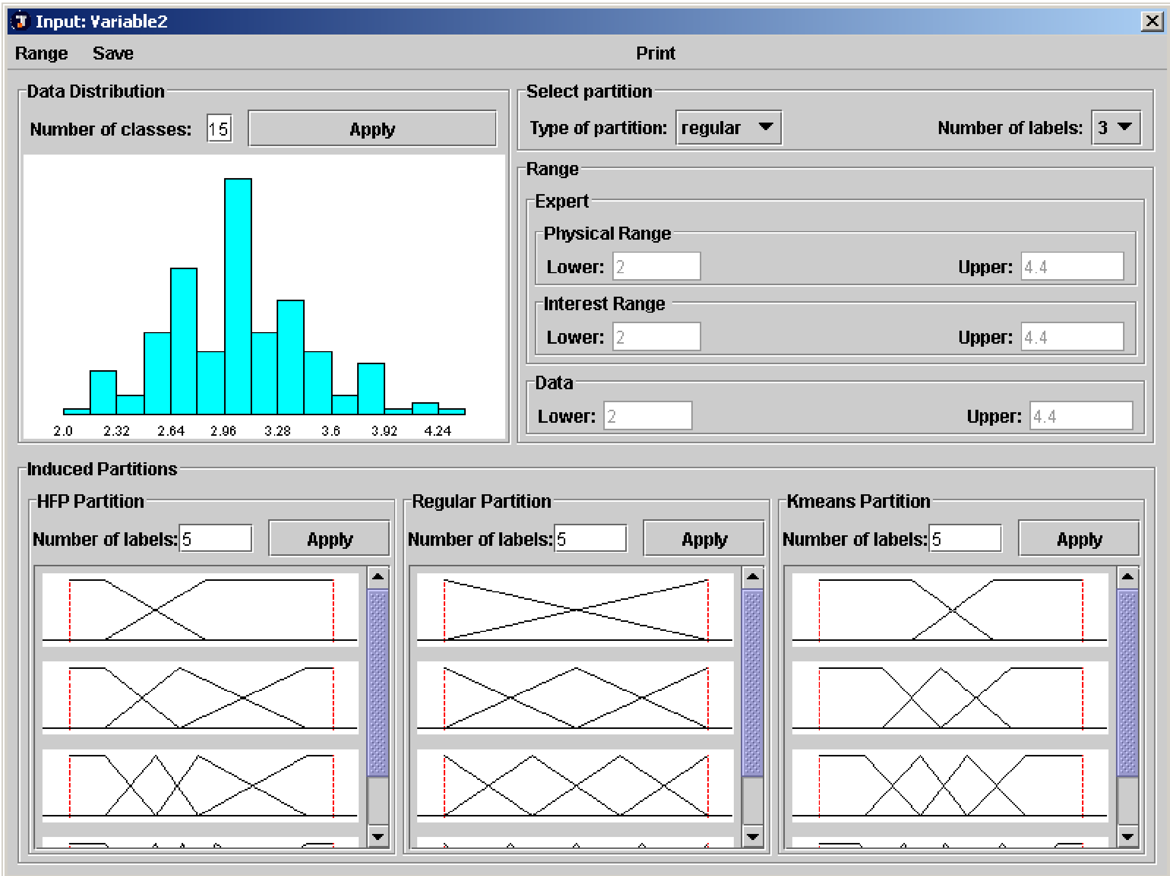


Figure 3: Fuzzy partitions generated by the knowledge extraction tool.

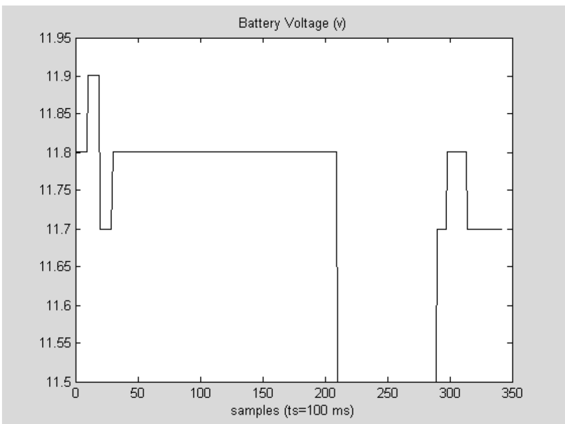


Figure 6: Battery voltage upon heavy obstacle collision.

- *Difference_of_battery_voltage* = -0.28 volts. Being $\mu_{negative\_big}(bat) = 1$.

These values will activate at different levels four rules of the system, where the highest activation (0.85) will be for the rule:

IF *Undershoot_depth* is *very_large* **AND** *Measured_linear_velocity* is *high* **AND** *Difference_of_battery_voltage* is *negative_big* **THEN** *Vehicle_drags_obstacle*

According to that, and independently of the characteristics of the inference process (for any aggregation operators and defuzzification method) the situation will be classified as a clear problem of dragged obstacle.

However, there are some situations in which the system does not run as well as expected. In order to improve system design, and then system accuracy, further work will consider automatic rule generation and their integration in the expert knowledge base. To make this integration easier the generated rules will use the readable fuzzy partitions already designed.

6 Conclusions

Some ground robot motion problems are considered in this paper and especially the detection, using robot motion parameters, of non visible obstacles using the usual sensorial capacities onboard the robot. The system we aim to design will be able to provide diagnosis as well as recovery actions upon these circumstances. The detection of collisions with non visible obstacles provoking motion problems is of prime importance for autonomous operation of ground robots in real environments.

As the obstacle characteristics are, obviously, unknown, the global system, i.e. robot and obstacle, cannot be accurately modeled from a quantitative point of view and only qualitative (or approximate) reasoning can be applied. As demonstrated throughout the paper, some linguistic relationships can be established between the obstacle characteristics and their influence in the robot motion variables upon collision. In such a framework, one should use all the available pieces of information for diagnosis and recovery action issuing.

The two kinds of knowledge, expert knowledge and data, convey complementary information. The objective is to extract their specific contribution to make the cooperation benefit for the system to be designed. Fuzzy logic, and fuzzy inference systems, are likely to offer a common framework. Nonetheless, the cooperation of expert knowledge and data in system design remains an open problem, especially when the goal is to get a system which is both accurate and interpretable.

In this paper this cooperation is restricted to variable partitioning. The distribution of data is used to design strong fuzzy partitions for each separate variable under expert control. This type of partitioning ensures each fuzzy set can be attached a linguistic label. The final semantic agreement is given by the expert: the fuzzy set centers must correspond to possible prototypes of the corresponding labels. Then, rules defined by these linguistic labels can be written by the expert. Further work will consider automatic rule induction and their fusion with expert rules.

The preliminary results show that the approach is appropriate but further analysis is required.

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