PATH DETECTION SYSTEM FOR AUTONOMOUS OFF-ROAD NAVIGATION

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ABSTRACT

In this article three different algorithms for path detection in unknown environments (structured / unstructured) are presented. The first algorithm is based on a distributed meta-heuristic method for combinatorial optimization problems known as the Ant Colony Optimization. The second algorithm foresees that, starting from a small area of the image considered to be part of a path suitable with good approximation for a moving vehicle, that area will be expanded in the directions where the image is similar, following certain functions. Finally, the third algorithm uses an approach to the topic of path detection based on 3D models. Some experimental results on sequences of images taken from a moving vehicle in different scenarios are then presented to demonstrate the validity of the three approaches.

1. INTRODUCTION

On 13th March 2004, in the desert areas of the Mojave between California and Nevada, the first competition for full autonomous ground vehicles took place: the DARPA Grand Challenge 2004 [1]. The challenge was to build an autonomous vehicle able to complete a long and difficult off-road path from Los Angeles to Las Vegas. The course could include unsurfaced roads, sandy and rocky trails, bushes, dry lakes and, in small percentage, paved roads. The course was supposed to be about 200 miles long, was defined by several thousand GPS way-points, and was not revealed until two hours before the event begun. The vehicles had to follow the GPS way-points as well as avoid natural and artificial obstacles, or other vehicles, without any remote human control.

This paper presents the three artificial vision algorithms developed as part of the navigation system of the TerraMax vehicle. TerraMax is the result of Oshkosh Trucks Co., Ohio State University, and University of Parma partnership. In particular the Artificial Vision and Intelligent Systems Lab of the University of Parma supplied a complete image processing system that, together with many other active sensors, performed the environment sensing: obstacle detection based on stereo vision, free space detection, and path detection based on monocular images, which is the main topic of this paper.

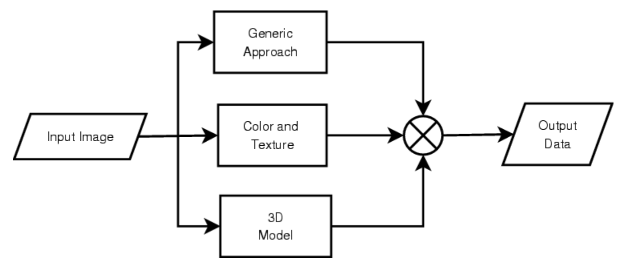


Fig. 1. Overall system. The input image is analyzed with three algorithm and the output is chosen using confidence information.

Lane detection on structured environments was successfully faced using monochromatic monocular images [2] [3], based on some *a priori* knowledge, like the existence of lane markers. Unfortunately this approach could not work in unknown environments. Figure 3 shows some typical scenarios of the Grand Challenge path. Stones or bushes could be considered road markers or obstacles *inside* the road boundaries, by simply varying their position. Sometime it is just impossible, even for a human being, to localize any path.

To avoid those limitations and build a robust system, three artificial vision algorithms have been developed and their outputs merged. A confidence parameter, provided by the algorithms, is used to weigh each contribution (figure 1).

This paper is organized as follows: Section 2 presents an evolutionary approach to path detection, based on the Ant Colony Optimization meta-heuristic; Section 3 describes a segmentation algorithm based on detection of homogeneous parts of the image, exploiting information about color and texture; Section 4 presents a 3D model approach and Section 5 briefly describes how the algorithms merge their output. Finally, Section 6 present some experimental results and conclusions.

2. ROAD DETECTION USING AN EVOLUTIONARY APPROACH

The underlining idea of this algorithm is the following: each boundary of the road is just one particular curve on the image, starting from the bottom and finishing on the horizon line. If we could find some *local* properties describing the probability that a pixel belongs to the boundaries of the road, then it would be possible to formalize the problem as an optimization problem. The optimal solutions are the ones that overlap with the largest number of pixels belonging to the boundaries of the road.

The optimization algorithm chosen is the Ant Colony Optimization (ACO) [4]: a distributed meta-heuristic method for combinatorial optimization problems, inspired by the communication system of biological ants based on pheromone. Therefore, the goal becomes to build two colonies, one for each side of the road, made by agents that, moving pixel by pixel, try to overlap with the optimal boundary curve on their side.

The first step is to define the heuristic and the cost function: frame by frame a special image, called *distance image*, is built to represent the distance of each pixel from the values of some statistical characteristics of the road. The application of a gradient operator leads to a new image, where the brightness of each pixel is proportional to the probability that the pixel belongs to the boundaries of the road. This image represents the heuristic function. The cost of each solution is inversely proportional to the sum of the pixels' brightness. Now each agent is placed on a feasible initial state (the red squares in Figure 3(*b*)) and starts to move, pixel by pixel, until it will have reached a final state (the upper white line in Figure 3(*b*)). The next pixel is chosen inside a set of feasible neighbors, which depends on the current pixel and on the *point of attraction*: the set of neighbors of (i, j) pixel is computed, frame by frame, to polarize the random moving components. This allows a better fit of the agents' exploration area to the actual road shape

The moving rules are divided in three levels: the first one is the *random-proportional*, where the probability to be chosen for a neighbor pixel is proportional to heuristic function and pheromone deposit; the second one is the *pseudo-random-proportional*, where the agents' heuristic exploitation behavior is improved; the third one is a *backtracking* behavior, with witch too much profitless paths are rejected and a new pixel on the same row is selected. When an agent has reached a final state the pheromone trail along its path is updated with a contribution inversely proportional to the path's cost.

Eventually two special agents, attracted only by pheromone, are executed in order to draw the final solution, that should be the maximum pheromone curve (white dots in Figure 3(*b*)).

3. ROAD DETECTION USING TEXTURE AND COLOR

Road is a comprehensive term including paved road, off road, human marked road and so on. Some features, common to every kind of road, should be chosen to be detected. The algorithm described in this section exploits the hint that *road* stands for the most homogeneous part of an image. To detect it a particular segmentation algorithm is applied to image.

Several algorithms can be found for image segmentation in literature[5]. The common approach is to join close pixels obtaining a large region composed by similar entities. In approach described in this section, images are decomposed in cells and a comparison is made between them. Using cells instead of pixels allows a comparison using both the average color value, calculated in different color spaces, and the information about the texture, like variance and roughness.

The goal of using different color spaces at the same time is to balance the weight of light in the color value [6]. In such manner two color spaces are chosen to bring this task: the source RGB color space, and the HLS derived color space. During the development of the algorithm, several other color spaces were considered (YUV, RGBN, HUE channel, etc.), but, due to their performance, only the best were chosen.

At the same time, the only information about color it is often not enough. Several information, not based on the average color, can be pulled out from cells: histograms, local contrast, and several statistical analysis as variance and Fisher's Index. After experiments, histograms and variance in RGB color space have been chosen.

However, choosing a good *comparing function* is insufficient to detect the road. Some functions, also those described above, work efficiently in some cases, but they are not the best in every situation.

To achieve better results in the majority of cases, different functions are mixed together using a variable weight. The sum of those different contributes is compared with a constant threshold ξ (having variable weights permits to fix this value to unit).

The equation model for this approach can be described as $\sum_{i=1}^{n} w_i f_i(x, y) < \xi$ where x and y are two near cells of the image and w_i is the weight associated to the comparing function f_i.

It is necessary to choose a root cell to begin the expansion. This cell must be part of the road. This assumption is made selecting in the first frame a cell in the central lower part of the image and searching in the next frames for a cell similar and near to the previous.

Beginning from this first cell, close cells are compared through the previous equation. If a cell satisfies the equation, it is included in the road space and analysis is continued until no more cells are discovered and added to road space.

Weights w_i change in real-time according to the result of the equation itself. Functions contribution are computed in some parts of the image and a linear system is resolved trying to gain an efficient result.

The green cells, shown in figure 3(c), satisfy the equation and are the output provided by algorithm.

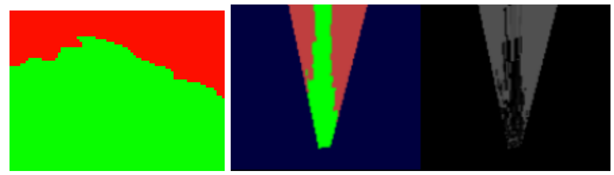
4. ROAD DETECTION USING 3D MODEL MATCHING

The algorithm explained in this section uses an approach to the topic of path detection based on 3D models. Each model is based on various parameters. This process involves the analysis of all parameters values interval and the evaluation of the adequacy of the obtained model to the processed image. Once the best matching model has been found, it is necessary to translate it in a map representing the space in front of the vehicle and on which to trace the path to be followed. The map will be successively sent to the data fusion managing system which, given the data coming from other sensors and algorithms, will establish the trajectory to be followed by the vehicle.

The parameters, previously cited, identifying each model, are of two types: those characteristics of the road (where with the term road we intend the path, not necessarily asphalted, followed by the vehicle) that are therefore slowly changing, as its *length*, *width* and *curvature*, and those indicating the vehicle's position in respect of the road itself, that will change as fast as bigger will be the speed and the ground's irregularity, as *pitch*, *roll*, *yaw*, *offset* in respect of the road middle line and *height of the camera* from the ground.

These parameters vary in an adequate interval, characterized by a minimum value, a maximum and an increment for its scanning. Combining all values for each parameter, we obtain that the total number of possible models, given by the product of the steps necessary to scan each parameter interval, rounds on 100 million models, a number unacceptable for a real-time application. Thus we had to compromise between frame-rate and analysis precision, reducing with adequate criteria, the number of evaluated parameters or their intervals. To compare each model with the acquired image, many techniques, based on correlation or symmetry, have been tested, applying them to the acquired image or to its segmentation (it consists of reducing the number of colors used to represent the image in order to make it appear more homogeneous).

The correlation involves the sampling of some points of the image, following the scheme of the 3D model projected on the image itself. The colors of such pixels are then compared in order to find an association between the various parts of the image, longitudinally sampled. Symmetry foresees the analysis of the various pixels in order to find image symmetrycal areas, using road's properties.



(a) (b) (c)

Fig. 2. Inverse Perspective mapping. From generic algorithm output (a), a top view of this area is generated using calibration information. This output contain both information about road (b) and confidence (c).

The results of those methods revealed themselves as unsatisfactory, thus making us introduce a further method, based on the individuation of discontinuities and on a preprocessing using agents. The preprocessing operation is able to highlight road's edges by finding colors' discontinuity. The obtained image is thus subsampled and parts that could make road recognition difficult, removed. At this point it is possible to compare the selected model with the processed image.

The last approach gives better results in respect of those obtained by using correlation and symmetry, nonetheless recognition errors remain. In the majority of cases, error is due to the detection of false negatives, whether cases of false positives detection remain rare. In particular the algorithm yields to the best results in case of paths presenting a certain structure.

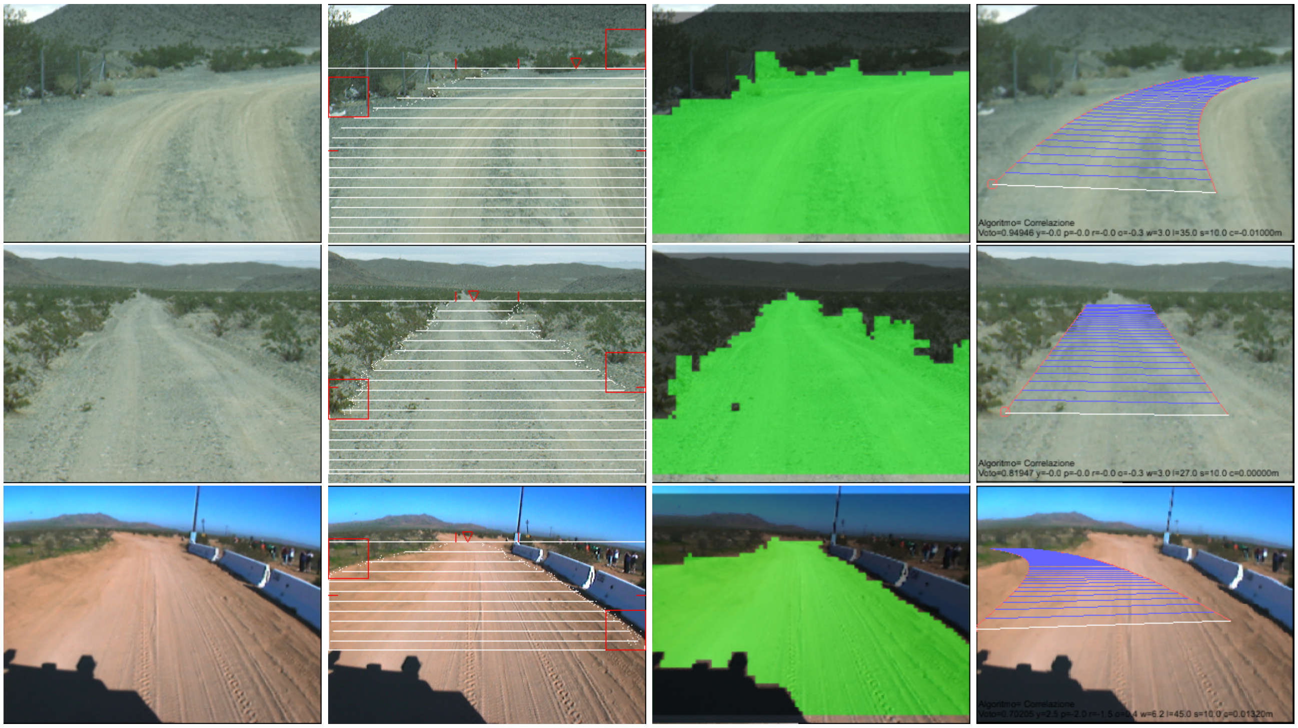
5. RESULTS FUSION

Each algorithm provides both information about road presence and a confidence value associated to this information.

The algorithms' output, as shown in figure 3, are mapped into a bird's eyes view [7], to obtain a map of the space in front of the vehicle as shown in Figure 2. This is achieved by the *Inverse Perspective Mapping* technique, that uses information about calibration and lens aperture to remove perspective and remap the image. The fusion of the outputs happens in this remapped space, working on cells of size 50×50 cm, and, for each cell, a unique result is provided, choosing the value having the highest confidence.

6. RESULTS AND CONCLUSIONS

In this paper, a robust path detection system, based on different image processing algorithms, is proposed. This system has proved to run at 10 Hz on the 3 GHz Pentum 4



(a) (b) (c) (d)

Fig. 3. (*a*) source image, (*b*) genetic approach, (*c*) color and texture algorithm, and (*d*) 3d model.

installed on the truck used for the competition.

The discused system has been tested on several color images (320 $\times$ 240) acquired by a camera installed on the truck, and figure 3 shows some experimental results in significant race and test scenarios.

The overall system has a good behavior, but the single algorithms still remain weak in some situations: for example when more than a road is visible the 3D modelling and the evolutionary approach will detect only one of those; on the other hand the color and texture algorithm suffers the sharp variations of road surface properties. The next step will be to overcome those problems, improving the single algorithms and the sensor fusion, looking forward for the DARPA Grand Challenge 2005.

7. REFERENCES

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