

Autonomous Agricultural Robot with Inductive Sensors for Real-Time Human Detection

Y. Kazekami^{1*}, S. Hara¹, K. Oki¹, A. Mino¹, S. Shinohara¹, M.Z. Aishah^{2,3}

¹Faculty of Engineering, Shinshu University, Nagano 380-8553, Japan

²Fakulti Teknologi dan Kejuruteraan Elektrik, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

³Electric Vehicle, Power Electronics, Electric Machine Design and Drives Research Group, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

*corresponding author's email: 24w2008h@shinshu-u.ac.jp

Abstract – This paper presents the development and verification of a real-time human detection system designed for autonomous agricultural robots. The system aims to enhance safety by preventing collisions between robots and human workers in the field. Traditional sensor-based detection methods like vision, infrared, and ultrasonic sensors have limitations in outdoor agricultural environments due to lighting, weather, and obstructions. To address these challenges, the authors propose a system utilizing permanent magnets and inductive sensors. The robot is equipped with a strong magnet, while human workers carry sensors that detect magnetic fields. When a dangerous proximity is sensed (magnetic field exceeds 1 mT), the system wirelessly sends an emergency stop signal to the robot. A prototype was developed using a radio-controlled excavator, microcontroller, and magnetic field sensors, and experiments confirmed successful detection and stopping at a safe distance of 60 cm. Finite element method (FEM) analysis further determined that a 25 kg magnet is needed to generate sufficient magnetic flux density for detection. This system provides a reliable safety solution for human-robot collaboration in agriculture, even under adverse environmental conditions.

Keywords: Agriculture robot, CAN-BUS communication, Human detection, Magnetic sensor, Permanent Magnet,

Article History

Received 7 April 2025

Received in revised form 20 May 2025

Accepted 10 June 2025

I. Introduction

In recent years, the agricultural industry has been facing a critical labor shortage, primarily attributed to the declining and aging population [1], [2]. This issue is particularly acute in Japan, where the number of workers in the primary industry has been steadily decreasing since 1955, raising concerns about the long-term stability of the national food supply [3], [4]. In response to these challenges, the agricultural sector is undergoing a paradigm shift through the integration of advanced technologies designed to improve productivity, operational efficiency, and safety. Among these technologies, autonomous agricultural robots have

emerged as a pivotal innovation for achieving sustainable and efficient farming practices [5] - [7].

These sophisticated robotic systems are capable of autonomously performing a wide range of tasks traditionally reliant on human labor, including planting [2], harvesting [8], [9], and monitoring [10] - [13]. By automating labor-intensive activities, dependence on manual labor can be significantly reduced, while operational efficiency is enhanced [14]. Despite their potential, the implementation of autonomous robots introduces novel challenges, notably those related to operational safety in environments where human presence is unavoidable. Due to the dynamic and unstructured nature of agricultural fields, the coexistence

This is an Open Access article distributed under the terms of the Creative Commons Attribution-Noncommercial 3.0 Unported License, permitting copy and redistribution of the material and adaptation for commercial and uncommercial use.

of autonomous robots and human workers necessitates the establishment of stringent safety measures. Any mishap involving robotic systems can result in severe consequences, including injuries or fatalities. To mitigate such risks, the development of robust, real-time human detection systems is essential for accident prevention and the facilitation of seamless human-robot coexistence.

This study proposes a reliable, real-time human detection framework aimed at enhancing the safety and effectiveness of autonomous agricultural robots. The system is designed to enable smooth integration of robotic technologies into agricultural operations, ensuring safe and efficient collaboration without direct human oversight.

II. Collision Detection System

A. Existing Collision Detection System

Recent studies have investigated a wide range of sensors and detection methodologies aimed at improving human-robot interaction and ensuring safety in agricultural environments. Vision-based systems, which utilize cameras in conjunction with image processing algorithms, have been extensively evaluated for their capability to recognize human features and gestures. For instance, deep learning approaches, particularly convolutional neural networks (CNNs), have been applied to detect human presence in agricultural fields [15], [16]. Although such systems demonstrate potential under controlled conditions, their performance often deteriorates under outdoor settings due to fluctuations in lighting, weather variability, and the presence of visual obstructions.

In addition to vision-based technologies, infrared (IR) sensors and ultrasonic sensors have been employed for proximity sensing and obstacle avoidance. IR sensors function by detecting heat signatures, rendering them effective for identifying human presence based on thermal emissions [17] - [20]. However, their accuracy tends to decline in high-temperature environments or when targets are partially occluded. Similarly, ultrasonic sensors, which detect objects through the emission and reflection of sound waves, exhibit reduced precision when interacting with irregular surfaces or soft materials. These inherent limitations compromise the robustness and reliability of both sensor types in the context of complex, unstructured agricultural settings.

B. Proposed Collision Detection System

To address the limitations of existing collision detection systems, a novel collision avoidance framework is proposed, utilizing magnetic field sensing and wireless communication, as illustrated in Fig. 1. In this system, a permanent magnet is integrated into the agricultural robot, while a magnetic field sensor is assigned to a wearable device carried by personnel in the field. Variations in the magnetic field intensity, resulting from the robot's proximity, are detected by the sensor. Upon recognition of a threshold magnetic field strength indicative of close proximity, a stop signal is automatically transmitted via wireless communication to halt the robot, thereby mitigating the risk of collision.

This approach offers enhanced reliability over conventional methods, particularly in harsh agricultural environments characterized by extreme weather conditions, visual obstructions, or airborne particulates such as dust. By relying on magnetic sensing, the system maintains consistent performance regardless of visual or acoustic interference, making it a viable solution for robust collision avoidance in unstructured agricultural contexts.

C. Equipment Configuration

This section details the system configuration developed to evaluate the feasibility of the collision detection mechanism described previously. As shown in Fig. 2, the platform utilized for testing is a 1/14-scale

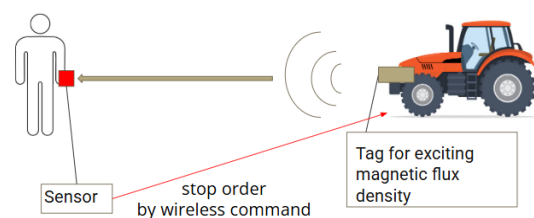


Fig. 1. Proposed Human Detection System



Fig. 2. External view of radio-controlled model of excavator

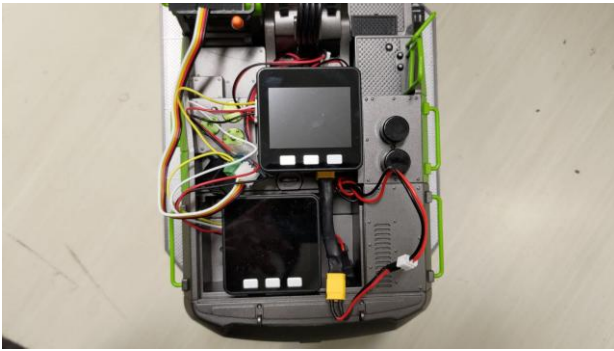


Fig. 3. External view of microcontroller (M5Stack Basic) on radio control model



Fig. 4. External view of Tesla meter

radio-controlled model excavator manufactured by Huina Construction Toys. The model is equipped with a crawler mechanism that enables omnidirectional mobility. For the purposes of this study, the model is treated as an externally controllable agricultural robot. The original design of the device requires a dedicated remote controller for operation; however, such remote-only control does not support integration with external systems or facilitate extended functionalities. To enable these capabilities, the model was retrofitted with a microcontroller, as introduced in the following section, allowing external command input.

Fig. 3 displays the M5Stack Basic microcontroller by M5Stack Technology mounted onto the model. Within this setup, the microcontroller handles bidirectional communication with an external PC, control signal processing for model operation, and emergency stop functions based on real-time sensor input.

Magnetic flux density measurements for detecting the proximity of a magnet are conducted using a tesla meter manufactured by KANETEC, as shown in Fig. 4. This sensor outputs digital measurement data via a USB-Serial interface, which is used to trigger emergency stop actions when specific threshold values are exceeded.

Figs. 5 and 6 illustrate the permanent magnet (N40) employed to generate the excitation magnetic field, along

with its physical dimensions and magnetization orientation. The magnet produces a concentrated field along its thickness axis.

To enforce emergency stops, a CAN-BUS blocker is implemented between the Bluetooth receiver and the main control system. When the tesla meter—part of the wearable module—detects a magnetic flux density exceeding a predefined threshold, a stop signal is transmitted to the CAN-BUS blocker. This signal is conveyed via M5Atom modules configured for peer-to-peer communication using the ESP-NOW protocol. The operational flow of the proposed collision detection system is outlined in Fig. 7.

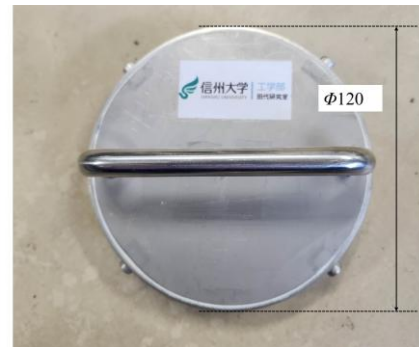


Fig. 5. External view of permanent magnet (unit: mm)

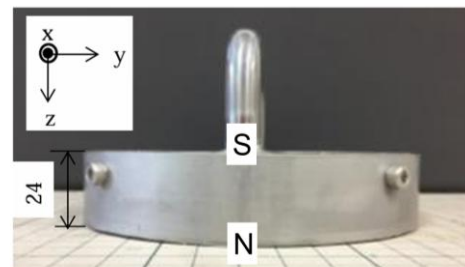


Fig. 6. Construction of the permanent magnet (unit: mm)

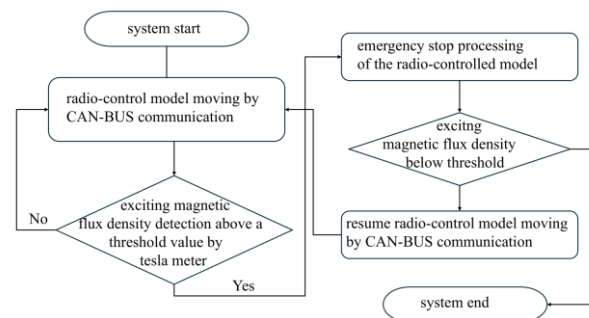


Fig. 7. Flowchart of proposed collision detection system

III. Verification of the Proposed Human Detection System

This chapter presents the development and evaluation of a prototype system designed to validate the feasibility of the proposed human detection mechanism. An overview of the experimental setup is shown in Fig. 8. A permanent magnet was affixed to the front of the radio-controlled excavator to ensure that a magnetic field would be generated in the direction of its motion. The excavator was maneuvered toward the tesla meter via remote control. For the purposes of detection, a threshold of 1 mT—approximately 10 times stronger than the geomagnetic field—was established.

Experimental results confirmed that the excavator halted prior to reaching the tesla meter. Once the magnetic flux density detected by the tesla meter exceeded the threshold, a stop command was transmitted through wireless communication, triggering the emergency stop mechanism and successfully interrupting the excavator's motion. These observations indicate that the prototype system fulfilled its functional requirements.

The subsequent chapter investigates the appropriate magnet size necessary to generate a magnetic field detectable at distances that align with established safety standards for agricultural robotics. This analysis is conducted using finite element method (FEM) simulations.

IV. Examination of Magnet Size Using FEM

A. Estimation of Detection Distance

Generally, the stopping distance D of a vehicle whose moving speed is v [m/s] can be expressed by (1).

$$D = (v^2 / 2\mu g) + L \text{ [cm]} \quad (1)$$

where μ represents a friction factor, g represents gravitational acceleration ($\cong 9.8 \text{ m/s}^2$), and L represents a reaction distance, respectively. Moving speed v of autonomous agricultural robots in weeding areas are limited to 10 km/h ($\cong 2.78 \text{ m/s}$). The friction factor for unpaved roads such as weeding areas can be approximated as 0.7. Reaction distance L is a value that depends on the human reaction time. For the proposed system, this can be assumed to be 0. The required stopping distance D for the proposed system is about 60 cm from equation (4.1). The value of the excitation flux required for detection is 1 mT, which is 10 times larger than the geomagnetic field.

B. Analysis Condition

The excitation flux density required for detection was defined as 1 mT at 60 cm in the previous section. In the current section, the magnet size that generates this excitation flux density was examined using FEM analysis. An external view of the analytical model is shown in Fig. 9, the analytical conditions in Table 1, and the size of the analytical model considered in Table 2, respectively. The magnet material was set to N40, which is one of neodymium magnets. It is desirable to generate a large excitation flux density in the travel direction. Therefore, the magnetization pattern of the magnet is a single-pole thickness direction magnetization.

C. Analysis Result

First, the eccentricity of magnetic sensors and magnets was investigated. It is important to extend the detection range because the worker and robot do not always line up in a straight line when mounting is assumed. The relationship between the eccentricity from the center of the magnet and the excitation magnetic field was clarified by analysis. In this report, the goal was to be detectable within a range of 5 cm in all directions from the center of the magnet. The measurement point was 60 cm away from the model surface and 5 cm vertically and horizontally from the model center, as shown in Fig. 10. The measurement interval was 2.5 cm each for a total of 25 points. The result was shown in Fig. 11. Fig. 11 shows excitation flux density at the center was reduced by about 46% at the edges compared to the center. To achieve a sensor resolution of 1 mT, the center of the magnet must be at least 2 mT.

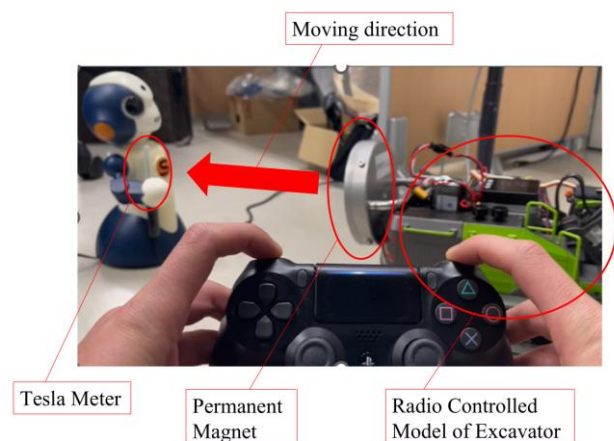


Fig. 8. External view of experiment configuration

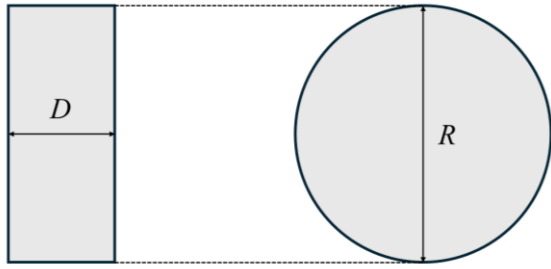


Fig. 9. External view of experiment configuration

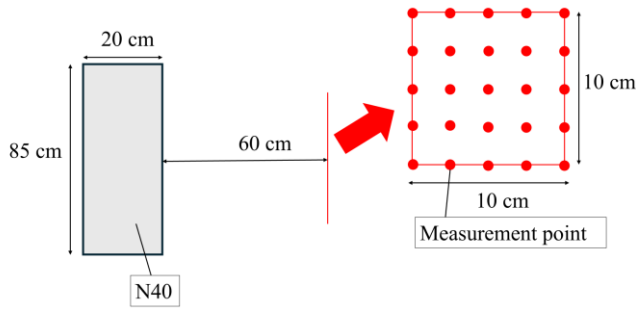


Fig. 10. Measurement point

TABLE I
ANALYSIS CONDITIONS

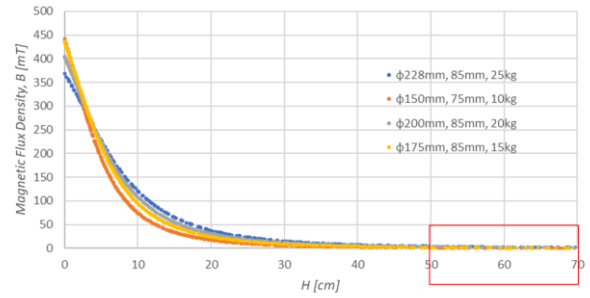
Item	Contents
Software	JMAG-Designer 21.2.01x
Element count	Approximately 1 million elements
Analysis type	Static
Model material	N40
Mesh size [mm]	1.0

TABLE II
CONDITION OF ANALYSIS TARGET

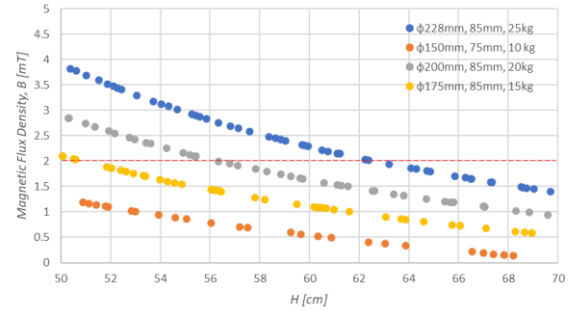
Radial, R [mm]	Thickness, D [mm]	Weight, M [kg]
228	85	25
200	85	20
175	85	15
150	75	10

66.2	84.8	91.9	84.8	66.2
84.8	106.6	114	106.6	84.8
91.9	113.9	121	113.9	91.9
84.8	106.6	114	106.6	84.8
66.2	84.8	91.9	84.8	66.2

Fig. 11. Magnetic flux density @ 60 cm from the magnet (unit:mT)



(a) Result overall



(b) Focus on the target distance

Fig. 12. Magnetic flux density vs distance

Next, the magnet size that generates the target excitation field of 2 mT at 60 cm was investigated. The excitation magnetic field from the center to 70 cm for the four magnet surfaces shown in Table 2 was clarified by analysis. Fig. 12 shows the decrease of magnetic flux density with distance for each weight. Fig. 12(b) is an enlarged view of the area circled in red in Fig. 12(a) near the target distance and the red line in Fig. 12(b) indicates 2 mT. Focusing on the magnetic flux density at 60 cm, we can see that the minimum weight of the magnet to achieve a magnetic flux density of 2 mT or higher is 25 kg.

V. Conclusion

A human collision system using inductive sensors was investigated as a robust human detection system that operates in real time to ensure safe and effective operation of autonomous agricultural robots. The outcomes were as follows:

1. A survey on various sensors and detection methods to enhance human-robot interaction and safety in recent agricultural settings was conducted. Recent studies have highlighted the potential of sensor fusion, where multiple sensors are combined to enhance detection capabilities.
2. A microcomputer-based collision detection system was constructed, and a prototype was built. A

stopping system using wireless communication was realized.

3. Magnet size capable of detecting a distance of 60 cm was examined. A magnet size was desirable of 25 kg or larger.

Acknowledgements

The authors would like to thank Associate Professor Kuniyoshi Tashiro, Professor Osamu Takyu, Professor Mitsuhide Sato and Professor Kazuki Kobayashi of Shinshu University and Dr. Fairul Azhar Abdul Shukor and Dr. Raja Nor Firdaus Kashfi Raja Othman of Universiti Teknikal Malaysia Melaka for supporting and advising this research. This research honors the Memorandum of Understanding between UTeM and Shinshu University.

Conflict of Interest

The authors declare no conflict of interest in the publication process of the research article.

Author Contributions

Y. Kazekami: Conceptualization, Methodology, Writing - Original draft, Supervision.

S. Hara: Simulation analysis, Writing - Review and Editing.

K. Oki: Software Implementation.

A. Mino: Software Implementation.

S. Shinohara: Hardware Implementation.

M.Z. Aishah: Literature Review, Writing - Review and Editing.

References

- [1] N. Murakami, "Status and Future in Robotic Harvester", Journal of the Robotics Society of Japan, vol. 39(10), pp885-887, 2021 (in Japanese)
- [2] L. Chris, "Recent Advances in Agricultural Robots for Automated Weeding", AgriEngineering, vol. 6(3), pp3279-3296, 2024
- [3] Bank of Japan, K. Kitamura: Current status and challenges of primary industry and current status of DX. [Online]. Available: https://www.boj.or.jp/finsys/c_aft/data/aft221221a2.pdf
- [4] Japan Ministry of Public Management, Changing Industrial and Occupational Structures. [Online]. Available: <https://www.stat.go.jp/data/kokusei/2005/sokuhou/03.htm>

- J. Seol, Y. Park, J. Pak, Y. Jo, G. Lee, Y. Kim, C. Ju, A. Hong, H. II Son, "Human-Centered Robotic System for Agricultural Applications: Design, Development, and Field Evaluation," Agriculture, 14, pp. 1-17.
- [5] Z. Saleem, F. Gustafsson, E. Furrey, M. McAfee, S. Huq, "A review external sensors for human detection in a human robot collaborative," Journal of Intelligent Manufacturing, 2024, pp. 1-25
- [6] L. Droukas, Z. Doulergi, N. L. Tsakiridis, D. Triantafyllou, I. Kleitsiotis, I. Mariolis, D. Giakoumis, D. Tzovaras, D. Kateris, & D. Bochtis, "A Survey of Robotic Harvesting Systems and Enabling Technologies", Journal of Intelligent & Robotic Systems, vol. 107(21), 2024
- [7] L. Tituaña, A. Gholami, Z. He, Y. Xu, M. Karkee & R. Ehsani, "A small autonomous field robot for strawberry harvesting", Smart Agricultural Technology, vol. 8, 2024
- [8] Soran Parsa, Bappaditya Debnath, Muhammad Arshad Khan & E. Amir Ghalamzan, "Modular autonomous strawberry picking robotic system", Journal of Field Robotics, vol. 41(7), pp. 2226-2246, 2024
- [9] X. Fan, X. Chai, J. Zhou & T. Sun, "Deep learning based weed detection and target spraying robot system at seedling stage of cotton field", Computers and Electronics in Agriculture, vol. 214, pp. 1140-1159, 2023
- [10] L. Quan, W. Jiang a, H. Li, H. Li, Q. Wang & L. Chen "Intelligent Intra-Row Robotic Weeding System Combining Deep Learning Technology with a Targeted Weeding Mode", Biosystems Engineering, vol. 216, pp. 13-31, 2022
- [11] Filipe Neves dos Santos, Heber Sobreira, Daniel Campos, Raul Morais, António Paulo Moreira & Olga Contente, "Towards a Reliable Robot for Steep Slope Vineyards Monitoring", Biosystems Engineering, vol. 83, pp. 429-444, 2016
- [12] Filipe Neves dos Santos, Heber Sobreira, Daniel Campos, Raul Morais, António Paulo Moreira & Olga Contente, "A compilation of UAV applications for precision agriculture", Computer Networks, vol. 172(8), 2020
- [13] I. Beloev, D. Kinaneva, G. Georgiev, G. Hristov, P. Zahariev, "Artificial intelligence-driven autonomous robot for precision agriculture," Acta Technology Agriculture, vol. 24(1), pp. 48-54, 2021
- [14] A.M. Ramalingeswararao, K. Kusuma Lakshmi, D.Sai Surya Sashank, K. Lakshmi Sirisha, Y. Nithin, "Smart Farming Robot for Detecting Plant Diseases Using Machine Learning," International Journal of Creative research Thoughts (IJCRT), vol. 12(2), pp. 2320-2882, 2024
- [15] K. Sarma, K. Das, V. Mishra, S. Bhuiya, D. Kaplun, "Learning Aided System for Agriculture Monitoring Designed using Image Processing and IoT-CNN," IEEE Access, vol. 10, pp. 41525-41536, 2022
- [16] Q. Guan, C. Li, L. Qin, G. Wang, "Daily activity recognition pyroelectric infrared sensors and reference structures," IEEE Sensors Journal, vol. 19(5), pp. 1645-1652, 2019.
- [17] B. Gao, A. C. Walhof, D.A. Laird, F. Toor, J.P. Prineas, "Analytical Evaluation of Mobile In Situ Soil Nitrate Infrared Sensor Designs for Precision Agriculture," IEEE Sensors Journal, vol. 21(18), pp. 20200-20209, 2021.
- [18] G. Rivera, R. Porras, R. Florencia, J.P. Sánchez-Solis, "LiDAR applications in precision agriculture for cultivating crops: A review of recent advances," Computers and Electronics in Agriculture, vol. 207(January), pp. 1-23, 2023
- [19] L. Liu, Y. Liu, X. He, W. Liu, "Precision Variable-Rate Spraying Robot by Using Single 3D LiDAR in Orchards," Agronomy, vol. 12(10), pp. 1-23, 2022