SENSOR INTEGRATION ON A MOBILE ROBOT

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ABSTRACT

The purpose of this paper is to show an application of path planning for a mobile pneumatic robot. The robot is capable of searching for a specific target in the scene and navigating towards it, in an a priori unknown environment. To accomplish this task, the robot uses a colour pan-tilt camera and two ultrasonic sensors. As the camera is only used for target tracking, the robot is left with very incomplete sensor data with a high degree of uncertainty. To counter this, a fuzzy logic - based sensor fusion procedure is set up to aid the map building process in constructing a reliable environmental model. The significance of this work is that it shows that the use of fuzzy logic based fusion and potential field navigation can achieve good results for path planning.

1. INTRODUCTION

Mobile robots have attracted several research activities for many applications, such as navigation. The key research areas are:

- *Sensor technology:*
  Mobile robots can be equipped with a variety of sensors, enabling the robot to gain some knowledge about its surroundings. The most common sensors are the infrared and ultrasonic devices, used in al sorts of configurations [2][3][4]. On the other hand, computer vision can be applied for robot navigation, using either monocular or stereo vision [5][6][7][8]. No matter what sensors are used, the basic problems to be solved are always the same:
  - What measuring strategy should be applied in order to collect the maximum amount of data in the minimum amount of time?
  - How can the error on the readings be minimized?
  - How big is the measurement error?
- *Sensor fusion:*
  If a robot needs to gain a more or less complete "image" of its environment, it cannot rely on only one type of sensor. Hence the need for an intelligent sensor fusion algorithm to combine the often erratic, incomplete and conflicting readings received by the different sensors, to form a reliable model of the surroundings. Sensor fusion has been subject to a lot of research [12][13], most of the proposed methods use Kalman Filtering [17] and Bayesian reasoning [15]. However, in recent years, there has been a tendency to make more and more use of soft computing techniques such as artificial neural networks [14] and fuzzy logic for dealing with sensor fusion. [16].
- *Map building & path planning*
  An autonomous robot must keep a kind of map as a model of its surroundings. These maps can be simple grid maps, topological maps [19], or integrated methods [20]. The used path planning technique depends highly upon the type of map chosen before. A survey of different methods can be found in [9].
- *Efficient control strategies:*
  All the different processes (sensor measurements, measurement processing, sensor fusion, map building, path planning, task execution …) must be coordinated in an efficient way in order to allow accomplish a higher goal [21]. A number of control strategies can be set up, varying from simple serial sense-model-plan-act strategies to complex hybrid methods. A discussion of some of these control strategies can be found in [22]. An interesting approach here, is to use fuzzy behaviours, partially overriding each other, to build up complex navigation plans, as discussed in [23][24][25]. In this paper we present a hybrid control strategy.

The rest of this paper is organized as follows:

The platform and control strategy are described in section 2, the data fusion and modelling are summarized in section 3, some results are presented in section 4 and finally, conclusions are given in section 5.

2. PLATFORM & METHODOLOGY

A mobile pneumatic climbing robot equipped with two ultrasonic sensors and a pan-tilt camera, as shown in Figure 1, has been used. [2]

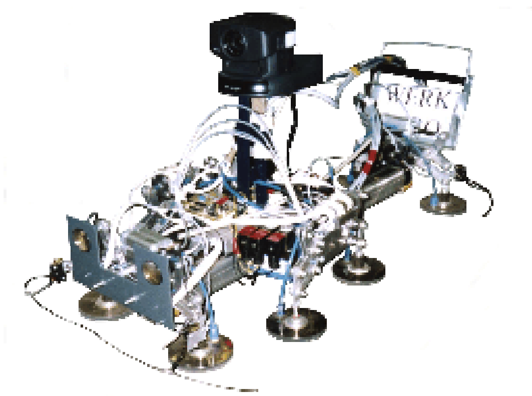

Figure 1: The robot platform

The ultrasonic sensors, in front of the robot, are capable of performing accurate distance measurements and help to build up a map of the environment. Their limited field of view and low angular resolution are compensated as much as possible by using intelligent processing techniques described in [10] and [11].

The pan-tilt camera has the ability to search for a colored target object and to keep it fixed in the centre of the image. The target detection and tracking algorithm [1], which relies on the color dissimilarity between target object and environment and estimates also the distance to the target object and this through a calibrated scaling process.

Figure 2 depicts the control and fusion process.

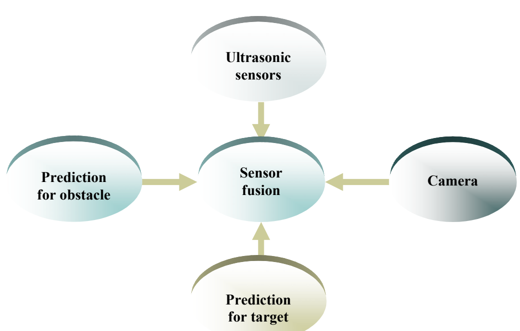

Figure 2: Sensor fusion

By integrating previous map and control information, predictions are made for the presence of the target and obstacles. Two mathematical sensors manage this data: the prediction for the target object localization and the same for an obstacle. Every sensor also returns an estimate of the measurement error. All the sensory data is combined by the sensor fusion procedure, which is handled using a fuzzy logic–based approach, increasing the individual sensor accuracy and gaining additional knowledge by comparing readings from multiple sensors.

After fusion, the data is ready to be processed for building up a map of the environment. In our approach, a potential field map is constructed. It ensures a logic and straightforward path planning behaviour. This process will also be discussed more in detail in the next section.

3. DATA FUSION & MODELLING

The sensor fusion module takes as input the data provided by four abstract sensors and delivers information for the map-building module, this data being a clear positioning for the target and an eventual obstacle. The idea is to calculate every output variable as a weighted average of these input variables; the fuzzy logic based data fusion determines the weights accorded to the input variables. The choice of the membership functions and the setup of the rulebase reflect some specific characteristics of the different sensors and observations derived out of prior experiments. These rules are then implemented using Max-Min aggregation and the resulting weight function is defuzzified using the centre-of-gravity method.

The map building and path-planning module must produce the best move the robot can do as a step towards reaching the goal. There is no need to perform a full path-to-target calculation every time, since it may be expected that the map will change as new information is gathered after the movement, so the rest of the path will become useless. The robot will have to manage with incomplete maps and will have to re-estimate a new path to the target after every step, since more information will be available every time. As explained earlier, we make use of two-dimensional potential field maps for robustness reasons. Potential field navigation techniques make use of artificial forces: repulsive forces at detected obstacles to keep the vehicle away and an attractive force at the goal point in order to move the robot towards the goal. The problem with this technique is the existence of local minima. In order to bypass this problem, in our implementation we consider the robot itself as an obstacle. By doing so, the robot creates a repulsive force away from the current position and will not get stuck in local a minimum. Using potential fields means that the Laplacian has to be calculated after every move, which is done by an iterative Gauss-Seidel method with successive overrelaxation. According to the boundary conditions set, the potential field takes a high value at the surface of obstacles and a minimum value at the goal point.

4. EXPERIMENTAL RESULTS

Due to our postprocessing techniques we can acquire very accurate distance measurements from the ultrasonic sensors and track down the erroneous angle readings.

The camera estimates the distance to the target object up to a precision of a few centimetres.

The actual working of the map building and path-planning module are shown by presenting the results of a real-world example. The environment set up for this experiment is sketched on Figure 3:

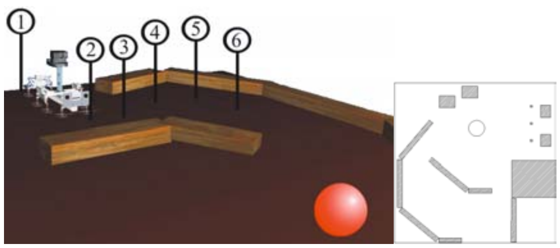

Figure 3: The lab environment

Figure 4 presents the potential field map at different stages along the way towards the target.

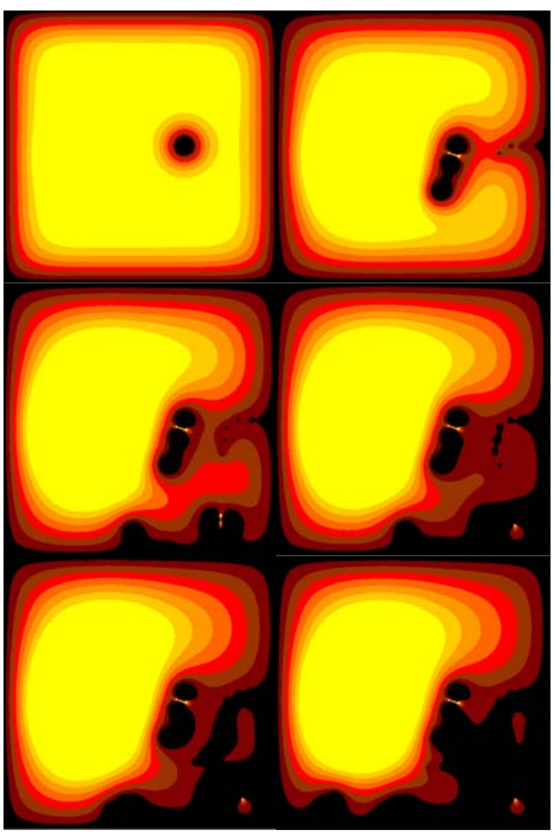

Figure 4: Potential field during a run

From the final potential field graph given in Figure 5, one can clearly see the path followed by the robot. Note also the correspondence between the environment as shown in Figure 3 and the potential field representation.

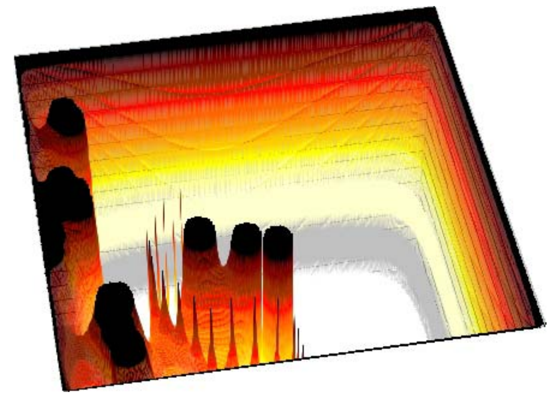

Figure 5: Potential field after completing a run

The robot is autonomous, yet all its actions, sensor readings and positioning data can be followed in real time on a graphical computer interface, depicted in Figure 6. If so wished. A user can change the robot behaviour or control the robot and camera manually.

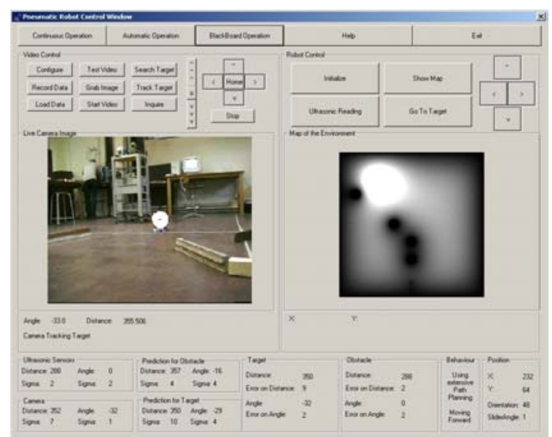

Figure 6: The robot control program interface

5. CONCLUSIONS

In this paper, we have demonstrated our solution for the map building and path planning problem applied to a mobile pneumatic robot. The results are very confident: the robot is able to navigate itself towards a certain target in a complex and a priori unknown environment with obstacles. This was no trivial task in view of the limited sensory equipment of the robot.

In the future, research will go out to implement more advanced techniques, teaching-by-guidance, automatic extraction of stable landmarks for efficient navigation and the implementation of a learning fuzzy logic controller with a massive rulebase.

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