VEHICLE FUZZY DRIVING BASED ON DGPS AND VISION

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Abstract

This document presents a fuzzy control application in the unmanned driving field. Two electric cars have been conveniently instrumented in order to transform them in platforms for automatic driving experiments. Onboard speed and steering fuzzy controllers are the core of the guiding system. Navigation is essentially DGPS-based providing obstacles detection and avoidance by means of artificial vision in a reactive manner.

1 Introduction

Aiming at creating vehicle automatic driving techniques, fuzzy controllers are a good tool to describe driving tasks in a near-natural language. So, an expert knowledge based system like this is easily modelled.

This paper presents an implementation of basic driving techniques, applicable to urban and non-urban environments. This implementation is based on fuzzy control using GPS and vision.

2 Platform Description

The common infrastructure consists of a street network, an aerial Local Area Network supplied by IEEE 802.11 WaveLAN cards [1] and a high accuracy Differential Global Positioning System (DGPS). This system improves the conventional GPS position measurement, based in C/A code and carrier phase, with 10-20 meters of precision, to 1-3 centimetres, adding to the standalone GPS receiver a data link with a fixed GPS base, which transmits the differential correction data [2].

The electric vehicles in use are commercial models. The main differences with conventional cars are in the throttle and the gear shift. The throttle is a potentiometer which acts upon the speed regulator and is actuated by the pedal. They have not mechanical gearbox and only forward and reverse motion can be selected.

The vehicles have been equipped [3] with a CCD camera, a GPS receptor, a DC motor attached to the steering wheel, an electronic circuit to drive the throttle signal and to acquire the tachometer signal and an industrial PC in which the control software is executed.

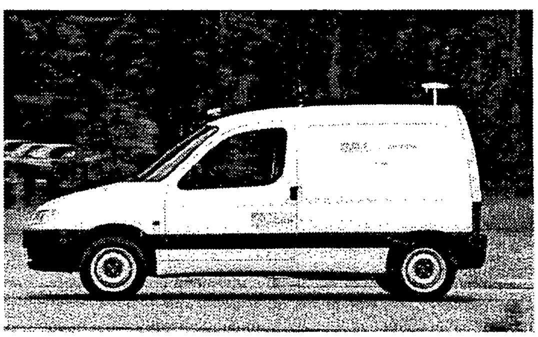

Figure 1. Testbed commercial prototype. Top left of car, the CCD camera. Top right, the GPS antenna.

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3 Logical Description

The representation of a circuit in order to perform the automatic driving is a concatenation of reference straight segments, represented by the North and East UTM coordinates of its extremes, previously obtained from the DGPS. The tracking of each segment and transition among them is done by means of the actuation upon the steering wheel, which is performed by a fuzzy controller [4][5]. This is accomplished by taking as inputs the orientation angle and the lateral error (in the rules, yaw and drift, respectively for short) between the car and the reference segment. The input data are computed from the positions acquired by the DGPS. Besides, a speed fuzzy controller has been implemented too. This controller provides an increment on the position of the throttle, taking as inputs the speed error and the acceleration [6].

3.1 Speed Fuzzy Controller

The aim of the speed fuzzy controller is to guarantee the car moves at the desired speed. The inputs are the speed error and the acceleration. The output is a change in the voltage of the throttle signal (an increment in this voltage is equivalent to increase the pressure on the throttle and a decrement is similar to decrease it). There are four rules which govern this behaviour (Table 1). The fuzzy strategies description language permits the utilisation of modifiers in expressions like *less than* or *greater than* .

Table 1. Speed fuzzy controller rules

if speed_error **is less than** zero **then** throttle down **if** speed_error **is greater than** zero **then** throttle up **if** acceleration **is greater than** zero **then** throttle up **if** acceleration **is less than** zero **then** throttle down
Speed_error = real_speed – desired_speed

3.2 Steering Fuzzy Controller

The steering fuzzy controller is in charge of tracking each reference segment as well as each transition between them. To achieve this, two sets of basic behaviours have been defined by means of two different fuzzy contexts, which are needed in order to emulate human driving: usually, in straight line driving, the vehicle speed is high and thus the steering wheel must be turned slightly and smoothly. However, in closed curves, the car speed is low and thus the driver moves the steering wheel widely and rapidly. The defined fuzzy contexts match these two observed driving modes and are applied to track the segments and the transitions respectively. Though the rules for both contexts are the same (Table 2), the membership functions of the linguistic values are different.

Table 2. Steering fuzzy controller rules

if yaw **is** left **then** steering right **if** yaw **is** right **then** steering left **if** drift **is** right **then** steering left **if** drift **is** left **then** steering right

3.3 Obstacle Detection and Avoidance

The main goal is to provide obstacle detection using computer vision. Additional inputs and rules must be added to both the speed and steering fuzzy controllers in order to account for obstacles.

The incoming image is on hardware re-scaled, building a low resolution image of what can be called the Area of Interest (AOI), comprising a squared area.

3.3.1 Road Estimation

Previous research groups [7] have widely demonstrated that the reconstruction of road geometry can be simplified by assumptions on its shape. Thus, we use a polynomial representation assuming that the road edges can be modelled as parabolas [8] in the image plane. Similarly, the assumption of smoothly varying lane width allows the enhancement of the search criterion, limiting the search to almost parallel edges. On the other hand, due to both physical and continuity constraints, the processing of the whole image is replaced by the analysis of a specific region of interest in which the relevant features are more likely to be found. This is a generally followed

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strategy [9] that can be adopted assuming a priori knowledge on the road environment. All these well known assumptions enhance and speed-up the road estimation processing [10].

The incoming image is on hardware re-scaled, building a low resolution image of what we call the Area of Interest (AOI), comprising the nearest 20 m ahead of the vehicle. The AOI is segmented basing on colour properties and shape restrictions. The proposed segmentation relies on the HSI (hue, saturation, intensity) colour space [11] because of its close relation to human perception of colours. The hue component represents the impression related to the dominant wavelength of the colour stimulus. The saturation corresponds to relative colour purity, and so, colours with no saturation are grey-scale colours. Intensity is the amount of light in a colour. In contrast, the RGB colour space has a high correlation between its components(R-B, R-G, G-B). In terms of segmentation, the RGB colour space is usually not preferred because it is psychologically non-intuitive and non-uniform. The scheme performs in two steps:

Pixels are classified as chromatic or achromatic as a function of their HSI colour values: hue is meaningless when the intensity is extremely high or extremely low. On the other hand, hue is unstable when the saturation is very low. According to this, achromatic pixels are those complying with the conditions specified in equation 1.

$$I > 90 \quad or \quad I < 10 \quad or \quad S < 10 \tag{1}$$

where the saturation S and the intensity I values are normalised from 0 to 100.

Pixels are classified into road and non-road (including obstacles). Chromatic pixels are segmented using their HSI components: each pixel in the low resolution image is compared to a set of pattern pixels obtained in the first image in a supervised manner. The distance measure used for comparing pixel colours is a cylindrical metric. It computes the distance between the projections of the pixel points on a chromatic plane, as defined in equation 2.

$$d_{cylindrical}(s,i) = \sqrt{(d_I)^2 + (d_{ch})^2} \tag{2}$$

with

$$d_I = | I_s - I_i | \tag{3}$$

and

$$d_{ch} = \sqrt{(S_s)^2 + (S_i)^2 + 2S_s S_i \cos\theta} \tag{4}$$

where

$$\theta = \begin{cases} | H_s - H_i | \; if \; | H_s - H_i | < \pi \\ 2\pi - | H_s - H_i | \; if \; | H_s - H_i | > \pi \end{cases} \tag{5}$$

Subscript i stands for the pixel under consideration, while subscript s represents the pattern value. An examination of the metric equation shows that it can be considered as a form of the popular Euclidean distance (L2 norm) metric. A pixel is assigned to the road region if the value of the metric $d_{cylindrical}$ is lower than a threshold T_{chrom}. To account for shape restrictions, the threshold T_{chrom} is affected by an exponentially decay factor yielding the new threshold value Γ that depends on the distance from the current pixel to the previously estimated road model, denoted by d as defined in equation 6.

$$\Gamma = e^{\frac{-Kd}{\hat{W}}} \cdot T_{chrom} \tag{6}$$

where $\hat{W}$ stands for the estimated width of the road and K is an empirically set parameter. This makes regions closest to the previous model be more likely to be segmented as road.

For achromatic pixels, intensity is the only justified colour attribute that can be used when comparing pixels. A simple linear distance is applied in this case, so that the pixel is assigned to the road region if the difference is lower than a threshold value T_{achrom}, similarly affected by an exponential factor, as equation 7 shows.

$$|I_s - I_i| < e^{\frac{-Kd}{\hat{W}}} \cdot T_{achrom} \tag{7}$$

Once the segmentation is accomplished, a time-spatial filter removes non consistent objects in the low resolution image, both in space and time (sporadic noise). After that, the maximum horizontal clearance (absence of non-road sections) is determined for each line in the AOI. The measured points are fed into a Least Squares Filter with Exponential Decay that computes the road edges in the image plane, using a second order (parabolic) polynomial. Using the road shape and an estimation of the road width (basing on the previous segmentation) the exact area of the image where the obstacles are expected to appear can be calculated. Obviously, obstacles are searched for only within the estimated area in the previous iteration. Image 1 depicts an example of lane tracking in which both the road edges and the centre of the road have been highlighted.

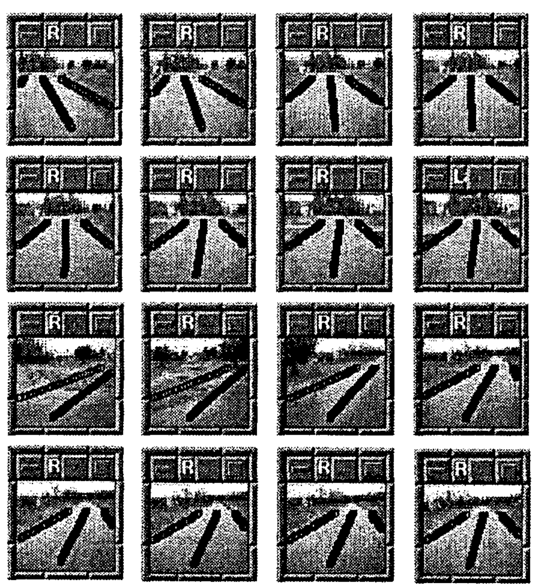

Figure 2. Lane tracking example

4 Experiments and Results

Next, the behaviour of the different subsystems is shown separately.

4.1 Speed Fuzzy Controller Results

The obtained results show an error less than 0.5 km/h when a constant speed is tried to be maintained (Figure 3).

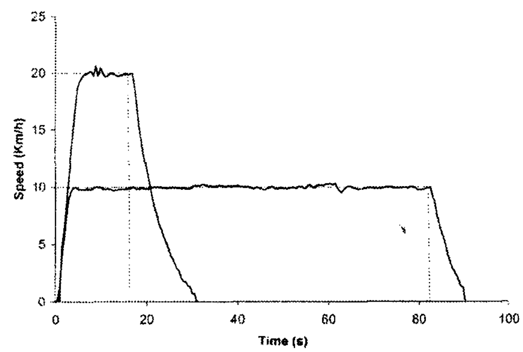

Figure 3. Speed controller behaviour example: step response at several speeds.

4.2 Steering Fuzzy Controller Results

The system is able to track straight segments at speeds up to 65 Km/h, which is the maximum speed the car can reach in the longest street (about 250 meters).

Furthermore, straight angle and more closed curves, like a circle to turn around, are tracked at speeds less than 6 Km/h (Figure 4).

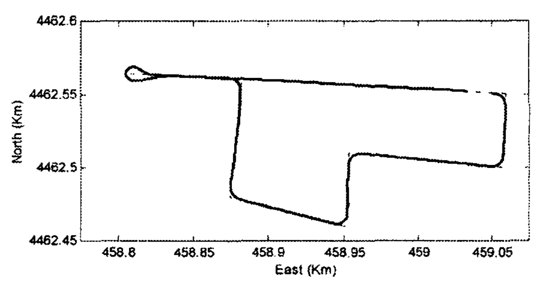

Figure 4. An steering control example: tracking of a circuit with several straight segments and curves (axes units expressed in UTM coordinates).

4.3 Obstacle Detection Results

Obstacles in front of the vehicle, such as cars, are detected with enough resolution within a safety distance of 10m ahead of the vehicle, processing up to

15 frames/s. Figure 2 shows a series of images covering a stretch of road where another vehicle appears in the opposite lane. The obstacle and lane positions are determined, as illustrated in the figure, so as to modify the fuzzy controller inputs both for angle and velocity to issue obstacles detection capacity.

4.4 Obstacle Avoidance Results

Obstacles detected along the vehicle path can be avoided by the fuzzy controller whenever the vision system determines there is enough space for the robot to perform the avoidance manoeuvring. It starts decreasing speed and modifying the turning response until the obstacle is surrounded. After that, normal tracking is resumed. In case that not enough space is detected, the vehicle stops.

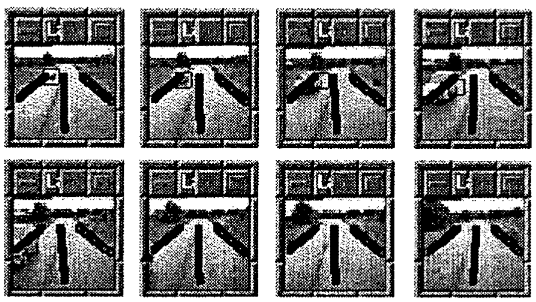

Figure 5. Obstacle and lane determination.

5 Conclusions

An autonomous navigation system based on cooperation between DGPS and vision has been designed and implemented on a commercial vehicle for unmanned transport applications. The technology techniques developed in this work can also be applied to provide assisted driving. Current tests are being carried out to enhance performance robustness.

The real application of theoretical and simulated fuzzy controllers is the main novelty of this vehicle driving system. This is not limited to platoon or highway tracking but it is a emulation of the human car driving applicable to any road circumstances like highway, platoons [12], city driving, overtaking [13], parking, etc. This system is adaptable to any circumstances if needed.

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