Fuzzy control for active perceptual docking

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Abstract

This paper demonstrates fuzzy control of heading direction for a mobile robot. The robot is engaged in a docking maneuver guided by an active perceptual behaviour. In order to dock, the robot must control its heading direction to move directly towards a target object. Previously, we have developed a technique in which the robot fixates on the desired target, and corrects its heading direction based on information derived from optical flow data from a log-polar camera. However, the optical flow data derived is noisy. Thus, when robot direction control is based directly on the optical flow data the resulting path is erratic. A smooth path is more direct and so faster, leads to less strain on motors, and simplifies fixation. Further, constant change in direction can result in wheel-slippage, leading to errors in odometry. The results show a significant smoothing of the robot path in simulation.

1. Introduction

This paper presents an approach for mobile robot motion control using a fuzzy controller. We make use of the TSK (Takagi-Segeno-Kang) fuzzy model to smooth the path of a mobile robot during a docking maneuver.

The major aim of the fuzzy control system is to smooth the path for robot docking, while not unduly impacting the time taken. A smooth path is important because it:

- simplifies fixation;
- reduces motor wear; and,
- improves odometric data.

Fixation adjusts the robot pan-tilt platform to ensure the object remains centred in the camera. If the robot undergoes a large rotational acceleration, the pan-tilt platform may require an even larger acceleration to compensate for robot rotation and translation. If there is no feedback from the robot drive system to the pan-tilt controller, fixation must be performed purely on visual data. Processing visual data quickly enough to keep up with large rotational velocities can be problematic, and is better avoided. Further, large accelerations are taxing on motors, and the mechanical base of the robot.

Finally, mobile robots often use wheel encoder odometry to track position. Wheel slippage is a major source of odometric error. Large accelerations, particularly rotational, cause slippage. Thus a smooth path is important for accurate navigation. However, it is important to balance the requirement of a smooth path with speed of convergence, i.e., the robot should avoid travelling in the wrong direction.

1.1. On the use of fuzzy control

Controlling a system means monitoring some characteristics, and, based on these values, applying different controls. An algorithm to transform sensor inputs into corresponding control values is a control strategy. For traditional control a strategy is created by deriving a precise mathematical model of system behaviour and a set of objectives that the control is to achieve. The control strategy can then be derived as it is a well-defined mathematical optimisation problem. However, traditional control cannot be applied unless [3]:

1. the model of the system is known;
2. the objective function can be formulated in precise terms; and,
3. the optimisation problem can be solved.

Fuzzy control can be used in cases where no model is available. Fuzzy control allows black-box identification of the system using supervised learning techniques.

1.2. Fuzzy control for mobile robot control

Robot sensor measurements are frequently noisy. Range sensor noise is quite well understood and can be modelled. However, for sensors such as vision, where a world model is required and complex algorithms may be used to interpret the raw sensor data before it is used for control, the situation is more difficult. Vision systems for complex problems are generally custom-made. Significant work would be required to model the noise introduced at each stage of the process. Further, in most cases, a robot is dealing with an environment that is partially known, or completely unknown. The environment may also be changing dynamically in unknown ways. Thus, a precise system model is not possible in many cases.

For the direction control system presented here, all we know that: the docking target object is fixated; and, the majority of points in a given image region are either behind, or in front-of the fixated object. Relative distances are unknown as is the distance from the target, which is changing over time. Also, the environment may be dynamic. In this case, deriving a precise mathematical model is a difficult problem.

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1.3.The TSK fuzzy model

Takagi and Sugeno proposed the T -S fuzzy model and a procedure to identify it from input/output data of a system. This method was extended by Sugeno and Kang. The TSK method consists of structure identification and parameter identification. The model consists of a set of implication rules with linear equations as consequent parts:
IF xt is Ai_l ..., xk is Aik THEN

$$Yi = Pie + p,rxl + ... + pikxk, \quad (1)$$

where pig, are consequent parameters, yi is the output from the rule, and Aij is a fuzzy set, j E (1,..k), and i E (1,..n), n is the number of rules, and k is the number of input variables.

Given an input $(zt, zs, ...z_k)$, the final output of the n implications of the fuzzy model is inferred as:

$$Y - \sim \sim_{\Gamma} t \frac{wiyi}{\sim i=1 \; Wi} \quad (2)$$

where wi is the weight of the ith rule and is calculated as:

$$w, = Ail (xi) A ... A Aik(zk) \quad (3)$$

Different definitions of A are possible, for instance [4]:

$$wi = \prod_{k=1} Aik(zk), \quad (4)$$

where $Aik(xk)$ is the grade of membership of zk in Aik.

1.4.Visual motion-based approaches to mobile robots and the docking problem

In order to be autonomous, a mobile robot needs to perceive and react to its environment. A control system is required to take noisy sensory inputs and produce smooth paths. Systems that use optical flow as their control input variables are popular in mobile robot navigation. However, the computation of optical flow without the use of models, in environments where light is not carefully controlled, often suffers from noise. This is particularly the case for high speed methods, required for effective real-time mobile robot navigation. Thus, it is important to examine control strategies for these systems to generate smooth paths from noisy input.

The control system presented in this paper is for heading direction control in docking. Docking is a fundamental problem in mobile robot research. A robot must be able to dock in order to be able to interact with objects in its environment.

2.Docking for a ground-based robot

Consider a ground-based robot, moving with a velocity vector W = (W5, WW) (Figure 1). The robot has a pan/tilt platform that is fixating on an object of interest. The platform has rotational velocities 8 and ϕ for pan and tilt respectively.

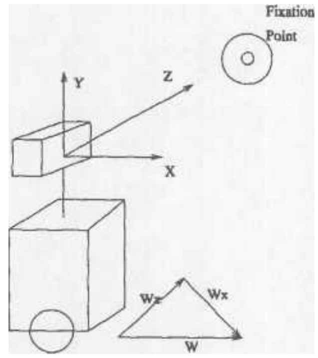


Figure 1: The robot moves on the ground plane, while the camera fixates on a point in the environment.

For the robot to dock with the target, it must adjust its heading direction so that W_x is reduced to zero. We require a control system to convert visual data to motor commands for this task. See [1] for full derivation of the visual data.

For an image point, the sign of y, the rotational component of optical flow in a log-polar sensor (see [2]) is determined by the sign of W_s and whether the corresponding world point is in front of or behind the fixation point. In many situations, we have knowledge of the depth of visible points from the context of a robot's task. For example, when the fixation point is on the ground, all image points below it are ground points that are closer to the robot than the fixation point. Note that the magnitude of y depends on the magnitude of the world point to fixation point distance, which is unknown.

3.Noise in the input parameter

There are two major sources of noise: flow calculations; and, the unknown environment. The optical flow method used [5] was selected because it did not require a scene model, and was fast. However, the data generated is noisy. Although the noise arises from the environment, as the environment is unknown, the noise is effectively random. 'We only know that, in general, the points in a particular region are close than, or further than the fixation point, thus we only know whether the ratio is greater than or less than zero, not its magnitude.

Further, even if we knew the input noise distribution, the flow magnitude is not known at any particular point, so the signal-to-noise ratio is unknown. We know that if a scene point is near the fixation point then the signal will be small, and that if it is far, the signal will be large. If the fixation point is on an object, far away in relation to object size, then all points on that object will be close to the fixation point.

n

4.A fuzzy control scheme

To derive a fuzzy control scheme, we collected data from mobile robot docking runs. This data includes the aggregated output from the optical flow data for each frame as the robot moved, $_E$ j, and the desired robot direction at this point, 60. The are up to 100 frames for each run, and several runs which took place under different conditions.

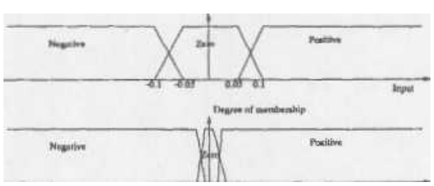
The only external system input is 7 for each frame. Since we assume the target is stationary, we can expect that the sign of W, will not change rapidly (until the system has converged). Thus, recursive information about which way we adjusted the heading direction last time is useful. Due to noise in the optical flow, the data from the previous frame may ease the effect of the occasional poor frame. However, this can be adequately represented as a factor contributing to the state variable of the previous output. The only output is the adjustment to the heading direction. Thus, we have two input variables and output variable.

In general:

- if the aggregate of the flow over the region of interest in the image is negative, then we should turn to the left;
- if aggregate is positive, turn right; or,
- If aggregate is zero, continue in the present direction.

Current Aggregate	State	Output
Negative	Left	Left
Positive	Righ	Right
Positive	Left	Zero
Negative	Right	Zero
Zero	Right	Small right
Zero	Left	Small left
Positive	Zero	Right
Negative	Zero	Left
Zero	Zero	Zero

Table 1: Fuzzy rules for docking control.



1.,-0.303

Figure 2: Fuzzy membership functions for the input variables.

The membership functions for the input variables were optimised using sample data. We used gradient descent based on the root mean square of the output errors.

5.Results

We present results of the control system running in simulation, demonstrating that the control system smoothes the path, preventing large accelerations. Each of the four runs presented includes around 60 iterations. These runs are compared against duplicated conditions where corrections to heading direction are made on the basis of raw image data (capped to a maximum).

	raw values	fuzzy control
mean	0.0018	0.00055
max	0.006	0.003

Figure 3: Reduction in robot acceleration. The maximum and mean change in the robot path using raw inputs and closed loop fuzzy control.

The robot simulator generates an image every p msec using the POVRAY ray-tracing package. The robot moves forward with fixed velocity. Heading direction can be changed by applying angular velocity: represented as a mean velocity value over p msec, i.e., given ramp up and ramp down of acceleration, average velocity, v will lead to ap radians over the interval between images, where a is set by the control system.

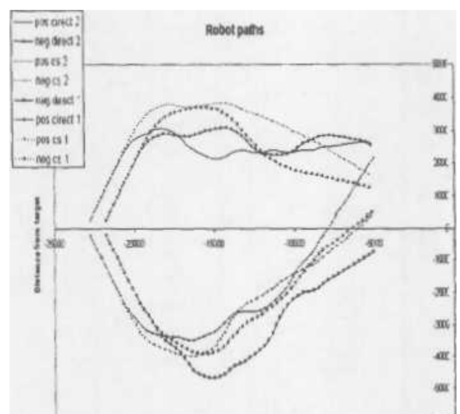


Figure 4: Path with respect to target. neg shows starting with a negative angle heading direction, pos is positive, direct shows heading change as truncated input value, where cs shows application of fuzzy control. In 1 the robot started at (-22000,0), in 2 (-23000,0).

The trials were: (1) robot began heading 45° to the left of the target; (2) same starting point, but heading 45° to the right; (3) approximately 4% further back, heading left; and, (4) same starting point, moving right.

Figure 5 shows heading direction angle over time, where zero is heading directly towards the target. The change in angle is greatly smoothed, with some of the brief periods of turning in the wrong direction completely suppressed. Figure 4 shows the path taken comparing fuzzy control and the raw input signal, demonstrating a smoother path with the control system. Figure 3 compares mean and maximum change in heading direction for all trials. Mean change in direction is reduced by a factor of three when the fuzzy controller is used.

There was also a marginal improvement in the percentage of time the control output directed the system to move to the left when it should have moved to the right, or vice versa.

6.Conclusion

We have implemented a fuzzy control system to smooth the path of a mobile robot that is guided by the rotational component of log-polar optical flow in controlling its heading direction to dock with a fixated object. Our results demonstrate that the control system can smooth the path and prevent the robot turning too rapidly, easing stress on the motors and making odometry more reliable. Further, there was no significant negative impact on the speed of convergence.

Fuzzy control has been demonstrated to be beneficial for controlling the path of a vision-guided mobile robot. In this case, traditional control systems were not appropriate as the system cannot be modelled mathematically with accuracy. Fuzzy control may be appropriate also for many other cases with vision-guidance of mobile robots, as it is frequently the case that the system cannot be accurately modelled.

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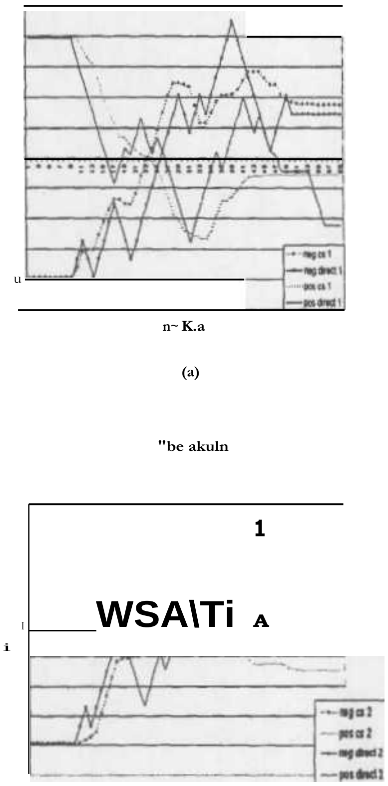

(a)

(b)

Figure 5: Heading direction with respect to target. The legend is the same as for the path graph, Figure 4. (a) Trials starting at (-22000,0). (b) Trials started at (-23000, 0).