OPTICAL TRACK DETECTION FOR MOBILE ROBOTS BASED ON REAL TIME FUZZY DECISION-MAKING

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Abstract. In this paper a method for optical track detection based on fuzzy decision-making is introduced. The method is robust to non-homogeneous lighting conditions, changing background pattern, flash lights and other spurious disturbances, and was designed for real time implementation as part of the guidance system of an autonomous mobile robot.

Key Words: Fuzzy Logic, Mobile Robotics, Real Time, Robot Vision.

1. INTRODUCTION

International Mobile Robot competitions are currently interesting *fora* where different research and pedagogic solutions are presented for the same, often challenging problem [1][4][6]. An autonomous mobile robot was built, entirely from scratch, to compete in the 5th and 6th editions of the *Festival International des Sciences et Technologies*, both held in Bourges, France, in 1998 and 1999.

In the *Open* class of the contest, where IST has competed since 1995, robots are desirably built from scratch and are designed to follow a 5cm wide track painted on a chessboard-like surface, composed of 2m side squares of alternating black and white colors. The track, shown in Fig. 1, has the opposite color of the corresponding background square and is composed of 2 meter long straight lines and one-fourth of a circle arc segments with 1 meter radius, in a total length of approximately 46m. There are track interruptions somewhere along the path, obtained by replacing the corresponding background square by one with the same color but with no track segment painted on. The robot must detect the interruption, and recover the track at the closest segment. There are also track intersections and the end of the main track is signaled by a T-shaped pattern.

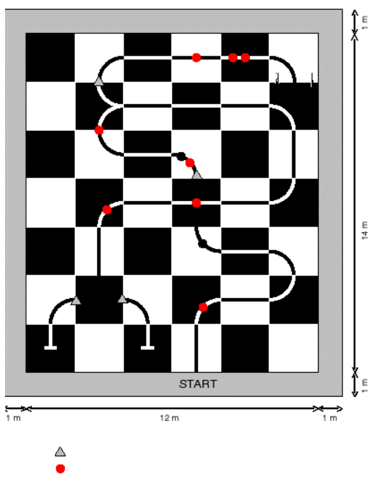

Fig 1: Typical setup for the mobile robot competition.

In this paper, the real-time detection and identification of the optical track to be followed, consisting of determining the parameters which characterize track position and orientation with respect to the vehicle, is fully described. The estimated track parameters are provided to the vehicle guidance system and should be robust to non-homogeneous lighting conditions, changing background pattern, flash lights and other spurious disturbances. Moreover, the track detection and identification algorithm should not require prior calibration (e.g., histogram checking to determine the optimal threshold between black and white colors) and should run as fast as possible, since its performance constrains maximum vehicle speed.

Several authors have used fuzzy logic for the navigation and behavior control of mobile robots. Tunstel and Jamshidi [11] introduced a hierarchical fuzzy control architecture which integrates fuzzy behavior control, synthesis and design. Pin [10] describes an automated generator of fuzzy rules under his *Fuzzy Behaviorist Approach* framework for rule-based development. Oriolo *et al* [8] introduced *fuzzy maps* to manage sensor uncertainty when planning robot motion. Ollero *et al* [7] use a fuzzy-based guidance controller for a mobile robot, designed to either follow programmed paths or walls and other environment features. In our work, a fuzzy guidance controller was also used, but here we concentrate on a fuzzy decision making [4] algorithm that has been developed to evaluate several features of the observed track image and detect a track in cases where an associated confidence factor, which is a function of those features, exceeds a given threshold. The track features are then used by the fuzzy guidance controller. The method has proven to be very robust under the competition environment, where non-uniform illumination, flash lights and changes in the light quality are constant sources of disturbances. The robot using this system got the 1st and 2nd prizes in its class among 10 teams from France, Portugal, Russia and South Korea, in 1998 and 1999, respectively.

The paper is organized as follows. In Section 2, the *track* concept in this case study is specified. The core of the paper is Section 3, where the track detection algorithm is described. The purpose of track detection is to provide information to the mobile robot guidance system so that it keeps the vehicle on the track. Track parameter identification is briefly referred in Section 4. Experimental results show the effect of applying the method over real image data on Section 5. The paper ends with conclusions and future work plans in Section 6.

2. TRACK SPECIFICATION

An 8 bit 200x150 pixel track image can be as complex as that shown in Fig. 2, where a track intersection and two red and black billiard balls are visible. The track to be followed by the vehicle must be correctly detected from such an image, so a first necessary step is to specify what a track is.

From the competition rules, the track can be quantitatively described by following features:

i) the track is well contrasted (black track on white background or white track on black background);
ii) the track has an approximate fixed width (close to 5 cm);
iii) track and background are painted with different uniform colors.

It is also reasonable to assume that the angle between an image column and the track as seen in the image never exceeds a given value (e.g., 30º), corresponding to an initial and while-in-motion vehicle alignment with the track such that this condition is met.

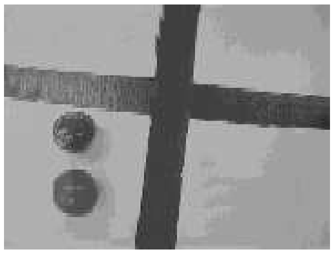

Fig 2: Track image.

3. TRACK DETECTION

Past and other team's experience [6] had shown that vision-based track detection is highly sensitive to changing lighting conditions and spurious noise (e.g., flash lights, light spots, non-uniform illumination) along the track. Therefore, a basic requirement for robust track detection should consist of using as much information regarding track features as possible to ensure that a track is present in some acquired image. Since the features are qualitatively described and it is important to handle their associated uncertainty (e.g., different pixel brightness will correspond to the same white floor under different light conditions), fuzzy linguistic variables are good candidates to characterize and quantify them. After this characterization is made, fuzzy decision making can be used to find the track on an image and to identify its associated parameters.

To detect a track on the image, the usage of full image processing methods [2] is not feasible due to the computational speed requirements. Instead, we chose to process image rows only. For a given row, a 1st order 1-D spatial derivative is computed at pixel k as

$$\frac{di[k]}{dk} = i[k+2] - i[k-2], \qquad (1)$$

where *i[k]*, *k*=1,...,200 is the pixel brightness. A derivative operator having high-pass filtering characteristics should always be associated with a low-pass filter, to reduce noise. In this case the 1-D [0.1 0.2 0.4 0.2 0.1] filter is applied before (1).

The simplest approach to track detection after applying (1) would consist of determining the maximum and minimum derivative values and assume that the track consisted of the intermediate pixels. However, pixel noise, the presence of other objects and shadows would make this method very unreliable. Track detection robustness was increased by the extraction of the three largest absolute values of the derivative *maxima* and *minima* as track boundary candidates, followed by a selection of the best maximum and minimum pair of derivatives (max-min pair), using fuzzy decision making.

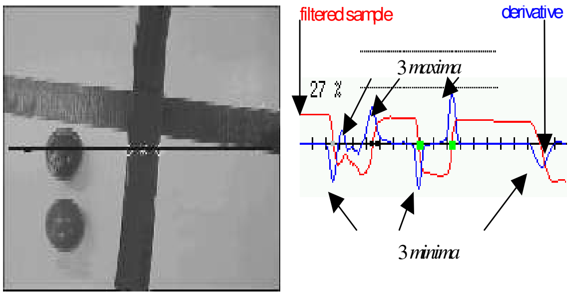

Fig 3: Results of processing an image row, showing the original brightness, its derivative, the three largest *maxima* and *minima* and a confidence level for the selection of the best max-min pair.

Under the above assumption of vehicle/track alignment the results of processing an image row directly correspond to the track features listed in the previous section:

i) the derivative *maxima* and *minima* display large values;
ii) the number of pixels within track boundaries is approximately constant;
iii) the pixel brightness of the original row is approximately constant between the track boundaries (a given derivative max-min pair).

Fuzzy decision making analysis is used to grade separately each track feature, and to obtain joint feature grades for each max-min pair, leading to the determination of the best pair, with an associated confidence level. This is detailed in the sequel.

3.1 Individual Features Grading

3.1.1 Feature 1: "Derivative amplitude is high"

To grade this feature, the fuzzy linguistic term `derivative amplitude is high` is defined for the fuzzy linguistic variable `derivative amplitude`, whose universe of discourse corresponds to the range of values taken by the derivative of pixel brightness. The corresponding membership function is depicted in Fig. 4 and was tuned based on experimental data under average lighting conditions.

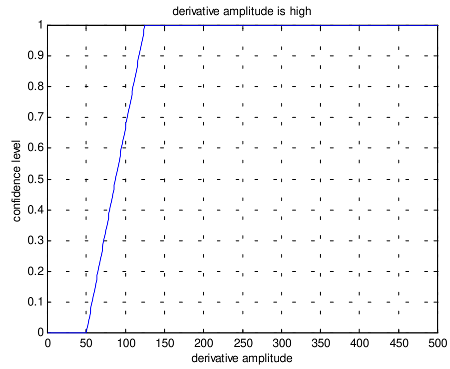

Fig 4: Fuzzy membership function for derivative amplitude.

Given a max-min pair with value-max and value-min values, respectively, the corresponding x-axis value will be calculated as

$$\text{derivative amplitude} = \frac{|\text{value-max}| + |\text{value-min}|}{2} \qquad (2)$$

and the associated confidence level is obtained from the `derivative amplitude is high` membership function.

3.1.2 Feature 2: "Track width is approximately W "

The value W=15 pixels has been calibrated for the situation when the track is orthogonal to the image sample row. In non-orthogonal scenarios, the track width will be slightly larger, as shown in Fig. 5.

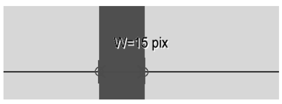

Fig 5: Track width in different situations.

Therefore we defined the asymmetric fuzzy membership function plotted in Fig. 6 for the linguistic term `track width approximately W=15` over the universe of discourse for the linguistic variable `track width`.

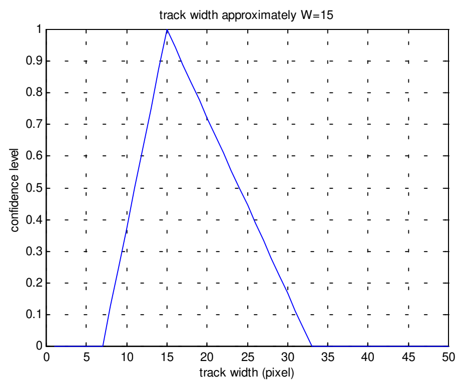

Fig 6.: Fuzzy membership function for track width.

For each max-min pair the confidence level is determined for a track width corresponding to the distance in pixel between the location of the max and min on the x-axis.

3.1.3 Feature 3: "Different background and track pixel brightness"

The major difficulty in this case, is to define the threshold to discriminate black and white colors. A fuzzy threshold is robust to ill lighting conditions, and is obtained by establishing one fuzzy membership function per color (black and white), as depicted in Fig. 7.

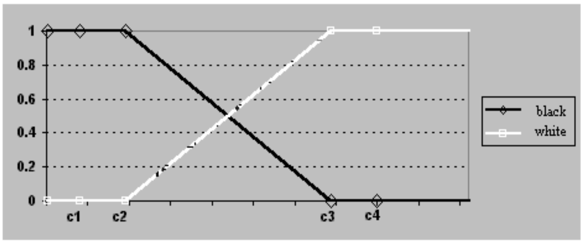

Fig 7: Fuzzy membership functions for black and white colors, defined over the universe of pixel brightness.

The fuzzy membership functions are dynamically adjusted for each sample, and were tuned based on experimental data, leading to the following expressions for the parameters in Fig. 7:

$$\begin{aligned} c_1 &= \text{cor\_min} \\ c_2 &= \text{cor\_min} + \frac{39\Delta_{cor}}{255} \\ c_3 &= \text{cor\_min} + \frac{215\Delta_{cor}}{255} \\ c_4 &= \text{cor\_max} \end{aligned} \qquad (3)$$

where

cor_max : sample maximum color value (in pixel brightness)

cor_min: sample minimum color value (in pixel brightness)

$$\Delta_{cor} = cor\_max - cor\_min \qquad (4)$$

The 39 and 215 values represent the maximum and minimum pixel brightness for which some color can be considered black or white, respectively. Within those bounds, the threshold changes from sample to sample adjusting itself to changes in light conditions.

Next, a fuzzy sentence is built to represent feature 3. Assuming that the background is represented by all sample pixels except those between the max and min positions (for some pair) and that the track is represented by those pixels between the max and min positions of the same pair, we have two alternatives for these colors, as illustrated by Fig. 8: a black track on a white background or a white track on a black background.

Fig 8: Black track on white background (left) and white track on black background (right) images.

Given the fuzzy membership functions for the black and white colors and these two possible track configurations, we are able to state the last feature in fuzzy linguistic terms:

{
(average color until the first edge is *white*) Λ
(average color between the two edges is *black*) Λ
(average color after the second edge is *white*)
}
V
{
(average color until the first edge is *black*) Λ
(average color between the two edges is *white*) Λ
(average color after the second edge is *black*)
}.

The sentence confidence level is obtained by the application of traditional fuzzy logic connectives [3] [9]:

Confidence level = max[min($color_1$ is white, $color_2$ is black, $color_3$ is white) ,
min($color_1$ is black, $color_2$ is white, $color_3$ is black)]

with: $color_1$: average color of the pixels until the first edge

$color_2$: average color of the pixels between the two edges

$color_3$: average color of the pixels after the second edge

x is A: membership of x ($x \in \{ color_1 , color_2, color_3\}$) in the fuzzy set A, A={black, white}.

3.2 Joint Feature Grading

After grading each max-min pair with respect to each track feature we have to combine all this information and infer which combination represents the track location best. The following matrix data representation was used:

$$\text{feature}_i = \begin{bmatrix} \mu_{11}(c_i) & \mu_{12}(c_i) & \mu_{13}(c_i) \\ \mu_{21}(c_i) & \mu_{22}(c_i) & \mu_{23}(c_i) \\ \mu_{31}(c_i) & \mu_{32}(c_i) & \mu_{33}(c_i) \end{bmatrix} \qquad (5)$$

Were μ_{jk} (c_i) represents the pair $(\max_j,\min_k)$ membership function concerning feature_I, i,j,k=1,2,3.

The max-min pair chosen to be the track representative is the one that maximizes the product of the feature membership functions,

$$\max\left(\begin{bmatrix} \mu_{11}[c_1]\cdot\mu_{11}[c_2]\cdot\mu_{11}[c_3] & \mu_{12}[c_1]\cdot\mu_{12}[c_2]\cdot\mu_{12}[c_3] & \mu_{13}[c_1]\cdot\mu_{13}[c_2]\cdot\mu_{13}[c_3] \\ \mu_{21}[c_1]\cdot\mu_{21}[c_2]\cdot\mu_{21}[c_3] & \mu_{22}[c_1]\cdot\mu_{22}[c_2]\cdot\mu_{22}[c_3] & \mu_{23}[c_1]\cdot\mu_{23}[c_2]\cdot\mu_{23}[c_3] \\ \mu_{31}[c_1]\cdot\mu_{31}[c_2]\cdot\mu_{31}[c_3] & \mu_{32}[c_1]\cdot\mu_{32}[c_2]\cdot\mu_{32}[c_3] & \mu_{33}[c_1]\cdot\mu_{33}[c_2]\cdot\mu_{33}[c_3] \end{bmatrix}\right).$$

This corresponds to choosing the best confidence level in the worst case, i.e., the one corresponding to the fuzzy intersection of all the features, therefore increasing the robustness of the method. In this case the intersection is represented by an algebraic product, instead of the more usual min connective. The track intersection with the image row under analysis is assumed to be the middle point between $\max_j$ and $\min_k$, with a μ_{jk} confidence level. When μ_{jk} is below a pre-defined threshold, the track is not considered as detected.

4. TRACK IDENTIFICATION FOR VEHICLE GUIDANCE

The purpose of track detection is to provide information to the mobile robot guidance system, which keeps the error between the vehicle and the track reference frames small. To achieve this, the guidance system needs ate least two parameters: the angle a between the vehicle longitudinal axis and the track tangent and the distance o between the vehicle and the track reference points. Even over curves, the portion of the track seen by the vehicle's vision system can be correctly approximated by a straight line. This is accomplished by determining the track intersection with two rows in the image (see previous section) one placed close to the top, and the other close to the bottom of the image. A straight line is adjusted to the intersection points. The equation of the straight line is used to determine a and o, as depicted in Fig. 9. When the track is not detected in one of the image rows, the corresponding row is moved down (in the case of the top row) or up (in the case of the bottom row) the image to search for a track. This is also useful to detect track interruptions, which were part of the competition challenge.
The track detection confidence level is used to weight the vehicle speed. When confidence decreases, so does the speed.

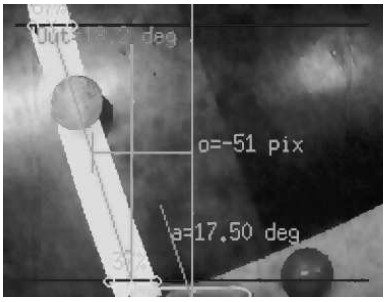

Fig 9: Track angle and offset with respect to the vehicle longitudinal axis.

5. EXPERIMENTAL RESULTS

Fig. 10 shows the results of applying the method to an image with several tracks of different widths and colors. In the figure, small circles represent the max-min pair chosen as the track representative, and crosses represent track intersections with image rows. Vertical and horizontal lines were analyzed, as well as black tracks on a white background and a white track on a dark background with widths slightly different from the nominal 15 pixel. For each line, pixel brightness and its derivative are shown, as well as the (non-normalized) confidence matrices for each of the 3 features. It can be seen that only one significant edge is detected over vertical lines, leading to very low confidence levels (1-2%) for the max-min pair. Over horizontal lines, the correct pairs are detected, with a larger confidence factor (17-37%). A straight line is adjusted to the straight line based on the three track intersections with the rows, resulting in a good estimate of track to be used by the guidance system.

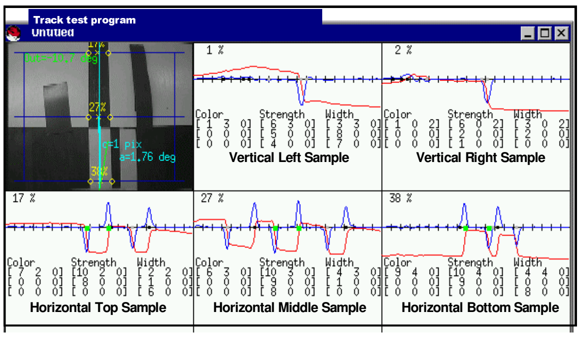

Fig 10: Experimental results. Pixel brightness is shown in red, its derivative is shown in blue.

The developed algorithm, based on fuzzy decision making theory, has proven to be very effective, fast and extremely robust, even at ill lighting conditions. The confidence level provided can be used to control the speed of the vehicle, making the vehicle slowdown when the conditions of visibility are bad and speedup when the conditions are good.

6. CONCLUSIONS AND FUTURE WORK

In this paper, a method for vision-based track detection using fuzzy decision-making was introduced. The algorithm presented runs in real time as part of the guidance system of a mobile robot designed to follow as fast as possible an optical track in a robot competition. Results show the robustness of the method under noisy conditions.

Future work includes the expansion of the algorithm usage for detection of the resuming point after an interruption, as well as, based on the processing of the track detected ahead of the vehicle, to increase or decrease the vehicle speed on-line, depending on whether a straight line or a curve is approaching, respectively. This has been done before with a less robust algorithm, which needed calibration for light conditions [6] .

7. REFERENCES

[1] J. D. Crisman (1996), “System Design Via Small Mobile Robots”, *IEEE Transactions on Education* Vol. 39, pp. 275-280, May

[2] R. C. Gonzalez, R. E. Woods (1992), *Digital Image Processing,* Addison-Wesley

[3] C. J. Harris, C. G. Moore, M. Brown (1992), *Intelligent Control, Aspects of Fuzzy Logic and Neural Nets*, World Scientific Publ. Co.

[4] J. Jones, A. Flynn, *Mobile Robots - Inspiration to Implementation,* A. K. Peters, 1993

[5] G. J. Klir, T. A. Folger (1988), "Fuzzy Sets, Uncertainty and Information", Prentice Hall, Englewood Cliffs, New Jersey

[6] P. Lima, C. Cardeira (1998), "Learning from Building Small Mobile Robots," *IST Science & Technology*, No. 3, December.

[7] A. Ollero, A.García-Cerezo, J.L.Martínez, A.Mandow (1997), "Fuzzy Tracking Methods for Mobile Robots", *in Applications of Fuzzy Logic: Towards High Machine Intelligence Quotient Systems*, Prentice Hall Series on Environmental and Intelligent Manufacturing

[8] G. Oriolo, G. Ulivi, M. Veneditteli (1997), “Fuzzy Maps, Managing Uncertainty in Sensor Based Motion Planning", *in Applications of Fuzzy Logic: Towards High Machine Intelligence Quotient Systems*, Prentice Hall Series on Environmental and Intelligent Manufacturing

[9] W. Pedryckz (1993), *Fuzzy Control and Fuzzy Systems*, Research Studies Press Ltd.

[10] F. G. Pin , “On Minimal Models and Automated Rule Generation with the Fuzzy Behaviorist Approach for Vehicle Navigation” (1997), *in Applications of Fuzzy Logic: Towards High Machine Intelligence Quotient Systems*, Prentice Hall Series on Environmental and Intelligent Manufacturing

[11] E. W. Tunstel, Jr. and M. Jamshidi (1997), “Intelligent Control and Evolution of Mobile Robot Behavior", *in Applications of Fuzzy Logic: Towards High Machine Intelligence Quotient Systems*, Prentice Hall Series on Environmental and Intelligent Manufacturing