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Unmanned Vehicle with Obstacle Avoidance: Comparison Study

Thongchai Phairoh
Virginia State University
tphairoh@vsu.edu

Abstract

A golf car is modified as the unmanned ground vehicle (UGV) platform. RTK GPS measure the location of the UGV, laser scanner measure the obstacle. The UGV can adjust the speed and steering wheel. Navigational systems for UGV can be considered in two phases, a path-planning phase and a path-following phase. Real-time obstacle detection and avoidance are the key issues relating to successful motion planning of a mobile robot. This study, navigation system, path planning and path following, is considered by using the minimized deviation from the given trajectory and ANFIS. The numerical simulation results show that both methods can avoid the obstacle.

Introduction

UGVs are mainly used in military, industry, agriculture and mining since they have the necessary loading capability. Navigational systems for UGV can be considered in two phases, a path-planning phase and a path-following phase. Real-time obstacle detection and avoidance are two of the key issues relating to successful motion planning of a mobile robot. Path-planning can be further subdivided into two categories as static (when the obstacles are stationary) and dynamic (when the obstacles are moving or changing shape or size). Many researchers concern on the obstacle detection and path planning. For trajectory tracking, many techniques are applied such as pure pursuit, vector pursuit, state feedback control, fuzzy logic control, or neural network control.

Figure 1: Actuator and sensor applied for UGV control.

Qu et al.(2004), Yang et al.(2008, 2009) studied optimal trajectory generation for non-holonomic mobile robots in the presence of moving obstacles. The trajectory was presented by a parameterized higher-order polynomial and is feasible for car-like robots whose motion is non-holonomic. Lu and Chuang (2005) applied fuzzy theory in the practical car-like mobile robot. For given the geometric data and desired destination, a collision-free trajectory connecting was constructed in the free configuration space and then a time parameterization for the trajectory is found under some certain constraints so that the trajectory becomes a reference trajectory. They did experiment with car-like mobile robot to dodge the obstacle and reach the target. Gomez Plaza et al. (2009) integrated the Cartesian space together with the kinematics and dynamics spaces of a car-like robot. They propose a new algorithm that obtains a minimum-time solution to the optimal motion planning of the vehicle.

Adaptive neuro-fuzzy inference system (ANFIS) methodology was proposed by Jang (1993). The ANFIS is a multilayer feedforward network which uses neural network learning algorithms and fuzzy reasoning to map an input space to an output space.

From our preliminary work, we already installed actuators and sensors for trajectory tracking in the golf car as shown in Figure 1. We developed golf car unmanned vehicle which can follow the trajectory Phairoh and Williamson (2008) and the field test results were according to numerical simulation results under preparation. Currently we need to improve our golf car unmanned vehicle for working in unknown environment with obstacle. In this study, we apply the obstacle avoidance control with minimize deviation from a given path, and apply ANFIS to control UGV.

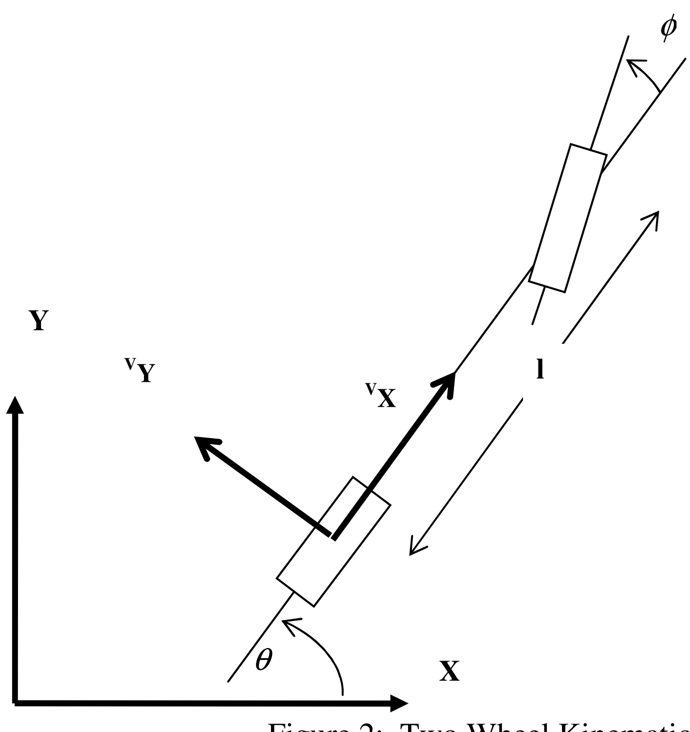

Figure 2: Two Wheel Kinematic Model of WMR.

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Car-like Mobile Robot

The frame coordinate systems for our unmanned vehicle are shown in Figure 2. Here, XYZ is inertial reference frame while ${}^{V}X^{V}Y^{V}Z$ is moving with the unmanned vehicle and the origin is located at center of the rear wheel. Since the vehicle is symmetric along its centerline, we consider a two wheel kinematic mathematical model, where the X and Y components of velocity is given as

$$\begin{aligned}\dot{x} &= V\cos\theta \\ \dot{y} &= V\sin\theta\end{aligned} \qquad (1)$$

Here, V is linear velocity of the unmanned vehicle and θ is orientation of the vehicle measured from the X-axis of the inertial reference frame. The vehicle's yaw rate, $\dot{\theta}$ is calculated from the front wheel angle, ϕ and V such that

$$\dot{\theta} = \frac{V\tan\phi}{L_b} \qquad (2)$$

The equation (1) to (2) can be written in state space model representation as

$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{\psi}\\ \dot{\delta}\end{bmatrix} = \begin{bmatrix}\cos\theta\\ \sin\theta\\ (1/l)\tan\phi\\ 0\end{bmatrix}u_1 + \begin{bmatrix}0\\0\\0\\1\end{bmatrix}u_2 \qquad (3)$$

, where u_1 is the UGV velocity, u_2 is steering wheel velocity.

Collision Avoidance Under Optimal Condition

The optimal trajectory with minimizing the cost function was developed by Qu et al (2004). For trajectory planning in the k[th], sampling period, that is, within the time interval,

$$t \in [t_k, t_f], k = 0,1,2,\ldots,\frac{T}{T_s}$$

, the boundary conditions of the k'th sampling period are given as follows:

$$x(t_k) = x_k, y(t_k) = y_k, \theta(t_k) = \theta_k, \phi(t_k) = \phi_k,$$
$$x(t_f) = x_f, y(t_f) = y_f, \theta(t_f) = \theta_f, \phi(t_f) = \phi_f,$$

In the time interval, $t_0 + kT_s, t_0 + (k+1)T_s$, the UGV trajectory will be

$$y = X\left[a_0^k, a_1^k, a_2^k, a_3^k, a_4^k, a_5^k\right]^T + a_6^k x^6$$

, where

$$X = \begin{bmatrix} 1 & x & x^2 & x^3 & x^4 & x^5 \end{bmatrix}$$
$$\left[a_0^k, a_1^k, a_2^k, a_3^k, a_4^k, a_5^k\right]^T = \left(B^k\right)^{-1}\left(Y^k - A^k a_6^k\right)$$
$$A^k = \left[\left(x^k\right)^6 \quad 6\left(x^k\right)^5 \quad 30\left(x^k\right)^4 \quad \left(x_f\right)^6 \quad 6\left(x_f\right)^5 \quad 30\left(x_f\right)^4\right]^T$$
a_6^k is a free design parameter.
$$Y^k = \begin{bmatrix} y^k \\ \tan\left(\theta^k\right) \\ \tan\left(\phi^k\right)/l\cos^3\left(\theta^k\right) \\ y_f \\ \tan\left(\theta_f\right) \\ \tan\left(\phi_f\right)/l\cos^3\left(\theta_f\right) \end{bmatrix}\theta_f \quad B^k = \begin{bmatrix} X\big|_{x=x^k} \\ \partial X/\partial x\big|_{x=x^k} \\ \partial^2 X/\partial x^2\big|_{x=x^k} \\ X\big|_{x=x_f} \\ \partial X/\partial x\big|_{x=x_f} \\ \partial^2 X/\partial x^2\big|_{x=x_f} \end{bmatrix}$$

The control input, car velocity
$$u_1^k = \frac{w_1^k}{\rho\cos\left(\theta_k\right)},$$

, and steering wheel angular velocity will be
$$u_2^k = \frac{3\sin\left(\theta_k\right)}{l\cos^2\left(\theta_k\right)}\sin^2\left(\phi_k\right)w_1^k + l\cos^3\left(\theta_k\right)\cos^2\left(\phi_k\right)w_2^k$$
Where

$$\begin{aligned} w_1^k &= \frac{x_f - x_k}{t_f - t_k} \\ w_2^k &= 6\left[a_3^k + 4a_4^k x_1^k + 10a_5^k\left(x_1^k\right)^2 + 20a_6^k\left(x_1^k\right)^3\right]w_1 \\ &\quad + 24\left[a_4^k + 5a_5^k x_1^k + 15a_6^k\left(x_1^k\right)^2\right]\left(t - t_0 - kT_s\right)w_1^2 \\ &\quad + 60\left[a_5^k + 6a_6^k x_1^k\right]\left(t - t_0 - kT_s\right)^2 w_1^3 + 120a_6^k\left(t - t_0 - kT_s\right)^3 w_1^4 \end{aligned}$$

Avoidance zone for obstacle i'th is
$$x_i' \in \left[\underline{x}_i', \overline{x}_i'\right]$$
$$\underline{x}_i' = x_i^k - r_i - r_0$$
$$\overline{x}_i' = x_i^k + r_i + r_0$$
The AGV should have the coordinate
$$\left(y - y_i^k - v_{i,y}^k\tau\right)^2 + \left(x - x_i^k - v_{i,x}^k\tau\right)^2 \geq \left(r_i + r_0\right)^2$$
$$\tau = t - t_k \quad \text{for } t \in \left[t_k, t_f\right]$$
Put AGV coordinate into the AGV no obstacle zone then we have

$$\min_{t\in[\underline{t}_i^*,\bar{t}_i^*]} G_i\left(t,\tau,a_6^k\right)\geq 0$$

$$\underline{t}_i^* = t_0 + kT_s + \frac{x_i^k - x^k - r_i - r_0}{v_x^k - v_{i,x}^k}$$

$$\bar{t}_i^* = t_0 + kT_s + \frac{x_i^k - x^k + r_i + r_0}{v_x^k - v_{i,x}^k}$$

$$\tau = t - t_0 - kT_s$$

$$G_i\left(t,\tau,a_3^k\right) = g_2(x(t),k)\left(a_3^k\right)^2 + g_{1,i}(x(t),k,\tau)a_3^k + g_{0,i}(x(t),k,\tau)$$

$[\underline{t}_i^*,\bar{t}_i^*]$ is the time interval (if exists) during collision may happen

$$g_2(x(t),k) = \left[(x(t))^6 - X\left(B^k\right)^{-1}A^k\right]^2$$

$$g_{1,i}(x(t),k,\tau) = 2\left[(x(t))^6 - X\left(B^k\right)^{-1}A^k\right]^2\left[X\left(B^k\right)^{-1}Y^k - y_i^k - v_{i,y}^k\tau\right]$$

$$g_{0,i}(x(t),k,\tau) = \left[X\left(B^k\right)^{-1}Y^k - y_i^k - v_{i,y}^k\tau\right]^2 + \left(x(t) - x_i^k - v_{i,x}^k\tau\right)^2 - \left(r_i + r_0\right)^2$$

$$\Omega_{O,i} \equiv \left\{a_6^k : \min_{t\in[\underline{t}_i^*,\bar{t}_i^*]} G_i\left(t,\tau,a_6^k\right)\geq 0\right\} = \left(-\infty, \underline{a}_{6,O,i}^k\right] \cup \left[\bar{a}_{6,O,i}^k, +\infty\right),$$

$$\underline{a}_{6,O,i}^k = \max_{x\in[x_0,x_f]} \frac{-g_{1,i} - \sqrt{\left(g_{1,i}\right)^2 - 4g_2 g_{0,i,j}^l}}{2g_2}$$

$$\bar{a}_{6,O,i}^k = \min_{x\in[x_0,x_f]} \frac{-g_{1,i} + \sqrt{\left(g_{1,i}\right)^2 - 4g_2 g_{0,i,j}^l}}{2g_2}$$

Optimal cost function

$$J_k\left(a_6^k\right) = \int_{x^k}^{x_f}\left[y - \frac{y_f - y_0}{x_f - x_0}\left(x - x_0\right) - y_0\right]^2 dx$$

We will get that minimize this cost function.

$$a_6^{k*} = -\frac{f_2}{2f_1}$$

$$f_1 = -\frac{\left(x^k - x_f\right)^{12}\left(t_f - t_0\right)}{12012}$$

$$f_2 = \frac{\left(x^k - x_f\right)^6\left(t_f - t_0\right)}{27720}[5\left(\left.\frac{\partial^2 y}{\partial x^2}\right|_{x=x^k} + \left.\frac{\partial^2 y}{\partial x^2}\right|_{x=x_f}\right)\left(x^k - x_f\right)^2$$

$$+54\left(\left.\frac{\partial y}{\partial x}\right|_{x=x_f} - \left.\frac{\partial y}{\partial x}\right|_{x=x^k}\right)\left(x^k - x_f\right) + 198\frac{\left(y_f - y_0\right)\left(x^k - x_f\right) - \left(y^k - y_f\right)\left(x_f - x_0\right)}{\left(x_f - x_0\right)}]$$

Coordinate Transformation

To calculate the obstacle object location in the world reference frame we need to transform from robot coordinate to world coordinate

$$^{W}P = {}^{W}_{R}R\,{}^{R}P + {}^{W}P_{RORG}$$

$$^{W}P_{RORG} = {}^{W}P - {}^{W}_{R}R\,{}^{R}P$$

$$^{W}_{R}R = \begin{bmatrix} \cos & -\sin & 0 \\ \sin & \cos & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Adaptive Neuro-fuzzy Inference System (ANFIS)

ANFIS possesses good capability of learning, constructing, expensing, and classifying. It has the advantage of allowing the extraction of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base. Furthermore, it can tune the complicated conversion of human intelligence to fuzzy systems. The main drawback of the ANFIS predicting model is the time requested for training structure and determining parameters, which took much time.

For simplicity, we assume the fuzzy inference system under consideration has two inputs, x and y, and one output, z. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if–then rules can be expressed as

$$\text{Rule 1: If x is A}_1 \text{ and y is B}_1 \text{ then z}_1 = p_1 x + q_{1y} + r_1$$

$$\text{Rule 2: If x is A}_1 \text{ and y is B}_2 \text{ then z}_2 = p_2 x + q_{2y} + r_2$$

$$\text{Rule 3: If x is A}_2 \text{ and y is B}_1 \text{ then z}_3 = p_3 x + q_{3y} + r_3$$

$$\text{Rule 4: If x is A}_2 \text{ and y is B}_2 \text{ then z}_4 = p_4 x + q_{4y} + r_4$$

The equivalent of ANFIS is shown in Figure 3.

In the first layer, input nodes, each node of this layer generates membership grades to which they belong to each of the appropriate fuzzy sets using membership functions.

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3,4$$

where x, y are the crisp inputs to node i, and Ai, Bi (small, large, etc.) are the linguistic labels characterized by appropriate membership functions μ_{A_i}, μ_{B_i} respectively.

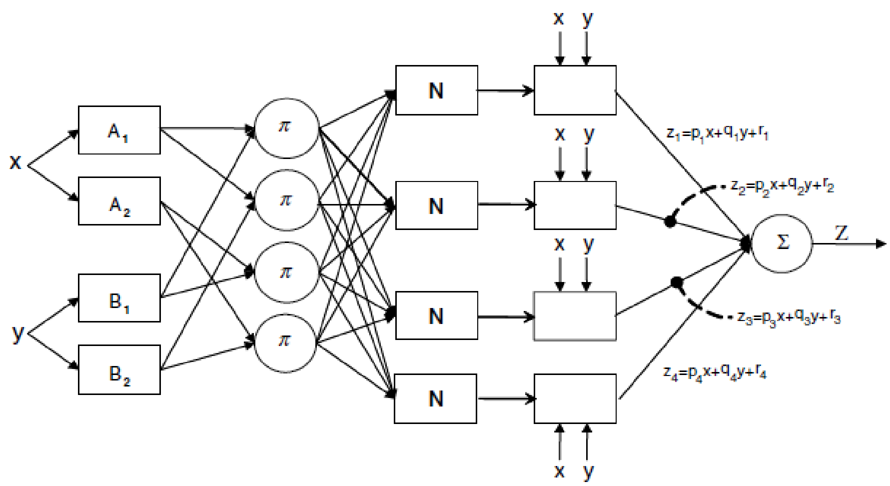

Figure3. ANFIS architecture for two-input Sugeno fuzzy model with four rules, Jang (1993).

$$\mu_{A_i} = \left[1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}\right]^{-1}, \mu_{B_{i-2}} = \left[1 + \left|\frac{y - c_i}{a_i}\right|^{2b_i}\right]^{-1}$$

In the second layer, rule node, the AND operator is applied to obtain one output that represents the result of the antecedent for that rule, i.e., firing strength. Firing strength means the degrees to which the antecedent part of a fuzzy rule is satisfied and it shapes the output function for the rule. Hence the outputs $O_{2,k}$ of this layer are the products of the corresponding degrees from Layer 1

$O_{2,k} = O_{1,i} \times O_{1,j}$, for $i = 1,2; j = 1,2; k = 1,2,3,4$

In the third layer, average node, the main objective is to calculate the ratio of each ith rule's firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \overline{w}_i = \frac{O_{2,i}}{\sum_{k=1}^{4} O_{2,i}}, i = 1,2,3,4$$

In the fourth layer, consequence node, it computes the contribution of each ith rule's toward the total output and the function defined as

$$z_i = O_{3,i} f_i = O_{3,i}\left(p_1 x + q_{1y} + r_1\right), i = 1,2,3,4$$

In the fifth layer, output node, it computes the overall output by summing all the incoming signals. Accordingly, the defuzzification process transforms each rule's fuzzy results into a crisp output in this layer

$$z = O_{5,i} = \sum_{i=1}^{4} z_i$$

The gradient descent method or back propagation is employed to tune premise parameters a_i, b_i, c_i, while the least-squares or back propagation method is used to identify consequent linear parameters p_i, q_i, r_i.

Numerical Simulations

We conducted numerical simulations to assess the performance of the controller, by using MATLAB. Initially, we selected a vehicle position at (0,0) and a 45-degree orientation in inertial reference frame. For a desired trajectory at starting position (0,0) and ending position (30,15). UAV radius is 2m, obstacle detection radius is 8m, obstacle radius is 3m, and obstacle position is (19,8). The result shows that the AGV can avoid obstacle.

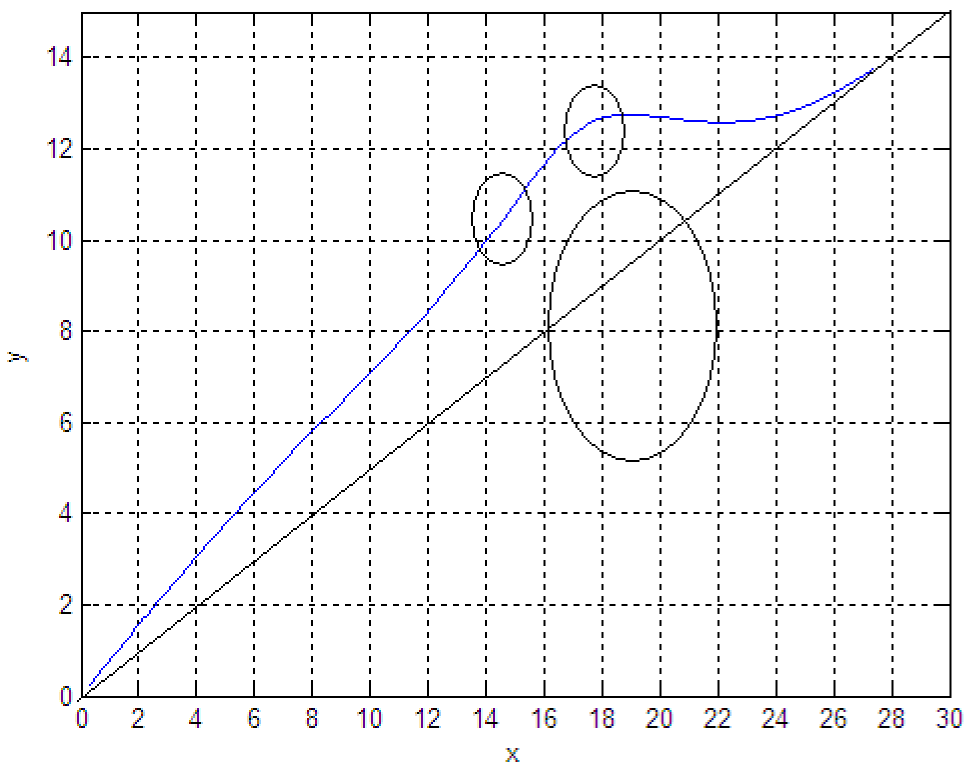

Figure 4. Collision free path trajectory of UGV

Conclusion

Optimal trajectory with obstacle avoidance work well. The obstacle shape was assumed to be cylindrical in shape. For future, we need to consider the obstacle in wall shape. The comparisons need to be done between optimal method and ANFIS (Need more time to debug the program, work will be added for the final one).

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Biography

THONGCHAI PHAIROH is currently an Assistant Professor of Technology at Virginia State University. Dr. Phairoh’s research involves in autonomous vehicle, dynamical systems and systems identification.