INTELLIGENT VELOCITY CONTROL OF MOBILE ROBOTS USING FUZZY AND SUPERVISED MACHINE LEARNING

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Abstract

This paper proposes an intelligent technique for velocity control of a wheeled mobile robot by simultaneously using a fuzzy controller and a supervised machine learning (SML) algorithm. The technique is suitable for flexible leader-follower formation control on straight paths where a follower robot maintains a safe but flexible distance from a leader robot. The fuzzy controller determines the ultimate distance of the follower with respect to the leader from the measurements of two ultrasonic sensors. The SML algorithm calculates an appropriate velocity for the follower based on the ultimate distance. Simulations showed the effectiveness of the proposed technique in adjusting the follower robot's velocity in order to maintain a flexible formation with the leader robot.

Keywords: Mobile Robot, Fuzzy Logic, Supervised Machine Learning, Velocity Control

INTRODUCTION

In the flexible leader-follower robot formation, unlike the rigid formation, the follower robot maintains an elastic positioning separation with the leader. This provides maneuverability which is essential for autonomous collision-free navigation in the presence of stationary and/or dynamic obstacles (Low, 2015). Mobile robots are often equipped with multiple sensors and digital signal transmitter and receiver devices for obstacle avoidance and simultaneous localization and mapping (SLAM) in most environments (Gonzalez et al., 2017; Gharajeh and Jond, 2020). In this paper, we consider a flexible two-robot leader-follower formation control scenario using fuzzy logic (Ferdaus et al., 2020) and supervised machine learning (SML) (Jiang et al., 2020) in which the follower is equipped with two ultrasonic sensors for distance measurement with respect to the leader. We propose a fuzzy-SML-based velocity controller for the follower robot to maintain the formation with the leader. The use of two ultrasonic sensors can reduce measurement errors and enhance the reliability of the controller.

THE PROPOSED TECHNIQUE

Consider a two-robot leader-follower formation control scenario in which the follower robot steers to keep a formation with the leader robot. Two ultrasonic sensors, installed on the forward motion direction of the follower robot, continuously measure its distance to the leader robot. Fig. 1 represents the workflow of the proposed intelligent technique for the velocity control of the follower robot. The technique is composed of a fuzzy controller and an SML algorithm to determine the ultimate distance to the leader and the velocity of the follower, respectively, in order to maintain the formation with the leader robot. The leader robot changes its velocity every t_2 seconds to a random value that is unknown to the follower and accordingly the follower robot regulates its velocity every t_1 seconds.

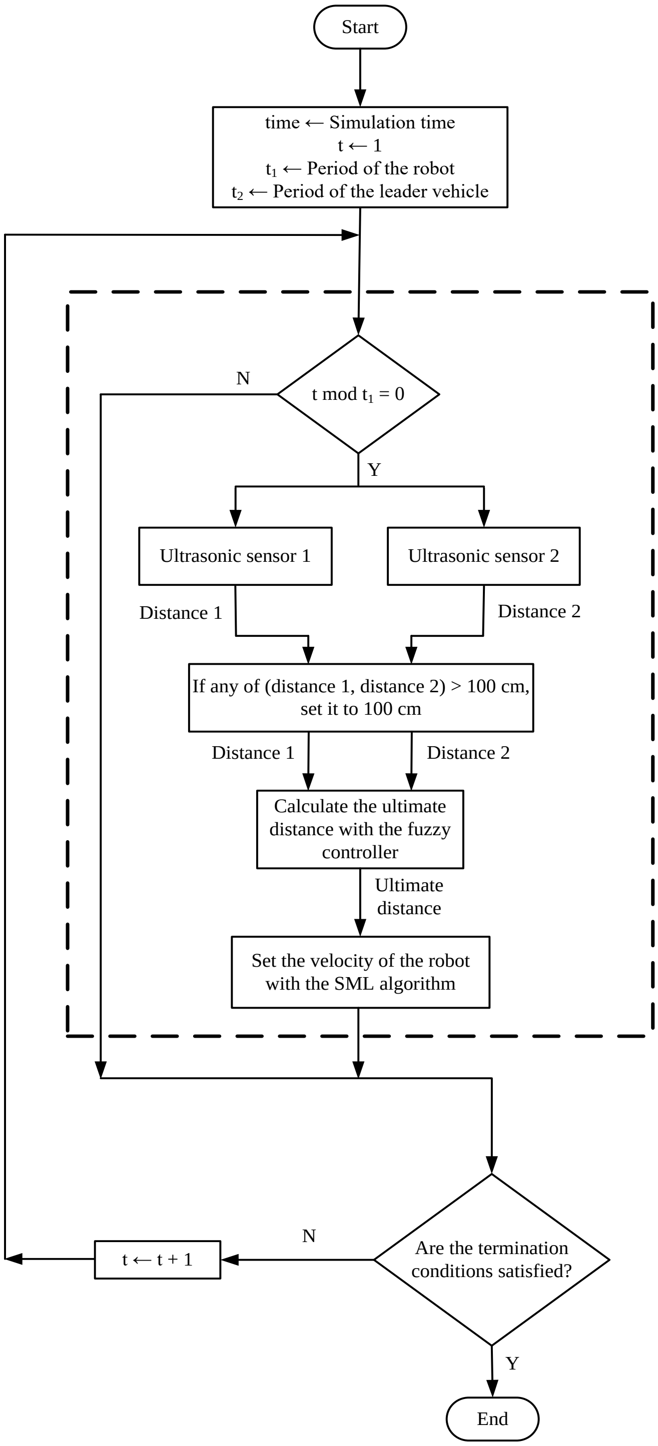


Fig. 1. The workflow of the proposed intelligent velocity control technique.

The fuzzy controller determines the ultimate distance between the follower and the leader based on its ultrasonic sensors measurements. It consists of two input parameters 'distance 1' denoted by x, 'distance 2' denoted by y, and one output parameter 'distance' denoted by *f*. The linguistic terms of all the parameters are specified as {very near, near, middle, far, very far}, and their universe of discourse is determined as {0,1, …,100} cm. Membership degrees of all the linguistic terms and quantitative amounts are determined by the bell-shaped membership function (Mamdani and Assilian, 1975). Fig. 2 shows the corresponding membership graph of the output parameter.

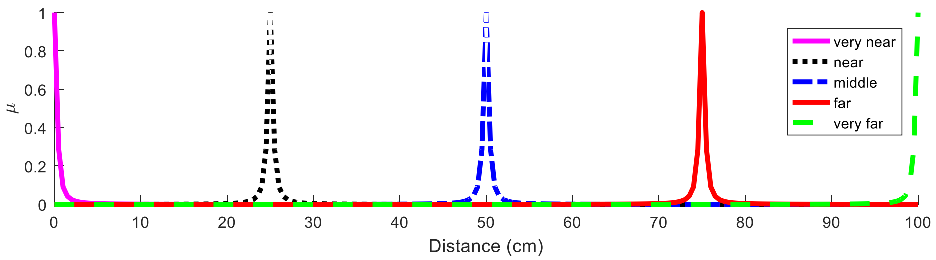


Fig. 2. Membership graph of the output parameter.

In total, 25 IF-THEN rules in form of:

Rule 10: If *x* is 'near' and *y* is 'very far' then f_{10} is 'middle'

are used in the fuzzy controller to generate the rule matrices. After all rule matrices are built by the max-min function, they are aggregated together by the max function to produce the total rule matrix that is given below:

$$F = \begin{bmatrix} 1.000000000 & \dots & 0.000039998 \\ \dots & \dots & \dots \\ 0.000039998 & \dots & 1.000000000 \end{bmatrix}_{201\times 201}$$

Finally, at the defuzzification phase, the crisp value of the distance is calculated by using the center of gravity method (Dubois and Prade, 2012).

The velocity of the follower robot is regulated according to the ultimate distance calculated by the fuzzy controller. If the distance is short then the velocity will be decreased; otherwise, it will be increased accordingly. The SML algorithm specifies the velocity based on the distance between the follower and the leader. A training dataset is used to train a linear regression model that updates the velocity of the follower robot as:

$$Diff_i = \frac{\sum_{j=1}^{S} |(\alpha D_j + \beta) - S_j|}{S}, \forall i \in \{1, \dots, N\} \quad \textbf{(1)}$$

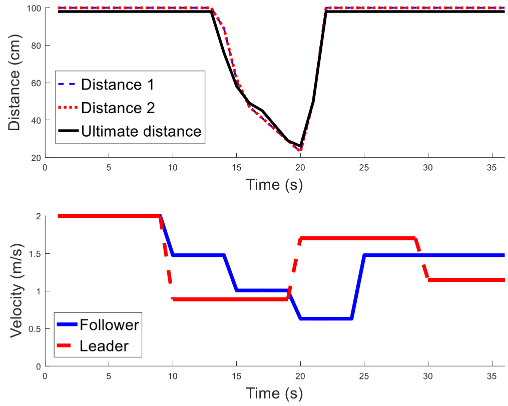
where N is the number of feasible solutions, $Diff_i$ is the difference (from the target) for each solution, S indicates the number of selections for each solution, D_j represents the distance for each selection, S_j is the number of randomized times for each selection, and α, β represent the weighting parameters (to be generated randomly). The weights having the least difference are selected as the best solution. The distance is in the range of [0, 100] cm, and the velocity is in the range of [0, 255] PWM which later is converted to an actual value as m/s. For $N = 20$ randomly generated α and β, the best solution with the minimum difference value $Diff_i = 0.11188$ is found at $\alpha = 1.9958$ and $\beta = 55.265$. Therefore, the velocity can be predicted by:

$$Velocity = \alpha.dis + \beta = 1.9958.dis + 55.265 \quad \textbf{(2)}$$

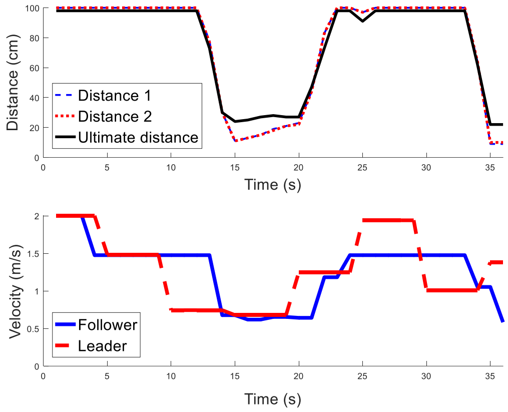
where dis indicates the ultimate distance determined by the fuzzy controller.

SIMULATIONS AND DISSCUSSIONS

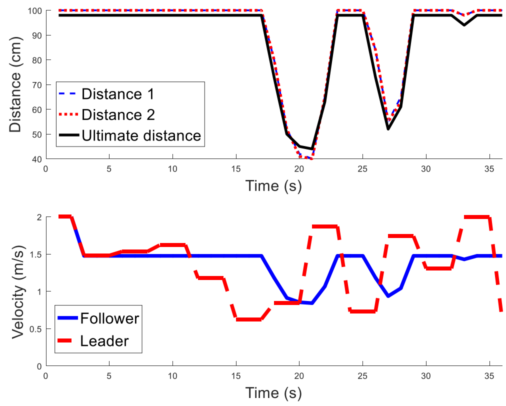
The proposed technique has been implemented in MATLAB and is integrated into a simulation robot in V-REP. Fig. 3 demonstrates the performance of the proposed technique under different assumptions of time parameters t_1 and t_2 as well as velocities of the leader. As it is seen, when the leader changes its velocity to a random value, the follower's velocity controller can adjust the follower's velocity appropriately, so, the formation is maintained without two robots being collided. Moreover, the time histories of the follower's velocities show relative smoothness that provide a stable motion. Fig. 3(f) shows when the follower's velocity has constrained to be less than 1 m/s, the controller steers the robot with the maximum velocity to keep the formation.



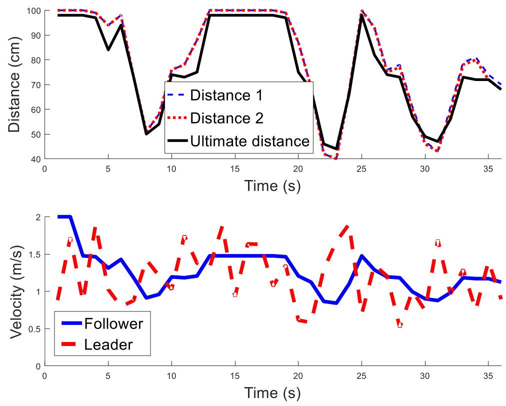
(*a*) $t_1 = 5\ s,\ t_2 = 10\ s$



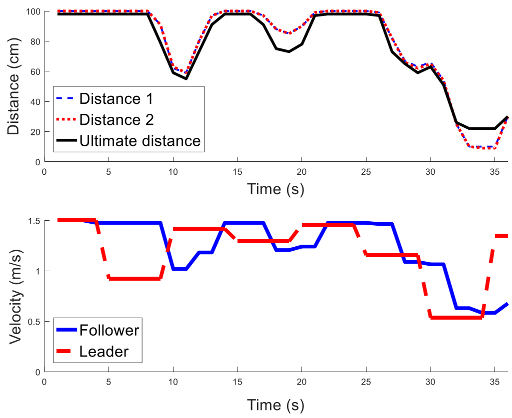
(*b*) $t_1 = 2\ s,\ t_2 = 5\ s$



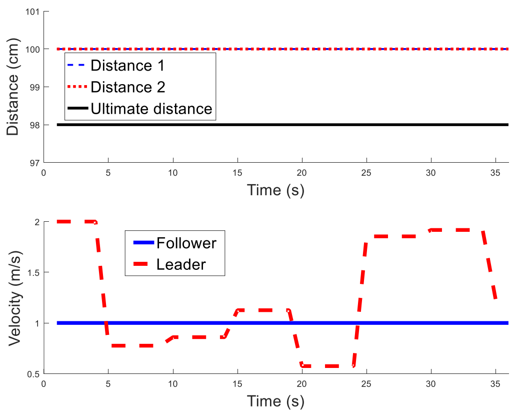
(*c*) $t_1 = 1\ s,\ t_2 = 3\ s$



(*d*) $t_1 = 1\ s,\ t_2 = 1\ s$



(*e*) $t_1 = 2\ s,\ t_2 = 5\ s$



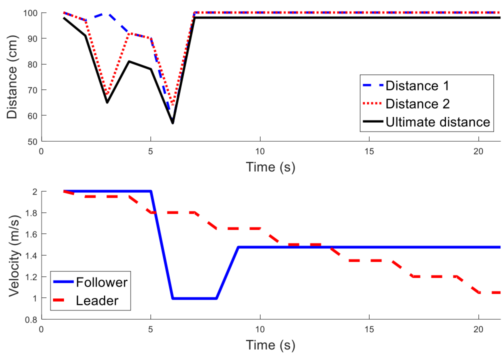
(*f*) $t_1 = 2\ s,\ t_2 = 5\ s$

Fig. 3. Time histories of the relative distances as well as velocities.

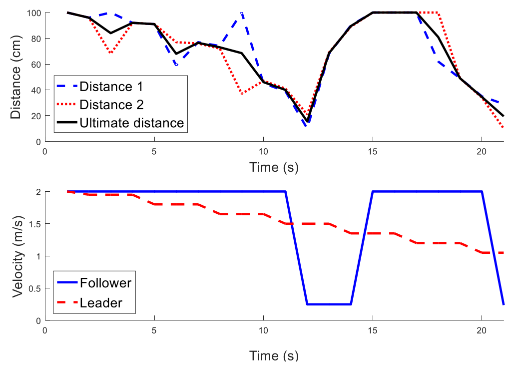
To compare the proposed technique with a static method, under an automated highway scenario, it is assumed that the robots move down a two-lane road (Fig. 4). The leader robot reduces its velocity from 2 to 0.5 m/s gradually while in the static method the follower robot regulates its velocity as

$$Velocity = \begin{cases} \dfrac{|dis - 100|}{T}, & dis < 50 \\ 2, & else \end{cases} \tag{3}$$

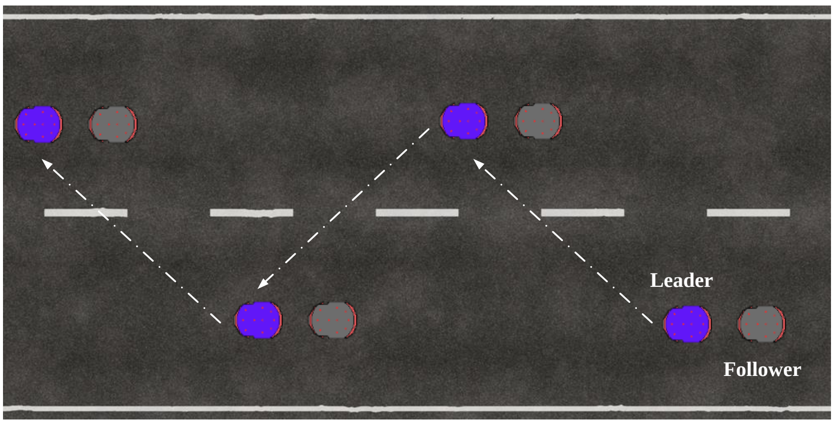
where dis is the average of Distance 1 and Distance 2, and T is the time interval between estimation steps. The simulation results in Fig. 4 show that using the static method the follower cannot efficiently adjust its velocity to follow up the leader with keeping a regular distance. In contrast, using the proposed technique the follower regulates its velocity intelligently and maintains its distance to the leader fairly after 7s.



(*a*) The proposed technique



(*b*) The static method



(*c*) Robots in the automated highway scenario.

Fig. 4. Comparison results of the proposed technique with the static method.

In future works, the fuzzy controller's performance will be evaluated under the assumption that one of the sensors malfunctions. Moreover, we will incorporate various techniques (e.g., neural networks) into the controller to enhance the learning capability of the system.

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