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Intelligent Mobile Robot for Agricultural Phenotyping Using Infrared Sensors, Embedded Vision, and Fuzzy Logic Control

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INTRODUCTION & AIM

Modern agriculture faces increasing demands for precision, sustainability, and automation, requiring intelligent technologies capable of optimizing crop monitoring while reducing human intervention. In this context, intelligent mobile robots, equipped with embedded sensors and vision systems, represent a promising solution for automated phenotyping and agricultural data collection [1].

This work focuses on the development of an autonomous robotic platform capable of navigating between crop rows while performing non-destructive phenotypic analysis. The proposed system integrates infrared sensors for obstacle detection and an onboard front camera for real-time image acquisition, providing accurate perception of the agricultural environment.

A hybrid Fuzzy–PD controller, implemented in Python within the Webots simulation environment, was used to ensure smooth and stable navigation, despite environmental uncertainties and the nonlinear dynamics of the differential robot model.

The main objective of this study is to demonstrate the effectiveness of combining fuzzy logic, embedded sensors, and vision-based perception to achieve robust and precise autonomous navigation for agricultural phenotyping tasks [2]. Through realistic simulations, this approach aims to pave the way for future field applications in precision agriculture.

METHOD

The E-puck differential-drive robot is equipped with infrared (IR) sensors to detect surrounding plants and follow a zigzag trajectory across crop rows. Its motion is governed by the kinematic model:

$$\dot{x} = v \cdot \cos(\theta), \dot{y} = v \cdot \sin(\theta), \dot{\theta} = \frac{v_R - v_L}{L} \qquad (1)$$

where v and ω are the robot's linear and angular velocities.

Each IR sensor S_i measures the distance:

$$d_i = f(S_i) + \varepsilon_i \qquad (2)$$

where ε_i represents sensor noise with variance σ_i^2, modeling measurement uncertainty. This uncertainty is handled by a fuzzy logic controller, which dynamically adjusts the robot's response to uncertain perceptions.

The fuzzy controller inputs are:

$$E_d = \sqrt{(x_g - x)^2 + (y_g - y)^2} \qquad (3)$$

$$E_\theta = atan2(y_g - y, x_g - x) - \theta \qquad (4)$$

where (x_g, y_g)denotes the position of the target point.

rule base of IF–THEN linguistic rules determines the angular correction Δω according to sensor readings. Defuzzification (using the centroid method) gives:

$$\Delta\omega = \frac{\Sigma_j[\mu_{j(\omega_j)} \cdot \omega_j]}{\Sigma_j[\mu_{j(\omega_j)}]} \qquad (5)$$

A Proportional–Derivative (PD) controller regulates the linear velocity:

$$\Delta v = K_p \cdot E_d + K_d \cdot \left(\frac{dE_d}{dt}\right) \qquad (6)$$

The final motor commands are computed as:

$$v_R = v + \left(\frac{L}{2}\right) \cdot (\omega + \Delta\omega) \qquad (7)$$

$$v_L = v - \left(\frac{L}{2}\right) \cdot (\omega + \Delta\omega) \qquad (8)$$

This hybrid control ensures smooth and safe navigation, where fuzzy logic manages sensor uncertainty, and the PD term stabilizes the trajectory tracking.

The following figure shows the Sensor-Based Fuzzy-PD Navigation Framework for Row-Crop Environments, illustrating the interaction between perception, fuzzy control, and PD regulation to achieve smooth zigzag motion.

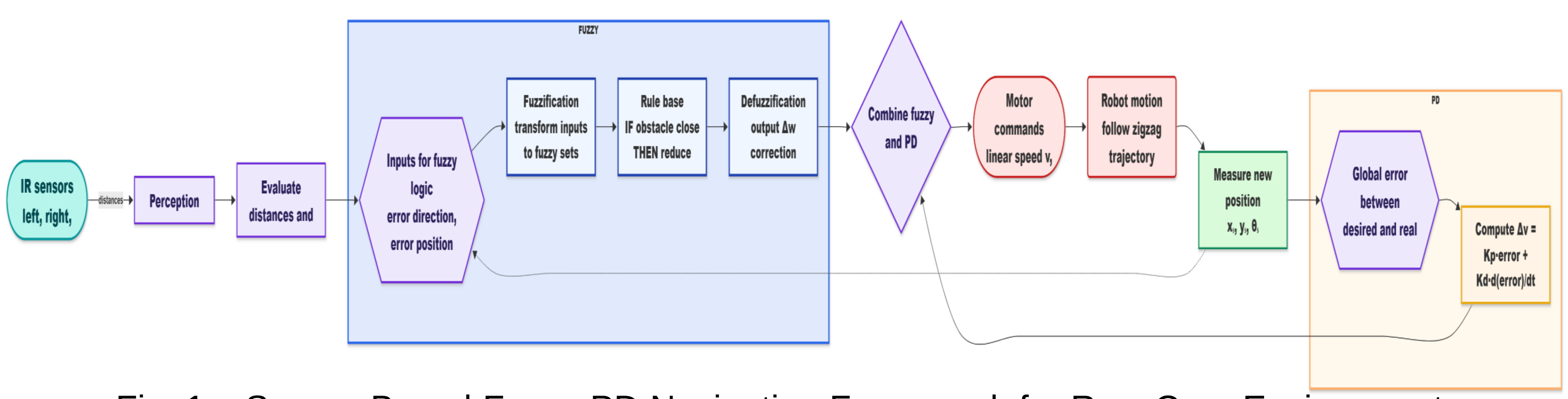

Fig. 1 – Sensor-Based Fuzzy-PD Navigation Framework for Row-Crop Environments

RESULTS & DISCUSSION

The experimental validation was carried out in the Webots simulation environment using the e-puck differential drive robot. The robot is equipped with a front camera and eight infrared (IR) sensors distributed around its chassis for obstacle detection and line following. The test scenario consists of autonomously tracking a zigzag trajectory between five parallel rows, simulating a structured agricultural field. The simulation data were processed and visualized in Python, enabling quantitative analysis of the robot's performance. The following figure illustrates the experimental validation in Webots.

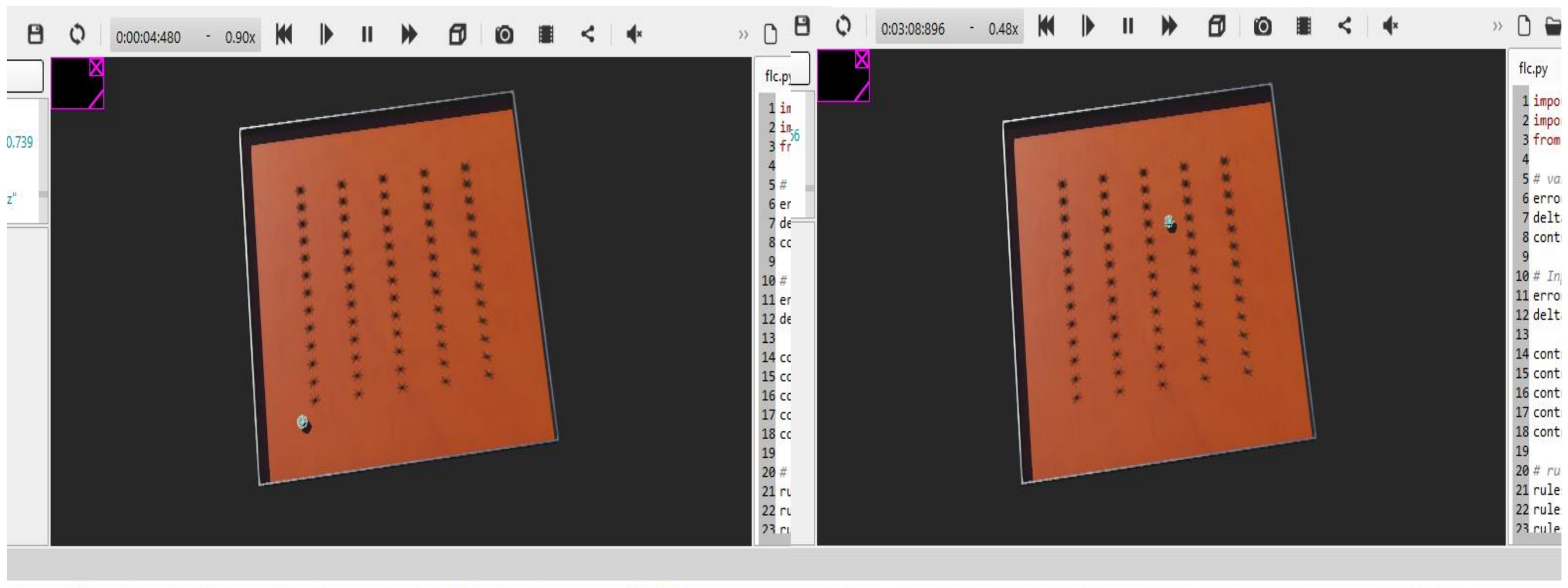

Fig. 2 – Simulation of autonomous zigzag navigation using the e-puck robot in Webots.

The trajectory tracking results (Fig. 3) show that the hybrid Fuzzy–PD controller allows the e-puck robot to accurately track the reference trajectory with smooth and stable motion. The robot follows the zigzag path with minimal deviation, demonstrating that fuzzy logic provides adaptive error correction while the PD component improves stability and responsiveness.

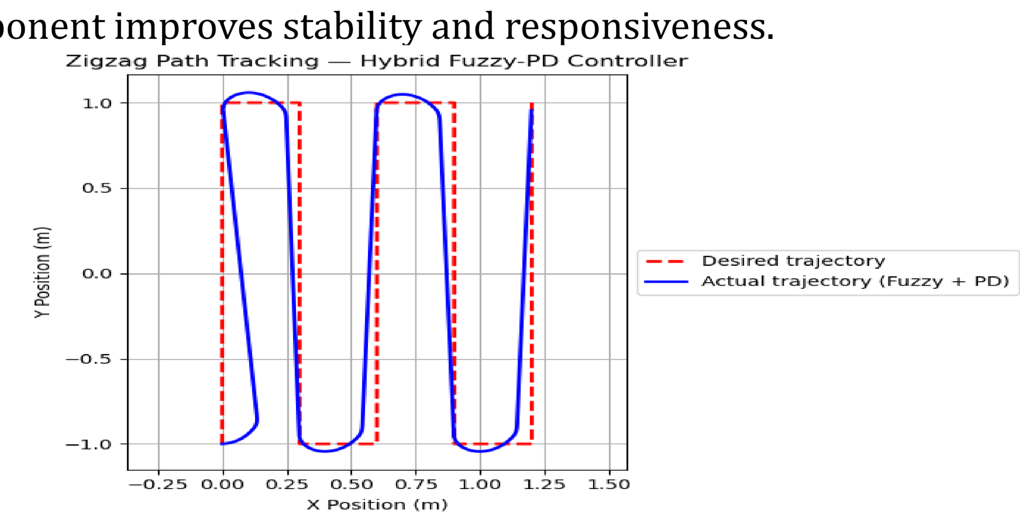

Fig. 3 – Comparison Between Desired and Actual Trajectories Using the Hybrid Fuzzy–PD Controller.

The X(t) and Y(t) results (Fig. 4) indicate that the e-puck's motion remains stable and consistent, with smooth transitions between rows and minimal oscillations. Minor delays are attributed to system inertia and gradual fuzzy correction, confirming the controller's robustness and dynamic stability for agricultural row-following tasks.

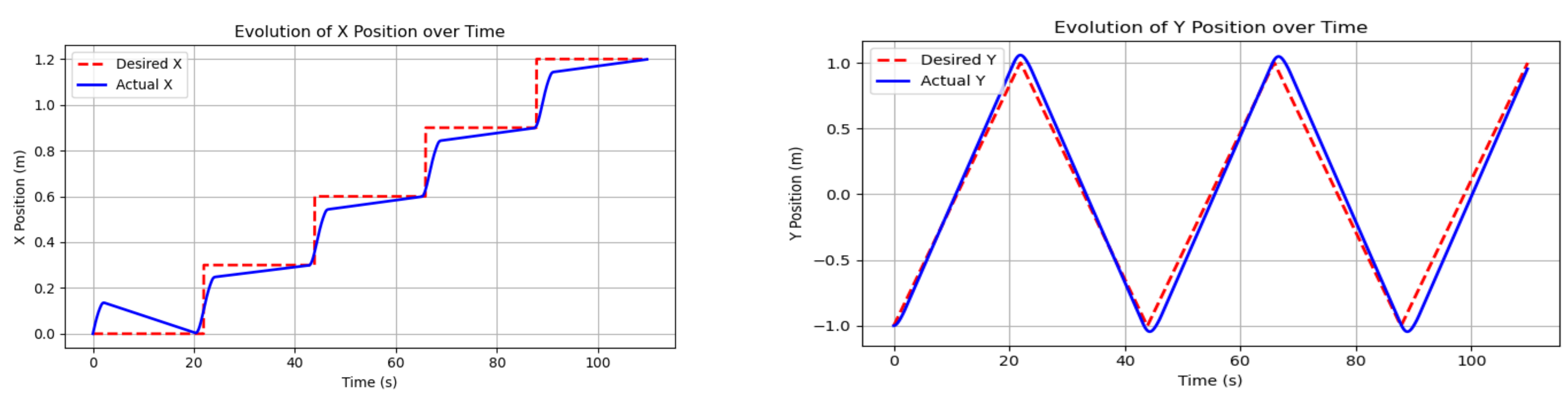

Fig. 4 – Tracking Performance of the X-Axis and Y-Axis Positions Over Time.

The hybrid Fuzzy–PD controller applied to the e-puck robot in Webots ensures smooth navigation, low error, and accurate tracking of agricultural paths, demonstrating the potential of combining fuzzy logic with a PD regulator for autonomous navigation in precision agriculture.

CONCLUSION

In the Webots simulation environment, the e-puck mobile robot equipped with an onboard camera and infrared sensors was used to achieve autonomous tracking of a zigzag trajectory between five agricultural rows. The hybrid Fuzzy–PD controller demonstrated smooth navigation, reduced steady-state error, and good adaptation to the nonlinearities of the differential model. The simulation results highlight the accuracy of the trajectory tracking and confirm the potential of combining fuzzy logic and infrared sensing for autonomous navigation and precision agricultural phenotyping.

FUTURE WORK / REFERENCES

Future work will focus on implementing this approach on a real agricultural robot to validate its effectiveness under real field conditions.

[1] : Shi, J., Bai, Y., Diao, Z., Zhou, J., Yao, X., & Zhang, B. (2023). Row detection BASED navigation and guidance for agricultural robots and autonomous vehicles in row-crop fields: Methods and applications. *Agronomy*, *13*(7), 1780.

[2]: Bengochea-Guevara, J. M., Conesa-Muñoz, J., Andújar, D., & Ribeiro, A. (2016). Merge fuzzy visual servoing and GPS-based planning to obtain a proper navigation behavior for a small crop-inspection robot. *Sensors*, *16*(3), 276.