

KNOWLEDGE-BASED INTELLIGENT DIAGNOSIS OF ANOMALOUS MOTION OF GROUND ROBOTS

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ABSTRACT

The paper describes a robotic application in which some fuzzy techniques have been used to analyze motion problems in a mobile robot. The robot is equipped with ultrasound sensors used for obstacle detection, but, in some cases, small obstacles are out of the range of the sensors and can be dragged by the robot without being detected. The effect of the external obstacle on the robot motion variables can be established by means of linguistic rules, making the use of fuzzy techniques. Using other variables such as measured velocity, undershoots of that velocity, or the derivative of the battery voltage, a fuzzy system is able to diagnose on robot motion problems.

KEYWORDS: Mobile Robot, Anomalous Motion Problems, Diagnosis, Fuzzy 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. The most common approach integrating soft computing techniques in robotics is that of applying it for navigation [1] and control [2]. 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 [4]. The use of fuzzy techniques in diagnosis problems has been previously considered [5] but mostly in the field of automation, without considering autonomous robots. It is also possible to find similar problems in the automobile industry, where some fuzzy approaches have been applied [6]. 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 [7].

2. PROBLEM ANALYSIS

The aim of this section is to provide a brief description of the AGV anomalous motion problems due to obstacle collisions, and justify the need for deploying intelligent techniques for diagnosis and recovery action issuing. The interaction between the vehicle and the colliding obstacle is of particular importance in order to appropriately identify and characterize the different variables involved in the process, and the expected global behavior of the system. Diagnosis on motion problems should be performed based on the observation of commanded and

measured variables such as vehicle linear and angular velocities, battery voltage, etc. Two main interactions between the robot and the environment have been identified: obstacle collisions and uphill-downhill slopes. Either of them can be represented by an external torque denoted by T_{WL} that is applied to the vehicle whenever an obstacle collision or a change in slope occur. Measured linear velocities vary gradually with slope changes, as the derivative of the slope is a quasi continuous function in practice, and thus, it does not yield abrupt T_{WL} inputs to the robot. On the contrary, colliding obstacles produce step torque inputs to the robot at the time the collision takes place. It inevitably causes a sudden variation of vehicle linear velocity that is rapidly compensated for by the low level velocity controller producing a short but deep undershoot in the value of velocity (v_{res}), as depicted in figure 1.a. This situation is clearly distinguishable from that caused by a change of slope (figure 1.b), indicating that the robot has collided against an obstacle on its way and that the obstacle is being dragged by the robot as long as its linear velocity has attained the commanded value.

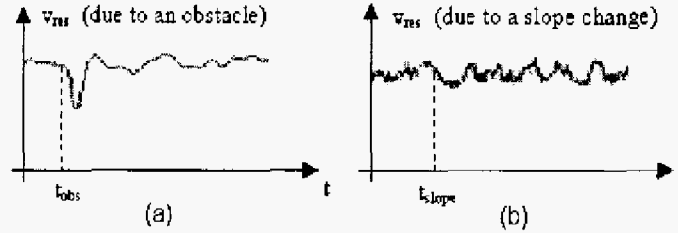


Figure 1. Variation of linear velocity. a) Due to a dragging obstacle. b) Due to a change of slope.

The dynamics of vehicle velocity, as a function of the external torque T_{WL} , can be described by the simplified expression provided in equation 1 as the relation between T_{WL} and the angular velocity of one wheel pair ω_{res} .

$$\omega_{res}(s) / T_{WL}(s) = (R_a + L_a s) / (k_T k_E (s\tau_m + 1)) \quad (1)$$

where R_a and L_a represent the internal electrical resistance and inductance components in the motor armature, k_T is the motor torque constant, k_E stands for the motor voltage constant, and τ_m stands for the mechanical time constant of the motor-load system. Accordingly, the duration of the undershoot is more or less proportional to τ_m . Likewise, τ_m is a function of J , the system inertia, which depends on the obstacle weight among other parameters. This means that the heavier the obstacle, the higher the value of τ_m and, consequently, the wider the duration of the undershoot. This simple reasoning could be used for diagnosis purposes in order to detect the collision and, possibly, to make the difference between a heavy and a non heavy obstacle. On the other hand, a similar reasoning can be followed so as to find a relation between the maximum velocity undershoot Δv and the system parameters upon obstacle collision. This relationship can be demonstrated to be the expression provided in equation 2 (an elastic conservative collision is assumed for simplicity).

$$\Delta v = v_i - v_f = v_i (m_{obs} / (m + m_{obs})) \quad (2)$$

where m and m_{obs} represent the mass of the vehicle and the obstacle, respectively, v_i stands for the initial velocity of the vehicle (before the collision), and v_f is the final velocity of the system composed by the vehicle and the obstacle after the collision. Two main conclusions can be derived from equation 2: on one hand, the heavier the obstacle the higher the amplitude of Δv ,

i.e., the higher the amplitude of the undershoot. On the other hand, the higher the initial velocity of the vehicle the higher also the undershoot. Although these are simple approximate statements, as no assumptions about the friction coefficient have been made, they can serve as a basic support for linguistic reasoning providing useful information in order to construct an intelligent diagnosis module. Due to the existence of non linearity in the system, which are difficult to model and identify, and considering the previous statements concerning the linguistic relation between the velocity undershoot amplitude and duration and the occurrence of a collision, the use of a fuzzy logic based diagnosis module becomes apparent and convenient.

3. FUZZY SYSTEM DESIGN

To deal with complex problems such as robot motion, expert knowledge is of prime importance to provide the main influential variables.

3.1 Expert Knowledge

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 next 7 input variables are proposed.

- Measured_linear_velocity.
- Commanded_linear_velocity.
- Undershoot_depth and Undershoot_width : 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.
- Difference_of_battery_voltage. It provides a differential measurement of the decrease in the battery voltage when colliding against an obstacle. This decrement is directly linked to the vehicle energy consumption, that should increase upon collision.
- A ring of 16 ultrasound sensors is used to provide range measurements around the robot. Range_measurements and its derivative, Derivative_of_range_measurements, are useful to provide information concerning robot movement with respect to its environment.

Let's consider the use of range measurements to get information about a possible situation of robot stalled. 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. The value of variable Range_measurements is null. 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 under 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:

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

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Another example of expert rule can be produced for the collision and drag case. The rule is provided as follows:

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IF   Undershoot_depth      is   medium   AND
     Measured_linear_velocity is   low      AND
     Difference_of_battery_voltage is   negative_small
THEN Vehicle_drags_obstacle is   true

```

This rule is complemented by a set of rules analyzing other combinations of terms relating different values of the 7 input variables, as well as by induced rules as described below.

3.2 Induced Knowledge

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. 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. 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. The experiment was carried out for two different commanded linear velocities. Upon collision, the undershoot had a depth of 25% of command velocity, for $v=25$ cm/s, while it had a depth of 44% for $v=11$ cm/s. We now use the results of a set of experiments producing this kind of preprocessed data, to define variable highly interpretable fuzzy partitions. The method we used, called hierarchical fuzzy partitioning (HFP), is described in [8]. Its originality relies in that it does not yield a single partition, but a hierarchy including partitions with various resolution levels. For each variable, the initial partition is made up of fuzzy sets centered about the input values, if there are a few of them only. If the input values are too numerous, they are first clustered into so called unique values. Instead of a descending procedure, an ascending technique has been applied. It consists of merging two adjacent fuzzy sets at each step, the ones which best satisfy a merging criterion. The criterion preserves the previous step structure by considering a special sum of distances over the training data set. These distances are conceived to reflect the fuzzy partitioning under design. Figures 2.a and 2.b show fuzzy partitions with different granularity that have been derived by using these two partitioning methods which are implemented in an open source software called FisPro [9].

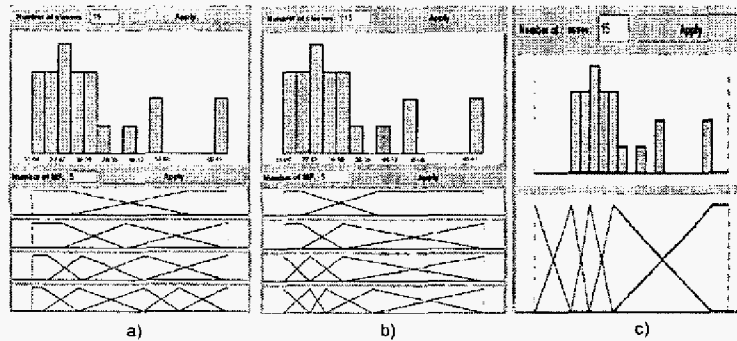


Figure 2. a) Fuzzy partitions using *k*-means. b) Fuzzy partitions using HFP. c) Selected partition.

Let us note that all the fuzzy sets of all these partitions can be assigned a semantic label. Analyzing the fuzzy partitions, we have determined that the best suited result 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. The final partition selected by the expert is shown in figure 2.c. 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 cm/s. Based on knowledge extraction automatic rules are generated using these fuzzy partitions.

4. RESULTS AND CONCLUSIONS

For performance analysis of our system, several motion trials using BART (Basic Agent for Robotic Tasks) 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 (whose mass is 12 kg) is moving straight ahead with a linear velocity of 150 mm/s. The robot collides with a heavy obstacle deliberately introduced in its trajectory and then the vehicle drags the obstacle. The preprocessed variables involved in this experiment are depicted in figures 3.a and 3.b.

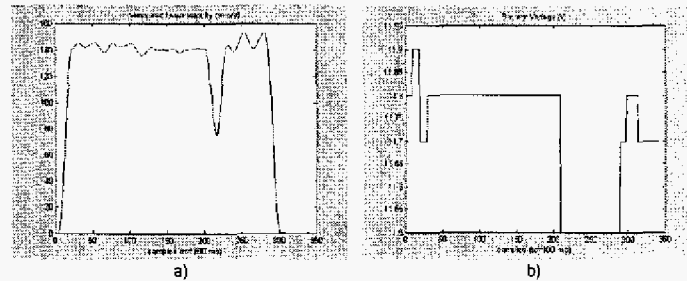


Figure 3. Vehicle variables upon heavy obstacle collision. a) Vehicle velocity. b) Battery voltage.

The values of the variables to be considered are: Undershoot_depth = 67 cm, Measured_linear_velocity = 143 cm/s. Difference_of_battery_voltage = -0.28 volts. These values will activate at different levels four rules of the system, where the highest activation (0.85) will be for the rule:

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IF    Undershoot_depth      is    very_large    AND
      Measured_linear_velocity is    high         AND
      Difference_of_battery_voltage is    negative_big
THEN Vehicle_drags_obstacle is    true
  
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Accordingly, 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. As conclusion, 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 is able to provide diagnosis as well as recovery actions upon these circumstances. 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. The two kinds of knowledge, expert knowledge and data, convey complementary information. 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. Preliminary results show that the approach is appropriate but further analysis is required.

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