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Experiments of Fuzzy Lane Following for Mobile Robots

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Abstract— **This paper reports experimental results concerning the lane-following problem for mobile robots. The path to be followed is acquired by a video-camera and the current advancing velocity of the vehicle is decided on-line by a fuzzy algorithm; this takes into account some geometric characteristics of the lane estimated in real time and the nominal desired speed of the robot. The obtained experimental results on a unicycle-like mobile robot confirm the effectiveness of the proposed approach.**

I. Introduction

In recent years much research effort has been devoted to the development of automated vehicle navigation systems; in fact, these might provide many advantages, ranging from increased safety of highways to decreased costs in automated factories. In this paper the problem of automated lane-following for mobile robots is considered; this consist in an autonomous vehicle which is in charge of following the path traced by a lane marked out on the floor. One major application field for the lane-following problem is, e.g., that of automated highways.

Effective experimental results of lane following have been obtained in [11] for a platoon of vehicles; in this work the case of fault diagnosis is studied in the Californian NAHSC (National Automated Highway System Consortium), in this case, however, the lane is recognized by a magnetic marker sensing system.

A more promising approach for applications in partially structured environments, such as in outdoor autonomous navigation, the lane-detection problem is faced by means of vision systems. Reference [15] adopts a stereo vision system working at 20 Hz where, together with lane finding, obstacle detection is also performed. A monocular approach, using neural network and fuzzy logic techniques, is instead presented in [8]. To optimally select the parameters of the lane, dynamic programming is used in [13]; the frequency of image acquisition varies from 11 Hz to 29 Hz. For the above papers [8], [13], [15], experimental results with data extracted by a human-driven car in normal traffic condition are reported. In [4] a monocular, monochromatic camera is used together with a statistical model of the lane in order to provide fast and robust lane detection. A theoretical approach to the vision-based road-following problem is given in [12]; the approach is unified with the camera fixation problem and it is grounded in the domain of the optical flow.

Concerning unicycle-like mobile robots, the work in [10] presents a visual servoing approach to solve the path-following control law directly in the image plane, thus without decomposing the problem into the lane detection and lane following subproblems.

In [1], [2] the problem of tracking a desired trajectory in presence of kinematic constraints is addressed. The trajectory is given in terms of the time history of desired vehicle positions and, by suitably introducing a virtual time, the algorithm slows down the time law so as to guarantee tracking of the given path under the assigned kinematic constraints. When the trajectory is slown down, a Fuzzy Inference System (FIS) [7] allows to exploit the forward path knowledge (i.e., the set of vehicle positions to be attained since the current virtual time to the current real time) by giving the vehicle some *predictive* actions.

In this paper the FIS algorithm developed in [1], [2] is used for the lane-tracking problem. In detail, a monocular video system acquires the data for the real-time lane detection; the estimated geometric characteristics of the lane in front of the vehicle then provide the forward path knowledge needed to decide on-line a proper advancing velocity. The overall algorithm, thus, only need to be initialized with

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the desired nominal cruise velocity. Experimental results with the unicycle-like Magellan Pro mobile robot confirm the effectiveness of proposed approach.

II. Proposed Algorithm

Our aim is to develop an algorithm capable of autonomously steering a mobile robot at a desired cruise velocity on a path marked out by a lane on the ground. The geometric characteristics of the path are estimated on-line by processing in real time the images of the lane acquired by means of a camera-based vision system; moreover, the cruise velocity should be lowered when not compatible with the maximum allowed vehicle acceleration at some point along the path. The algorithm's output is thus the linear and angular vehicle velocity to be fed as reference velocity to the low level motion control of the mobile robot.

Since the problem at hand is similar to that faced by car drivers, the proposed approach is to emulate a human-like behavior to adapt the cruise velocity to the characteristics of the path. The idea of giving a desired behavior to an autonomous robot is not new in the robotic literature, see, e.g., [3], [5], in this paper the desired behavior is implemented through a FIS. This is based on a set of very simple fuzzy rules, detailed in the next Subsection, e.g., allowing the full nominal cruise velocity on a straight and clear road, while conveniently decreasing the speed in the approach of a narrow bend.

At each time instant, the output of the fuzzy system is the current reference advancing velocity of the mobile robot; this is then converted into proper linear and angular velocity references for the low level motion control of the vehicle [2].

A. Fuzzy Inference System

The FIS is in charge of handling information such as "the next bend is too narrow for the current velocity" or "how far is next narrow bend?". The output of the FIS is a reference cruise velocity of the vehicle that best fits the geometric characteristics of the path.

Being vague concepts, narrowness of a bend and the distance from a narrow bend can be considered as fuzzy variables; of course, the narrowness of a bend is related to its curvature, that can be computed by several methods, e.g., as in [1], [14].

The output of the FIS is the variable $v \in]0, v_{max}]$, that represents the value of the currently allowed cruise velocity; by making v sufficiently small, the vehicle can describe any large path curvature.

Under the constraint of a maximum allowed angular velocity ω_{max}, the maximum curvature c that can be achieved by the vehicle travelling at the speed v is

$$c = \frac{\omega_{max}}{v}. \tag{1}$$

By defining as $\hat{c}$ an estimate of the first next curvature narrower than c that will be met in the incoming path, the following value is used as the FIS input *curvature*

$$\Delta c = \hat{c} - c. \tag{2}$$

This value can be viewed as a measure of how much the next bend is narrower than the one currently achievable by the vehicle.

The membership functions of the variable *curvature* are shown in Figure 1. Notice that the membership sets *small, appropriate, large* have been chosen considering that a large value means that the achievable curvature is smaller with respect to the required one. Moreover, after normalization, the value $\Delta c = 0$ corresponds to the value 0.5 and thus the membership function *appropriate* takes its highest value.

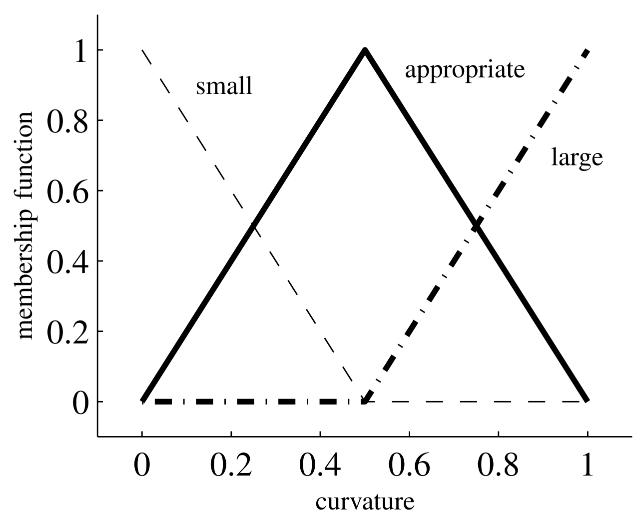

Fig. 1. Membership function of the normalized variable *curvature*.

The value of the distance from the next narrow bend is expressed by means of the variable q. Its definition is strongly influenced by the sensor used to extract path information; for example, in [1], [2] a time distance is used, since the desired trajectory is given in terms of a time law. In case of the use of a video-camera the curvilinear abscissa reconstructed from the image might be used.

The membership functions of the variable *distance* are similar to those shown in Figure 1 with reference to the variable *curvature*. In this case, the membership sets are *close, medium, far* and they have been chosen considering the space needed to stop the vehicle at the current velocity with the given acceleration bound.

Based on the two defined variables, the set of fuzzy rules that implements our human-inspired behavior for the lane-following problem is:

1. `if (curvature is small) then (increase` v`);`
2. `if (distance is far) then (increase` v`);`
3. `if (distance is medium) and (curvature is not small) then (keep the value of` v`);`
4. `if (distance is close) and (curvature is appropriate) then (keep the value of` v`).`
5. `if (distance is close) and (curvature is large) then (decrease` v`).`

Notice that, due to the hierarchical approach, all the 9 possible cases are compacted in 5 rules. Figure 2 represents the surface of the rules above.

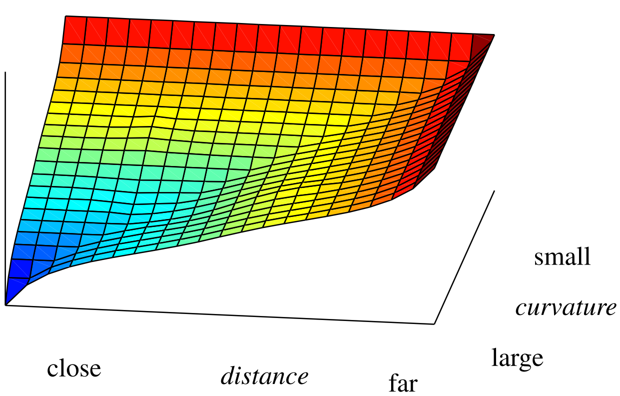

Fig. 2. Surface of the developed rules.

It must be remarked that the FIS described in this Section adopts practically the same rules and membership functions as those used in [2]. There is a major difference, however, in the fuzzyfication step, since the desired path is now acquired on-line through a video system. In particular, the fuzzyfication process also filters the data in order to generate smooth values and the filter's bandwidth must be properly chosen.

III. Experimental results

The vehicle used in the experiments is the Magellan Pro mobile robot, shown in Figure 3, manufactured by Real World Interface [9]. The low level controller, working at a sampling frequency of 40 Hz, is derived from the controller reported in [6]. The tracking error is affected by friction, gear backlash, wheel slippage and other undesired effects, e.g., a strong overshoot in step response of the native PID controller of each wheel of the vehicle.

Fig. 3. Magellan Pro mobile robot.

The video acquisition system is composed by a ccd monochrome camera with a framegrabber mounted on the vehicle, working at a sampling frequency of 2 Hz. Because of this low sampling frequency the maximum linear velocity has been limited to 20 cm/s, in order to allow lane detection in real-time. A sample image acquired during one of the experiments is shown in Figure 4. The quality of the image is poor and the resolution is low (160×120 pixels); moreover, high distortion on the image's borders is experienced.

Fig. 4. Sample image acquired during an experiment.

To model the camera view a pin-hole projection is assumed [14]. Let define as $f_c = [\, f_{c,1} \quad f_{c,2} \,]^{\mathrm{T}} \in \mathbb{R}^2$ the effective focal lengths and as $c_c \in \mathbb{R}^2$ the principal point, both expressed in pixels. The vector $p^c = [\, x^c \quad y^c \quad z^c \,]^{\mathrm{T}} \in \mathbb{R}^3$ is a point in the camera reference frame, expressed in meter. The pin-hole projection is defined as:

$$p^{\bar{p}} = \begin{bmatrix} x^{\bar{p}} \\ y^{\bar{p}} \end{bmatrix} = \begin{bmatrix} x^c/z^c \\ y^c/z^c \end{bmatrix}. \tag{3}$$

In pixels, it is

$$p^p = \begin{bmatrix} f_{c,1} & 0 \\ 0 & f_{c,2} \end{bmatrix} * p^{\bar{p}} + c_c. \tag{4}$$

The given point can be expressed in a different reference frame, e.g., a vehicle-fixed frame, $p^v \in \mathbb{R}^3$ by the known relation:

$$p^c = R_v^c p^v + t_c \tag{5}$$

where $R_v^c \in \mathbb{R}^{3\times 3}$ is the rotation from the vehicle-fixed to the camera-fixed frame and $t_c \in \mathbb{R}^3$ is the vector connecting the camera-fixed frame to the vehicle-fixed frame expressed in the camera frame.

For our specific experimental set-up a calibration procedure has been followed, using a software toolbox developed by J.-Y. Bouguet and inspired by [16]. The following numerical values have been obtained:

$$\begin{aligned} f_c &= [\,213 \quad 218\,]^{\mathrm{T}} \\ c_c &= [\,80 \quad 60\,]^{\mathrm{T}} \\ t_c &= [\,0 \quad 0.3945 \quad -0.0032\,]^{\mathrm{T}}\ \mathrm{m}, \end{aligned}$$

with the camera-fixed frame rotated of 26 deg with respect to the y axis of the vehicle-fixed frame. The radial distortion has been neglected. The conversion from the image's pixels to the vehicle-fixed frame, and further to an inertial-fixed frame, is correctly defined since, by definition, we make the assumption that all the relevant points are on the ground.

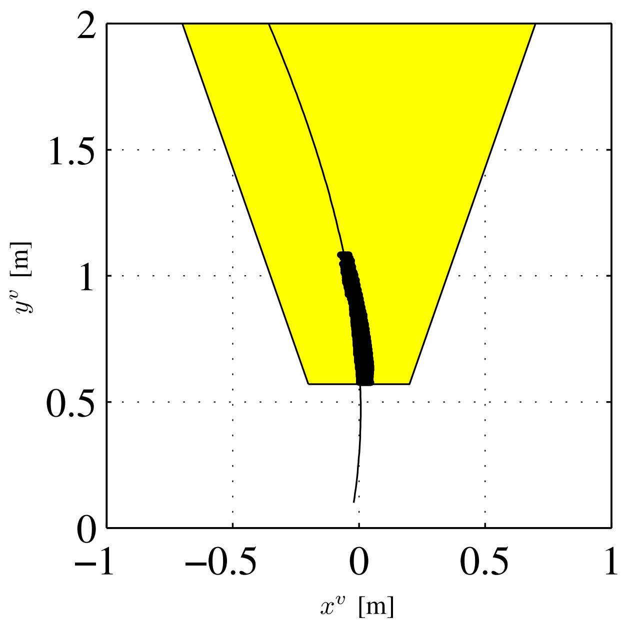

Fig. 5. View on the ground plane (in vehicle-fixed coordinates) of the image in Figure 4. The yellow (gray) area is the map of the image area, the extracted lane and its interpolation can be noticed.

Figure 5 shows how the image data reported in Figure 4 are projected on the ground plane with reference to the vehicle-fixed frame. The lane is modelled as a third-order polynomial [14] and, in order to obtain the polynomial coefficients, a simple interpolation between the points recognized as owning to the lane (see the tick line in Figure 5) is performed. Due to the poor quality of the image and the low sampling frequency those are further smoothed by a first-order filter and used to generate the reference angular velocity. Notice that image processing techniques for lane extraction are out the scope of this paper and this problem is not discussed here.

The case study has been designed to reproduce in scale a highway-like path: considering a curvature of ≈ 500 m for cars travelling at ≈ 100 km/h, we have chosen a curvature of the lane of about 3 m for our robot travelling at a maximum speed of 20 cm/s. The maximum angular velocity ω_{max} has been set to

$$\omega_{max} = 7^\circ \ \mathrm{deg/s}.$$

In Figure 6, the normalized input *curvature* to the FIS is shown. Around $t \approx 10\,\mathrm{s}$ the algorithm detects a narrow bend; in fact, at the current linear velocity, the bend cannot be approached keeping the desired path.

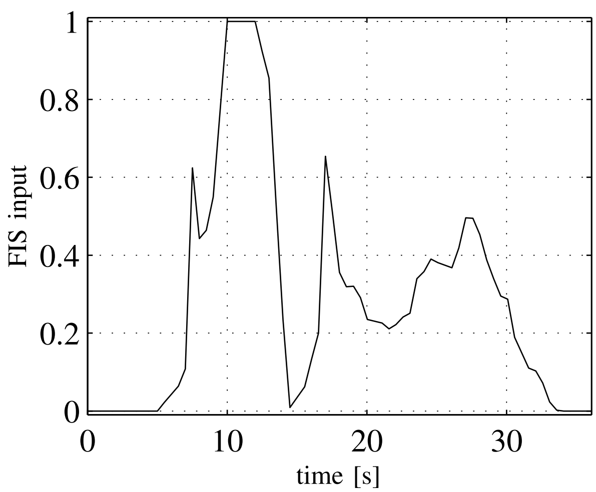

Fig. 6. Normalized input *curvature* of the FIS algorithm.

At that point, the FIS must command the vehicle to decrease its velocity; this can be seen in Figure 7, where the output of the FIS is plotted. It can be easily recognized that across the high-curvature tract the velocity is quickly slowed down from the nominal $20\,\mathrm{cm/s}$ to $15\,\mathrm{cm/s}$; afterward, the cruise velocity is progressively restored to its nominal value.

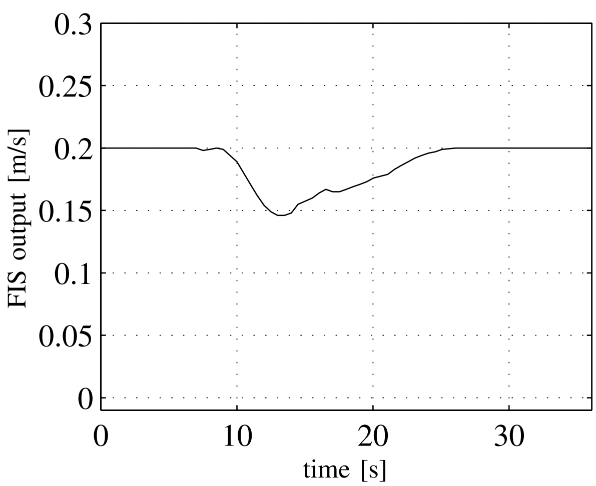

Fig. 7. Output of the FIS algorithm. It can be recognized that the algorithm requires to slow down the vehicle in presence of the band and to successively accelerate when the band is terminated.

Figures 8 and 9 show the linear and angular velocities commanded to the low level controller. It can be recognized that, for this specific experimental study, the linear velocity is close to the FIS output while the angular velocity is affected by the noise of the lane-extraction algorithm.

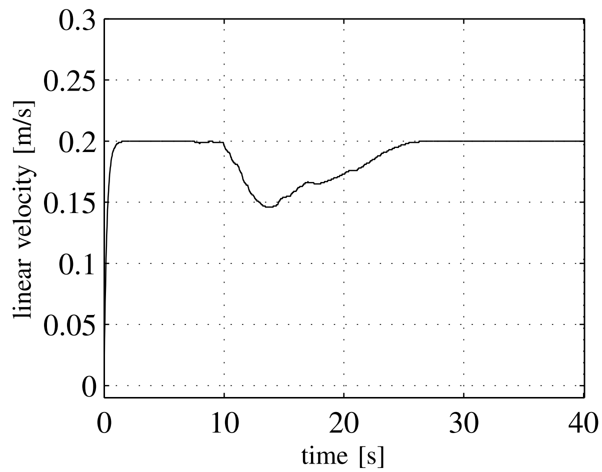

Fig. 8. Time history of the linear velocity of the vehicle.

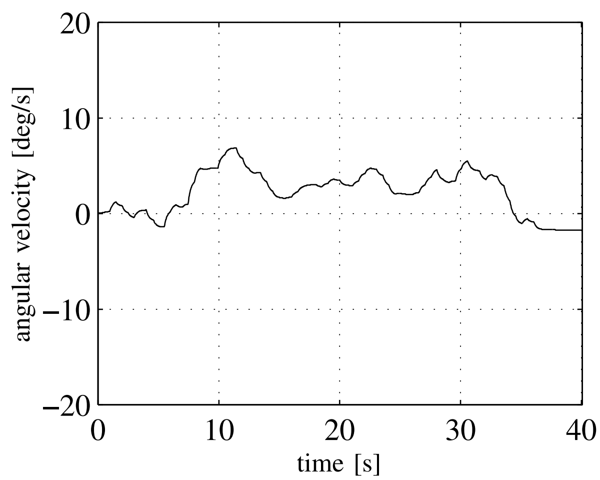

Fig. 9. Time history of the angular velocity of the vehicle. The signal is affected by the noise coming from the features extraction that suffers from the poor resolution and low sampling frequency of the vision system.

The total path executed by the vehicle, drawn with respect to an inertial frame, is reported in Figure 10.

Finally, to investigate the robustness of the proposed approach with respect to different operating conditions, a number of experiments have been run by changing the lighting and varying the low level control gains. These resulted in the set of paths plotted in Figure 11, which show the reliability of the developed algorithm. It must be remarked that the plotted inertial coordinates have been obtained by resorting to dead reckoning techniques; therefore, a certain

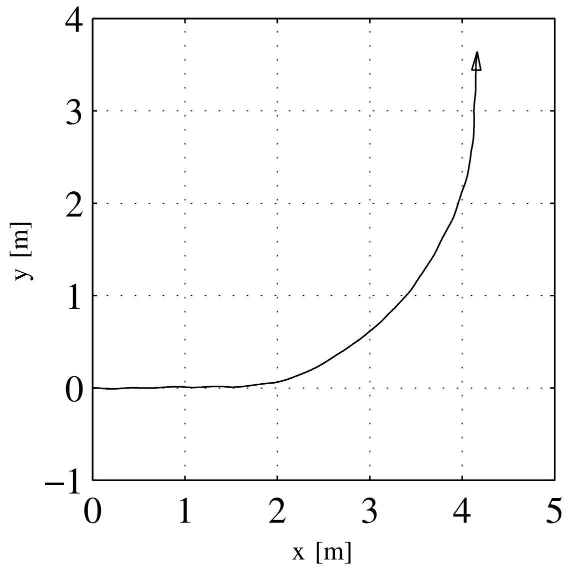

Fig. 10. Path followed by the vehicle during an experiment.

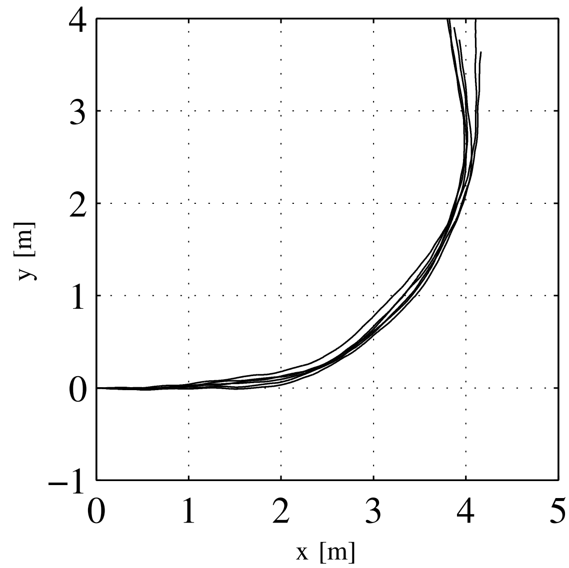

Fig. 11. Paths followed by the vehicle during different experiments with different light conditions and low level control gains. The path have been reconstructed by means of the sole odometry.

inaccuracy must be considered.

IV. Conclusions

In this paper experimental results concerning the lane-following problem for Magellan PRO, a unicycle-like mobile robot, have been presented. A fuzzy algorithm has been designed that handles the real-time information about the incoming path's characteristics given by a video-camera to decide on-line the cruise velocity of the mobile robot. The fuzzy rules developed easily take into account the path's curvature; future improvement might concern a FIS aimed at handling different sources of information such as, e.g., the velocity of a leader vehicle or the presence of an obstacle coming from several sensors.

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