Adaptive Visual Guidance of Mobile Robots based on Takagi-Sugeno Model

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In industrial applications arises the need for a high level cognition system to guide mobile robots robustly. This article addresses an integrated solution to achieve this task. The proposed system exhibits robust tracking of a visual guide and provides an adaptive interaction, which maintains the stability of the overall system against fluctuations of internal or external system parameters. Moreover, the proposed guidance system counteracts the noise influence regarding vision and sensory entries. This system relies on a biologically inspired sensor integration, this means that outcomes of both of vision system and distributed sensors are fused to obtain a high precision guidance. This study has been implemented on the B21-RWI robot platform (laboratory for autonomous mobile robots, university of Tübingen).

Introduction

Recently, a variety of robot platforms e.g. helpmates, nursebots, tourguide, service, entertainment, and domestic robots are used in public venues. So, the demand for an adaptive robust visual guidance is becoming a serious task. A dominant approach in robotic guidance is to use the skin colour and facial features of a person to guide robots visually. This trend of research is really successful in human-robot interaction, especially to interpret human intentions. On the other side, this approach failed to guide robots visually because of many plausible reasons. At first, robots must be in front of the person and too close to him, to define the skin colour and to extract facial features. Second, this approach can be applied if and only if the motion is too slow. Third, this system fails to distinguish the affinity in features if presents [8,9]. The strategy is to build a vision system, which can pursue a unique coloured guide in a dynamic environment using a binocular vision system. Moreover, other distributed sensors collaborate to support the robustness of the overall system [1]. The adaptive control of robot's navigation (heading and translation) depends primarily upon outcomes of the laser range finder and the binocular vision system. In emergencies, all associated distributed sensors e.g. vision, laser, sonar, tactile and button sensors collaborate to hinder collisions [1,5,13,16]. The remainder of this article is organized as follows; section (1) focuses on recognition of visual guides. Furthermore, it will explain how to estimate guide's spatial and geometrical characteristics based on the principal of position sensitive devices (PSD). Moreover, it will illustrate how to steer the robot adaptively with a visual feedback. Section (2.1) will present the modelling of robot dynamics using the auto regressive exogenous (ARX) paradigm and section (2.2) explains how to employ the recursive least squares (RLS) algorithm to estimate ARX model parameters. Section (3) will demonstrate applying of Takagi-Sugeno (TS) algorithm to underlie the adaptive navigation regarding perceptions from both of vision system and laser range finder [6,7,16,17]. Finally, Section (4) will introduce the conclusion of the subject under study.

1. Visual Tracking

To resemble the human behaviour in object tracking, we have to close the loop between the binocular vision system and robot's actuators. The main goal of the vision system is to extract the object (guide) and to calibrate its size and range geometrically [10,11], see figure 1.

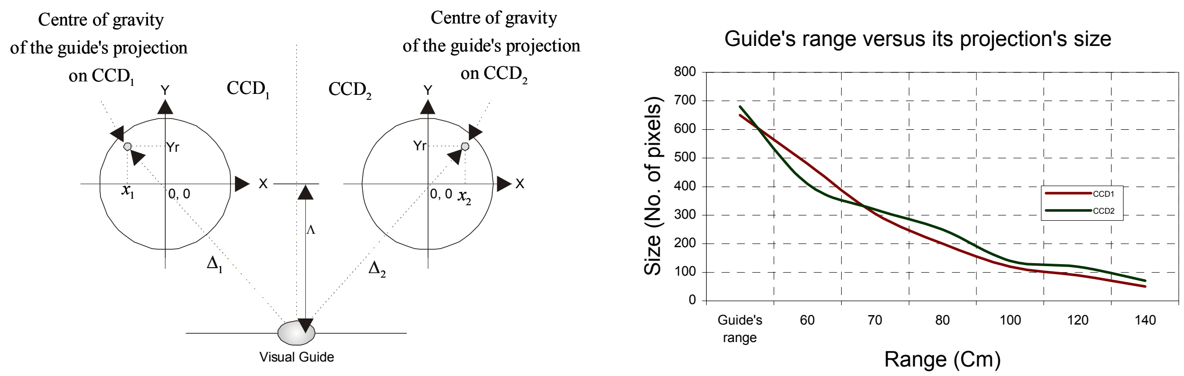

Figure 1. Geometrical ranging of a visual guidance using stereo CCD cameras

The aim is to guide the robot using an object which has a highly saturated and homogeneous colour. To recognize the visual guide the following procedure has been applied:

- Converting the colour model from RGB to HSI
- Using Gaussian filter to omit high frequency noises
- Object filtering by extracting a set of pixels representing the guide, corresponding pixels of a particular degree of HSI, see figure 2
- The offset noise is neglected by thresholding the lower limit of extracted pixels, that compensates errors caused by robot's motion e.g. silhouettes, erosion and dilation
- Deducing the guide's centre of gravity
- Calibrating guide's range and size, see figure 1

The presented results show that the relation between guide's range and its projection's size is exponential. The object's projection on both CCD cameras is used to deduce the guide's centre of gravity (COG) and guide's size, where N_1 is the number of pixels on CCD_1 and its centre of gravity is the point $P_1(X_1, Y_1)$, while N_2 is the number of pixels on CCD_2 and its centre of gravity is the point $P_2(X_2, Y_2)$.

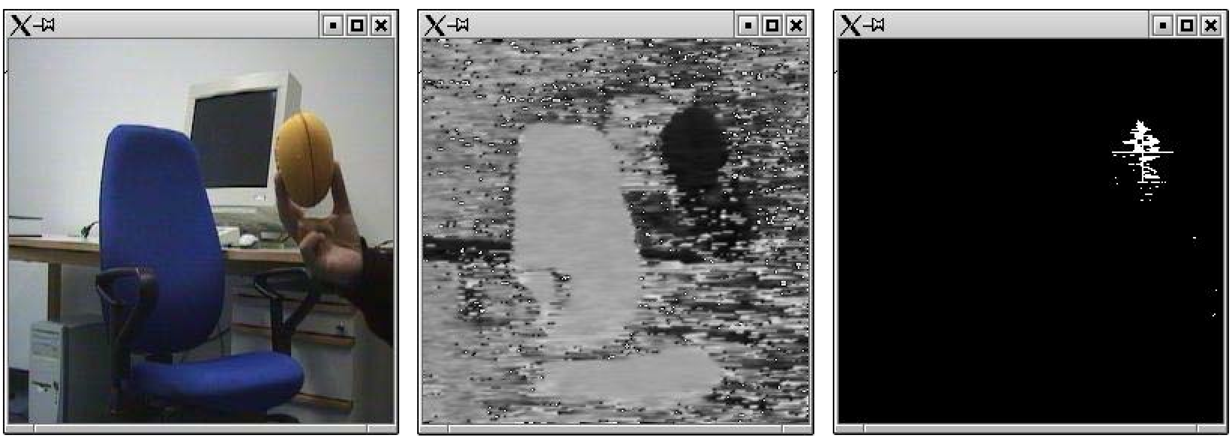

Figure 2. Visual object extraction

For more information about the preceding procedure, review [2,3,4,10,11,14,15]. To adapt robot's navigation, both of laser range finder and binocular vision system have effectively collaborated to control the heading and the longitudinal velocity. Meanwhile, other sensors, sonar and tactile sensors, serve to avoid collision in emergencies. Figure 3 illustrates the structure of the robot's control system with a visual feedback.

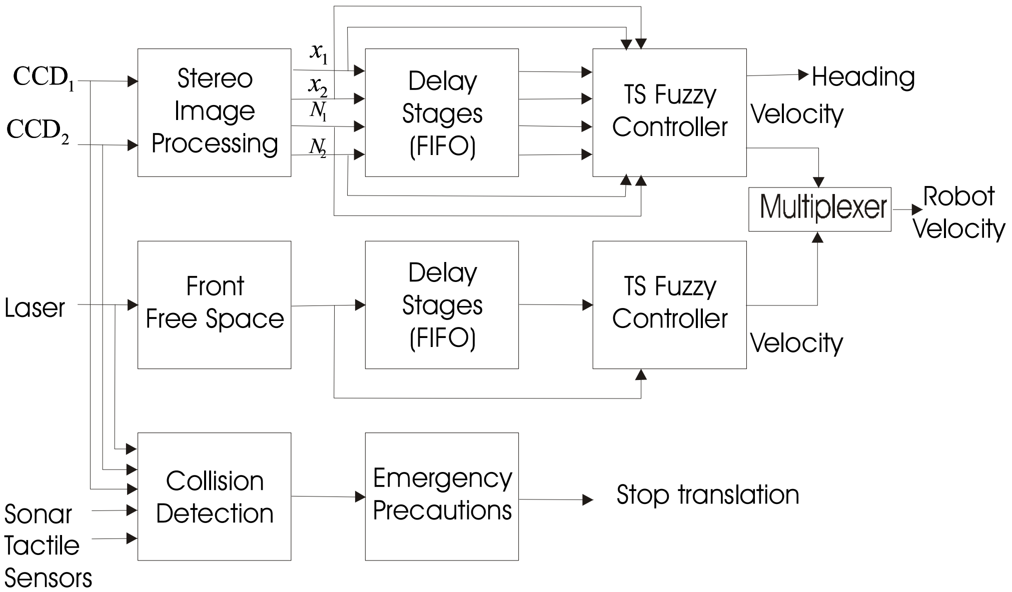

Figure 3. Adaptive fuzzy control with a visual feedback

2. Modelling of Robot Dynamics
2.1. ARX Modelling paradigm

The discrete ARX modelling paradigm of robot dynamics is derived from Kalman filter, see figure 4. This structure takes into account both the observed state υ_k and the reference control signal λ_k which is given by:

$$\upsilon_k = \sum_{i=1}^{n_a} a_i \upsilon_{k-i} + \sum_{i=0}^{n_b} b_i \lambda_{k-i} + \eta_k \qquad (1)$$

Where η_k is a modelling residual, Gaussian noise, n_a is the model order of the observed state (also called the number of poles), while n_b is the model order of the control signal (also called the number of zeros). The operator q^{-1} is the back shift operator or delay, where $q^{-1}\upsilon_k = \upsilon_{k-1}$, that follows:

$$\begin{aligned} &A(q^{-1})\upsilon_k = q^{-1}B(q^{-1})\lambda_k + \eta_k, \ where \\ &A(q^{-1}) = 1 - a_1 q^{-1} - a_2 q^{-2} - \ldots - a_{n_a} q^{-n_a} \\ &B(q^{-1}) = b_0 + b_1 q^{-1} + b_2 q^{-2} + \ldots + b_{n_a} q^{-n_b} \end{aligned} \qquad (2)$$

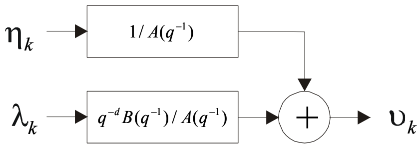

Figure 4. ARX modelling of robot dynamics

In this case the observed state υ_k is the robot's longitudinal velocity/heading while the reference control signal λ_k is the guide's range and/or the obstacles histogram. The Gaussian distributed noise η_k, associated with the observed output, enables applying identification algorithms e.g. RLS or Least Mean Squares (LMS) to estimate model parameters (coefficients). In another modelling techniques e.g. auto regressive moving average (ARMA), the noise is coloured (non-Gaussian). The no-Gaussian noise impedes applying parameter's identification algorithms. The ARX modelling form is applicable only within linear or quasi-linear systems. Therefore, we can apply it within adaptive navigation systems, while this algorithm fails to cope with position control systems of mobile robots due to their enormous non-linear odometric errors [1].

2.2. RLS Estimation of Model Parameters

Now let us explain, how to estimate ARX model parameters *A*(*q*−1) and *B*(*q*−1). The RLS is a stepwise learning algorithm, this means that, estimation of robot's model parameters yields a gradual convergence. Compared with the LMS algorithm (batchwise learning), the RLS needs a lower computational power and it is more stable than the LMS. The LMS algorithm relies upon matrix inversion and some matrices are not invertible, so applying this technique to some models seems critical. We can initialise the RLS identification process using an empty vector. Also, we can initialise it using fuzzy and neural nets. Figure 5 shows the output of ARX dynamics model with respect to the actual output. The output of the ARX model seems smooth due to filtering of high frequencies also, this figure shows the convergence of parameters during the learning process.

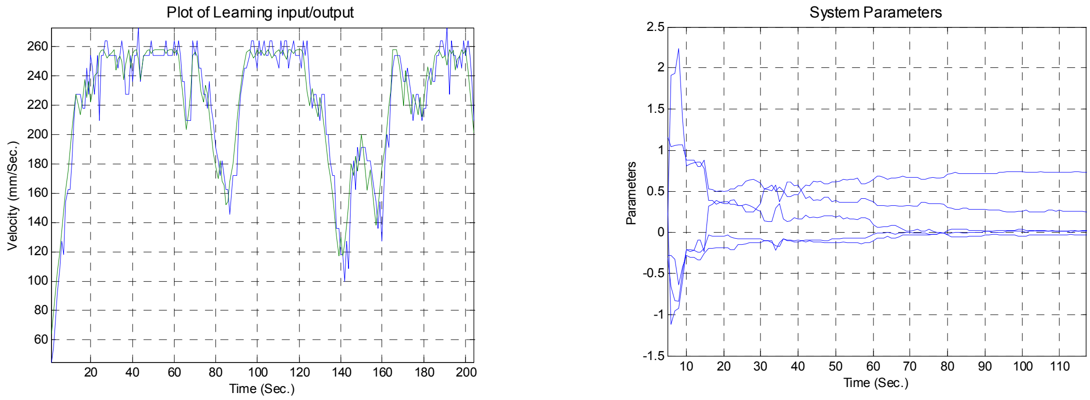

Figure 5. Robot's output versus model's output and ARX parameters convergence

The estimation process can be accomplished according to the following. At time step (*k* + 1):

1. Form Γ_{k+1} new input/output patterns

$$\Gamma_{k+1}^{T} = \left[\upsilon_{k+1} .... \upsilon_{k-n_a} \lambda_k .... \lambda_{k-n_b} \right] \tag{3}$$

2. Calculate the estimation error ε_{k+1} as follows

$$\varepsilon_{k+1} = \upsilon_{k+1} - \bar{\upsilon}_{k+1} = \upsilon_{k+1} - \Gamma^T_{k+1}\Theta_k \tag{4}$$

3. Calculate Ψ_{k+1} (based on Kalman filter)

$$\Psi_{k+1} = \Psi_k \left[I_m - \frac{\Gamma_{k+1}\Gamma^T_{k+1}\Psi_k}{1+\Gamma^T_{k+1}\Psi_k\Gamma_{k+1}} \right] \tag{5}$$

4. Update parameters Θ_{k+1}

$$\begin{aligned} &\Theta_{k+1} = \Theta_k + \Psi_{k+1}\Gamma_{k+1}\varepsilon_{k+1} \\ &where\ \ \Theta^T_{k+1} = [1 - a_1 .... - a_{n_a} + b_0 + ... + b_{n_b}] \end{aligned} \tag{6}$$

5. Wait for the next time step to elapse and loop back to step (1)

3. Fuzzy Controller

In 1965, Zadeh published his paper (Fuzzy Sets). After that scientists worldwide developed different algorithms to design a fuzzy logic controller (FLC) such as; E. Mamdani 1975, Takagi-Sugeno 1985 and Tsukamoto fuzzy model. Fuzzy inference systems (FIS) introduce a considerable solution to the subject of regulation and control of mobile robots [12]. The fundamental three phases of FLC are; fuzzification, inference engine design and defuzzification. These three phases are analogous to three phases of stochastic based control systems; modelling, identification and controller design, see figure 6. A FLC is an intelligent control system that smoothly interpolates between rules. A fuzzy set may be represented by a mathematical formulation known as a membership function. That is, associated with a given linguistic variable (e.g. mobile robot velocity) are linguistic values or fuzzy subsets (e.g. slow, fast, etc.), expressed as membership functions, which represent uncertainty, vagueness, or imprecision in values of the linguistic variable, see figure 6. This function assigns a numerical degree of membership, in the closed unit interval, to a crisp (precise) number. Within this framework, a membership value of zero/one corresponds to an element that is definitely not/definitely a member of the fuzzy set. Partial membership is indicated by values between 0 and 1. Implementation of a fuzzy controller requires assigning membership functions for inputs and outputs. Inputs are usually measured variables, associated with the state of the controlled plant that are assigned membership values before being processed by an inference engine. The heart of the controller inference engine is a set of if-then rules whose antecedents and consequents are made up of linguistic variables and associated fuzzy membership functions. Fuzzy set intersection, or conjunction, operators in the antecedent are generally referred to as t-norms. They commonly employ algebraic min or product operations on fuzzy membership values. Consequents from different rules are numerically aggregated by fuzzy set union and then defuzzified to yield a single crisp output as the control for the plant. The most popular FLC algorithm is the discrete Takagi-Sugeno fuzzy model, the consequent part of the rules is described by nonfuzzy analytical functions.

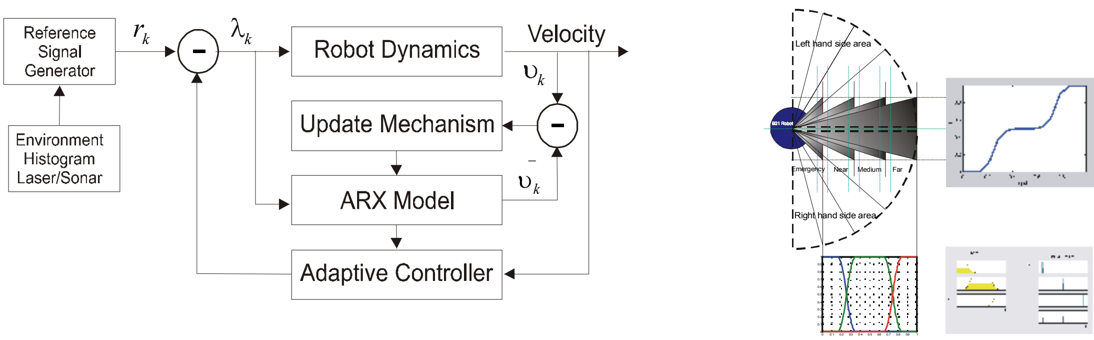

Figure 6. Adaptive FLC system of robot's longitudinal velocity and heading

The discrete FIS considered in this paper is defined by the following implications:

1. The centroid or the centre of gravity (COG) defuzzification rule (g) is expressed by:

$$g = \frac{\sum_{i=1}^{n} \omega_i g_i}{\sum_{i=1}^{n} \omega_i} \tag{7}$$

2. Formulating the controller's state representation (g_{k+1}) is done as follows

$$g_{k+1} = \frac{\sum_{i=1}^{n} \omega_{i,k} \{A(q^{-1}) g_k + B(q^{-1}) \upsilon_k\}}{\sum_{i=1}^{n} \omega_{i,k}} \tag{8}$$

3. Driving the controller observed state o_k

$$o_k = \frac{\sum_{i=1}^{n} \omega_{i,k} S(q^{-1}) g_k}{\sum_{i=1}^{n} \omega_{i,k}} \tag{9}$$

4. Calculating the feedback signal λ_k

$$\lambda_k = r_k - F(q^{-1}) o_k = r_k - \frac{\sum_{i=1}^{n} \omega_{i,k} F(q^{-1}) S(q^{-1}) g_k}{\sum_{i=1}^{n} \omega_{i,k}} \tag{10}$$

Figure 7 (the left hand side) shows that the robot's output follows the reference signal smoothly with a high level of correlation and the right side illustrates the optimising of FLC parameters using the correlation technique.

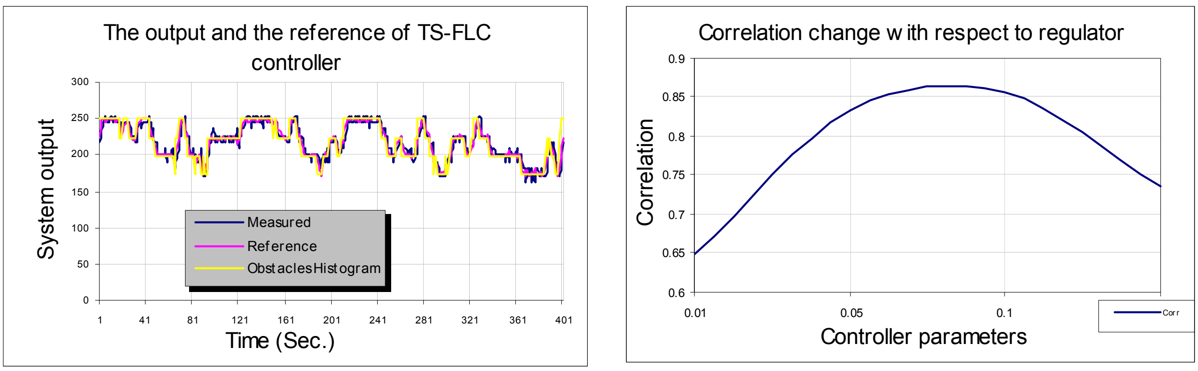

Figure 7. Results of the FLC system and optimising of controller parameters

4. Conclusion

The applied visual tracking algorithm exhibits higher reliability and achieves the goaled robustness. Moreover, the integration between the binocular vision system and distributed sensors succeeded to donate the robot more autonomy and adaptability. The FLC has the capability to be applied in applications, with no models available. Moreover, the FLC can interpolate the classical stochastic control techniques. Applying FLC techniques to control systems damps oscillations of the observed system output which achieves higher correlation between the system observed output and the reference signal. We must take into consideration that the COG function fails to deal with some types of membership functions.

Acknowledgment

I would like to acknowledge the financial support by the German Academic Exchange Service (DAAD) of my PhD scholarship at the university of Tübingen.

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