Advancing Mine Detection Through Multi-Agent Systems: Collaborative Robotics for Enhanced Efficiency and Safety

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Abstract: - This study investigates how to apply a multi-agent system (MAS)-based process on robotic platforms to mine detection, especially improving collaboration/communication between agents. Agents can communicate and collaborate by sharing sensor data relevant to the task, sharing requests for tasks to be acted on by agents, applying standard protocols, wireless communications, message passing, etc. Using a publish-subscribe architecture will enable the agents not to force all agents to receive all information and use decentralized decision-making to promote adaptable behavior. In addition, through adaptive communications protocols, a better means of data sharing, adaptations of behavior, and higher-order activities will be simpler. Finally, a shared state of relevant communication will allow collaborative robotic agents in an MAS to have higher accuracy and efficiency to clear minefields while improving safety and effectiveness.

Key-Words: - Multi-agent systems, Mine detection; Collaborative robotics, Adaptive communication, Decentralized decision-making, Sensor data sharing, Robotic coordination.

Received: October 8, 2025. Revised: February 15, 2026. Accepted: March 17, 2026. Published: April 16, 2026.

1 Introduction

Mobile robots can be applied today in many scientific, technological, and operational circumstances, establishing their value across different operational contexts, [1]. Using the communicative and operational features of robots involves notable tasks, such as requesting environmental data through sensor systems, turning it into management information by interpreting environmental sensor data, planning movement in dynamic environments, and initiating the planned movement by precise action for the task, [2].

Based on the type of environment or task required, robots must have advanced sensors and dynamic abilities, [3]. Traditional robotic systems have used single microprocessor control architectures, which restrict the responsiveness of actuators as the microprocessor collects data from the sensors on the robot and outputs control signals to the motors and actuators, [4]. The obstacles to consider with this architecture comprise heterogeneity and latency related to the integration of multiple data sources and the limitations in speed of response for the actuation of devices, which affects the overall reliability and adaptability of the entire infrastructure. The focus of this paper is to present a system architecture designed through a multi-agent system within a single robotic platform or distributed across multiple robotic units, specifically used for mine/metal detection. This approach involves a complex block diagram architecture with multiple microprocessors working together to control the movement of the mobile robot.

Two microprocessor systems were used in the proposed architecture. The first microprocessor is associated with and controls the sensors. This gives the user information in real time regarding the robot's environment. Meanwhile, the second microprocessor uses sensor inputs and outputs control signals to the wheel drive motors. The architecture comes with redundancy and fail-safe options to enhance the robustness and fault tolerance of the robot system. Thus, if one of the processors fails, these options allow for the robot system to continue to an alternative state of operation. For example, the robot can provide different modes, such as manual operation if a controller wants to operate the robot directly, autonomous operation using sensor inputs, or auxiliary sensors such as an Earth magnetic-field-based sensor for safe navigation/orientation. We can design flexible and robust multi-agent systems on multiple robotics platforms to increase the ability of mobile robots to work on tough missions such as mine/metal detection and improve efficiency, reliability, and safety in various operational contexts.

2 Utilizing Robots in Mine and Metal Detection

The use of robots for mine and metal detection has taken off in the past few years, as it makes the detection operations safer and more efficient. By sending robots into the dangerous areas, we can protect people from getting hurt and make the detection process faster and more accurate. Robots for mine and metal detection offer significant improvements compared to manual methods. We summarize the key benefits in the following points:

1. Safety Enhancement: Robots with sensor systems can trek through tough spots with greater accuracy and stamina. This is beneficial for human safety because robots can perform sketchy tasks. They are also built with armor and safety features, which help protect them from potential threats, [5]. This is especially important when it comes to keeping people safe during detection operations. Really, it is about making the whole process less risky for humans", [6], [7].

2. Efficient Exploration: Robots equipped with specialized sensors can quickly scan large areas of land in a short time, [8], [9]. They are also incredibly accurate, which means they can spot potential threats and weird readings that might be hidden from view. This helps in clearing the minefields faster and considerably accelerates the overall detection and removal process compared to the time taken by humans. Furthermore, the robots can make detailed maps of the areas they survey, [10]. This is extremely useful because they can refer to these maps or use them to analyze the space they are in.

3. Adaptability to Terrain: One impressive feature of robots is their ability to effectively navigate diverse challenging terrains, [11], [12]. They can traverse rough surfaces, climb over things, make it up steep hills, and deal with all sorts of obstacles. This means that they can cover a lot of ground and reduce the chances of missing any hidden threats or mines. Additionally, these robots can change how they are moving, walking, or rolling based on the terrain conditions, which helps them get around efficiently.

4. Remote Operation: It allows operators to control robots from a distance, [13]. With real-time feedback from the cameras and sensors on the robot, they can make decisions and change the robot's path if needed. This makes it a lot safer for people since robots can handle the stuff. It is also convenient that robots can be controlled from a command center so that multiple people can work together and keep an eye on things at the same time. It is basically a hub where everyone can collaborate and see what's going on.

5. Collaboration: When multiple robots work together, they can do a better job of detecting mines and metals, [14], [15]. By communicating with each other and coordinating their movements in a way that they can cover a lot more ground. This makes the entire process more efficient and accurate. Since they can share information in time, they can analyze their surroundings together and spot potential threats more quickly. Having multiple robots collaborate makes them much more effective at detecting objects. They can clear the areas faster and get the job done better.

6. Integration of AI and Machine Learning: Robots can autonomously recognize and categorize potential threats. This allows these robots, along with AI and machine learning algorithms, to ease the burden on human operators while accelerating potentially life-threatening recognition, [16]. Robots use these advanced technologies to build upon their own experiences, improving their detection capabilities over time. Utilizing these advanced technologies substantially increases the number and speed of detections and classifications, [17]. Robots can also adapt to evolving threats and anomalies through continued learning and stay ahead of the latest threats, such as the newest types of mines and metal objects, [16].

7. Continuous Monitoring: Robotic systems can also facilitate the continuous monitoring of defined high-risk areas, such as minefields. When robots continuously keep an eye on a sensitive area, they can respond quickly and prevent any harm to people who are close to these areas, [18]. Thus, by improving the awareness of robots through continuous monitoring, we can improve the safety of people and detect in real-time any imminent harmful situations, thereby shortening the time required to respond to any possible dangerous situations. In addition, we can deploy robots with environmental sensors for monitoring air quality, temperature, or other conditions. As a result, data collected from these sensors can be used for further analysis and can improve the safety measurements.

3 Problem Formulation and Robot Implementation

When it comes to mine detection, controlling a robot's movement and acquiring information from both onboard sensors and external sources are extremely challenging. The main method for tackling such an issue is to develop a complex multi-agent system surrounding the robot. This multi-agent system not only enhances the robot's adaptability but also allows it to perform optimally in difficult and dangerous situations. In its current form, the robot is equipped with an on-board suite of sensors, including ultrasonic distance sensors and a magnetometer, both of which are essential for mine detection. This allows the robot to form a representation of its own local space; from there, it can make decisions and navigate.

The hardware configuration of the autonomous robot is conceived with greater specificity to satisfy the rigid demands of mine detection applications as follows:

- The robot has four reverse-collector motors with metal spur gears to provide a robust locomotion system over difficult terrain.
- The robot is statically stable with four-wheel rollover resistance. There are two ultrasonic range finder components for distance sensing.
- Microcontroller units (MCUs) for polling sensor data, displaying the information, and controlling the motor mechanism with accuracy of factors.
- Motor Drivers for responsive control of DC gear-motors.
- Bluetooth radio modules to afford seamless wireless communication.
- Infrared Motion Sensors for motion detection.
- Piezoelectric buzzer for auditory alerts.
- LED indicators for operational modes and use for path illumination.
- Rechargeable battery.
- The robot has an RC5 infrared receiver that can be operated remotely.
- The robot uses intelligent sensors to monitor the environment for thermal sensing.
- The robot uses an alphanumeric LCD to provide visual feedback, 16 × 4.

Figure 1 (Appendix) shows the pertinent microprocessor control system of the mobile robot, illustrating the integration of various control system elements for mine detection. Figure 1 (Appendix) is relocated to the Appendix for clarity.

Control commands are transmitted to the robot through Bluetooth radio modems, which encapsulate the destination microcontroller address to ensure correct command execution. This robot is extremely useful for real-life mine detection operations. With its complex sensor suite and multi-agent systems, a robot can be used to expertly detect and deactivate mines in dangerous environments. The robot's flexibility also allows it to assimilate data from different sensor types and make the necessary sensor fusion to allow the robot to drive, using advanced techniques to improve detection performance and operational efficiency of mine clearance missions.

4 Applying Multi-Agent Systems to Robotic Mine Detection

Multi-Agent Systems (MAS) allow robotic systems to improve mine detection by allowing for collaborative exploration of dangerous locations with faster detection. This paper advocates for the use of MAS, where each robot acts as an independent agent and can communicate and collaborate with other agents to reach a common goal. As a result, a single network of robots could be created that can survey an area and detect mines in an overall more efficient and safer time period than conventional land mine detection methods.

Any area that has a target density of dangerous objects is first partitioned into smaller sections, with each robot given a specific area to explore, allowing multiple areas to be scanned simultaneously and allowing for the survey of the area to be cut down in time spent. Another positive attribute of MAS is resource distribution, as resources can be allocated to robots in areas of higher risk, and they can determine how to allocate robot coverage.

In recent years, MAS has become a solution for solving complex problems in various domains, such as robotics, transportation, and healthcare. In the field of robotics, MAS offers flexibility in establishing a framework to coordinate many autonomous agents in an efficient manner to achieve a shared goal. One area, swarm robotics, exemplifies the potential of MAS to coordinate a large number of simple robots to perform a range of tasks, such as surveillance, exploration, and environmental monitoring. This decentralized form of organization creates an opportunity for robustness, scalability, and adaptability to operate in dynamic environments and represents MAS's real-world application. Additional cases of MAS applications with transportation systems can be observed, particularly for autonomous vehicles and traffic management. Given the MAS premise, autonomous vehicles can communicate and work together through their agents to route themselves safely through a busy road network or determine more efficient increments in their routes. This not only facilitates vehicle flow but also leads to better traffic management to create fewer incidents of congestion and flat-out accidents. MAS vehicles and traffic management systems can also more effectively locate traffic signals and respond to real-time data to inform actions.

In healthcare, MAS has been utilized for distinct purposes, such as monitoring patients, diagnosing medical issues, and delivering drugs. An autonomous agent in MAS would allow for constant monitoring of patient health and response to urgent matters if needed. MAS-based diagnostic systems can use machine learning and the analysis of historical or continuous medical data to assist medical professionals in diagnosing clinical issues. Beyond diagnostic applications, MAS can also help coordinate robotic agents that deliver drugs to specified targets or perform minimally invasive surgery, which can also provide better treatment options and care for the patient.

In addition to the fields already specified, MAS has gained traction in fields such as environmental monitoring, disaster response, supply chain management, and smart grid systems. MAS sensor networks are emerging as a valuable solution in environmental monitoring applications to consistently and efficiently collect and analyze data to determine things such as air and water quality, pollutants, and natural disaster predictions. In the realm of disaster response, we can envision scenarios where robots, with or without humans, drones, and other responder personnel, need to eventually be well-organized in search-and-rescue operations, inspect infrastructure, and perform general disaster recovery missions. We can likewise see examples in supply chain management to administer autonomous agents in any decentralized inventory or distribution chain process (e.g., inventory, logistics, distribution, etc.). Similarly, MAS in smart grid systems assists with efficient energy distribution, demand response, and load distribution-balance to also improve energy efficiency and sustainability.

In [19], MAS was recently applied to an optimized literature search to support biomedical knowledge retrieval. The authors presented a framework that uses multiple autonomous agents to navigate vast amounts of biomedical literature. It was shown that the operation of the agents working in tandem was able to search for users much more efficiently than the same task performed by single agents. This was fascinating research because it has overcome some obvious and significant issues in biomedical fields, in which the rapid development of scientific literature is a daunting challenge of information retrieval (often of urgent need).

Reference [20] proposed a similar solution using a multi-agent recommender system based on the same problem of extracting user interests. This study utilizes autonomous agents with sophisticated algorithms, which gather data pertaining to user behaviors and preferences and make personalized recommendations. These recommendations improve the user's overall experience and help the user choose relevant literature in different fields. The use of MAS within recommender systems has shown great potential for addressing information overload issues and improving recommendation performance.

Reference [21] describes how MAS can be utilized in vehicle-to-vehicle (V2V) communication networks to increase communication reliability and efficiency in the presence of noise. Cooperative agents can be utilized to transmit data between vehicles and improve the overall network performance. Although this work is not directly related to literature search and recommendation systems, we note that it illustrates the flexibility of MAS to address communication issues in applications not related to literature searches.

This paper [22] describes the applicability of MAS principles to the online parameter estimation of DC-DC converters. A communication channel was established using the OPC protocol, and autonomous agents were able to observe and adjust the parameters of the converters online. This work illustrates how MAS can be applied to industrial automation and control systems, creating the potential to optimize performance and reliability.

Artificial intelligence (AI) and deep learning algorithms enhance the capabilities of robotic systems in mine detection. Each robot is equipped with AI sensors and cameras, which can independently identify potential mine threats using predefined patterns and characteristics. Deep learning models can also help distinguish many mine types for each robot based on the availability of older mine data to train the algorithm, in this case, reducing false positives as well as false negatives.

When using MAS, robots can work jointly, making decisions, and sharing 'info' to make a comprehensive decision. Because they can communicate regularly and in real time, the robots ultimately use these shared decisions to coordinate strategies in consideration of the environment and any potential danger, and help position them to complete the mine detection mission effectively.

MAS for robotic mine detection enhances the safety and efficiency of actions in hazardous environments. The use of autonomous robots means that the assignment of hazardous tasks is directed toward the robot, protecting human operators from potential dangers and saving lives and injuries. In addition, MAS designs cover larger areas with speed and efficiency, making mine identification and neutralization faster. In addition, MAS-enabled robotic systems have the flexibility and adaptability to be used in a wide variety of military and humanitarian applications. In military operations, MAS robots can help identify and clear minefields to protect troops and assist military objectives. In a humanitarian context, MAS robots are valuable in mine clearance, including the eradication of land mines and unexploded ordnance, to assist regions with the removal of dangerous explosives and allow individuals the ability to rebuild and develop their regions.

5 Advanced Robotic Mine Detection System: Technology and Operation Overview

Our advanced mine detection system uses state-of-the-art technology to accurately and efficiently identify both surface and underground mines. At the core of our system is the Pulse Induction mechanism, which is a groundbreaking method for detecting metal. Unlike traditional methods, our system sends out a short magnetic pulse and then detects the pulse that is reflected, which changes in shape when it encounters metal. This change triggers the amplification and analysis process in a pulse detector. When metallic objects come near the coil, they disrupt the magnetic field and create eddy currents within the coil. This process, similar to how loudspeakers work, generates a signal indicating the presence of metal. However, our coil creates its own magnetic field, which is essential for detecting non-magnetic objects. The changes in magnetic fields caused by the detected metals are then converted into binary data (0s and 1s) by an Arduino. This, along with ultrasonic readings, helps determine whether the mine is on the surface or buried underground.

To enhance operational efficiency and safety, our system (Figure 2, Appendix) incorporates various sensors and control mechanisms. An LM35 sensor regulates internal temperature, activating 12V fans when necessary to prevent overheating. Additionally, the GY-91 sensor, in collaboration with an encoder, facilitates precise localization. This localization data, alongside mine detection information, is processed by a Raspberry Pi, which serves as the central control unit. Figure 2 (Appendix) is relocated to the Appendix for clarity.

The designed robot's movement is powered by DC motors and metal gear servo motors, allowing for versatile motion capabilities. Ultrasonic sensors help determine mine depth, while the LM35 temperature sensor prevents overheating. A 12V lamp and siren alert upon mine detection, controlled by a relay for efficient management.

The developed system operates through two interconnected nodes in mapping detected mines. Node A starts with an empty field map, and Node B builds the field map as it receives data from the sensors. The sensors of this system output the type and location of the mine through Node B, as the robot scans, with the careful application of mathematical algorithms, combined with various sensor readings that are able to accurately plot the mines. As a result, together, the process makes a complete map of the Node A field, detailing the detected mines, identified as distinct types of mines, including annotated locations. Through carefully considered design and efficient technologies, our advanced robotic mine detection system is ready to operate accurately and safely in complicated or difficult conditions.

6 Communication Among Robotic Agents in a Multi-Agent System

In implementing a MAS for mine detection, individual robotic agents must communicate effectively for the collective effort to be successful. Robotic agents in the MAS framework (Figure 3, Appendix) use different communication methods to share important information, coordinate their actions, and improve mine detection operations. Figure 3 (Appendix) is relocated to the Appendix for clarity.

Robot agents use standard data exchange protocols to support smooth communication within the MAS network. They employ common protocols like TCP/IP, UDP, and MQTT to send sensor data, images, and control commands between agents. These protocols ensure dependable and efficient data transmission, allowing agents to share real-time information crucial for collaborative decision-making and mine detection. Wireless communication modules like Wi-Fi, Bluetooth, or Zigbee are integrated into robot agents to enable wireless connectivity within the MAS network. Through wireless communication, agents can exchange sensor readings, status updates, and task assignments, enabling coordinated actions and effective collaboration. Robot agents use message passing mechanisms to exchange structured messages containing relevant information. These messages may include sensor readings, environmental observations, detected mine locations, and task assignments, allowing agents to maintain situational awareness and coordinate their actions appropriately.

Robotic agents in a MAS often use a publish-subscribe architecture to communicate. Agents publish messages to specific topics and subscribe to relevant topics to receive updates and notifications. This allows them to exchange information selectively based on their roles, tasks, and expertise, making communication more efficient. In a decentralized multi-agent system, robotic agents make local decisions based on available information and predefined rules or algorithms. They communicate with neighboring agents to coordinate their actions without needing a central controller. This decentralized decision-making allows the system to operate effectively in dynamic and uncertain environments.

Robotic agents use adaptive communication protocols that can adjust transmission parameters based on network conditions and resource availability. This optimizes communication bandwidth, latency, and reliability, ensuring efficient data exchange even in challenging environments. Effective communication among robotic agents is crucial for the successful operation of a multi-agent system in mine detection. By using sophisticated communication mechanisms, agents can collaborate synergistically to enhance detection accuracy, coverage area, and overall efficiency, contributing to safer and more effective mine clearance operations.

7 Algorithm for a Multi-Agent System for Mines Detection

The following algorithm describes the coordinated work of MAS-enabled robotic agents to effectively detect mines in perilous environments. This demonstrates the difficulties and complexities of detecting mines in a multi-agent system.

1. Initialization:

- At the commencement of the work, the MAS is initialized with a predetermined number of robotic agents, each of whom is uniquely identified in the system.

- Inter-agent communication protocols and message formats have been established to enable effective data sharing between agents.

2. Sensor Data Collection:

- Each robotic agent captures sensor data from sensors, including ultrasonic distance sensors, magnetometers, and metal detectors.

- The sensor data are processed to identify potential mine threats while gathering relevant environmental data.

3. Local Decision-Making:

- Each agent makes local decisions about its mine detection strategies based on the sensor data collected and its own defined set of decision-making rules or algorithms.

- Exploration priorities are assigned by prioritizing exploration areas based on the agent's sensor readings that identify areas with anomalous readings related to mine detection.

4. Communication and Collaboration:

- Agents communicate with their neighboring agents, sharing sensor data, observations, and task assignments.

- Agents rely on predefined communication protocols to generate and share information with neighbors in the MAS for communication.

5. Collaborative Decision-Making:

- Agents collectively analyze the shared sensor data and observations and make collaborative decisions concerning mine detection strategies.

- When agents encounter conflicting information in their reports, they apply consensus-based decision-making techniques to improve their detection effort.

6. Task Assignment:

- Collaborative task allocation is performed, with agents dynamically assigning exploration tasks based on identified priorities and available resources.

- The allocation of any exploration task assignment considered other criteria, such as each entity’s agent position relative to the targets and agent capabilities.

7. Exploration and Detection:

- The agents explore their assigned exploration areas and systematically search for mine threats where they apply sensor-data fusion techniques.

- The communication of the collected sensor data is improved by fusing information from multiple sensors to corroborate the claim to find a mine threat.

8. Reporting and Feedback:

- Whenever an agent finds a potential mine threat, the agent reports to the entire MAS network level with previously agreed-upon communication modes utilized.

- Feedback mechanisms ensure that detection results are shared, providing collective awareness of mine detection progress.

9. Adaptive Behavior:

- Agents adapt their exploration and mine detection actions based on real-time feedback and changes occurring in the environment.

- Agent decision-making relied on decentralized options, where agents could choose what to do to adjust their schemes to accomplish real-time mine detection efficiently.

10. Iterative Refinement:

- The MAS adjusts the exploration and detection tasks by employing iterative improvement based on detection feedback.

- The MAS makes improvement decisions about agents’ parameters, such as the task allocation algorithm, decision-making rules, and communication protocols.

11. Termination:

- Mine detection is completed after the exploration area is completely surveyed and potential mine threats are identified and reported.

- Either way, the agents could either continuously monitor or report a return status back to their station to begin further analysis and/or debriefing.

8 Simulation Experiment using JADE

To evaluate the performance of the proposed multi-agent system for mine detection, a comprehensive simulation environment was developed using the JADE framework. The simulation represented a 100 × 100 m minefield divided into 1 m grid cells and populated with varying mine densities. Each robotic agent was simulated as a JADE agent equipped with virtual metal detectors, magnetometers, and ultrasonic sensors, with Gaussian noise added to mimic real conditions. Wireless communication constraints—such as limited range and packet loss—were incorporated to ensure realistic agent interactions. Agents operated autonomously following a sense, decide, communicate, move loop while sharing information through structured messages. The environment supported decentralized decision-making, publish–subscribe messaging, and adaptive behaviors driven by sensor fusion and consensus mechanisms. Each experiment was repeated 30 times with randomized conditions, and key performance metrics such as detection accuracy, false positives, area coverage, communication load, and detection speed were measured.

Each robotic agent in the JADE-based simulation operates autonomously by continuously executing a loop of sensing, local processing, communication, decision-making, and movement. At each cycle, an agent collects sensor readings from its simulated metal detector, magnetometer, and ultrasonic sensors, and evaluates the likelihood of nearby mines based on these observations. The agent then shares structured messages with nearby agents, including its position, sensor readings, and local decisions. Incoming messages from neighbors are processed to update the agent's situational awareness and refine its mine detection confidence using consensus or sensor-fusion rules. Movement decisions are guided by frontier exploration strategies and obstacle avoidance, prioritizing unexplored or high-likelihood areas. Communication is constrained by a configurable range and simulated packet loss to mimic realistic wireless conditions. All agent activities—including sensor readings, messages sent and received, movement paths, and local decisions—are logged for post-simulation analysis. This setup allows each agent to act independently while maintaining collaboration with other agents to maximize mine detection accuracy, coverage, and efficiency. The simulation aimed to analyze system scalability (different team sizes), robustness (varying packet loss), and environmental difficulty (mine density). Team sizes of 5, 10, and 20 agents were tested under low, medium, and high mine densities. Communication performance was evaluated under 0% and 10% packet loss. At the end of each trial, detected mines were compared to ground truth to compute TP, FP, FN, accuracy, precision, recall, F1-score, area coverage, and average detection time. This setup enabled a controlled and statistically reliable evaluation of multi-agent behavior under realistic constraints. The following tables present the summarized numerical results obtained from the simulation. Table 1 shows a summary of three team sizes, while Table 2 shows the effect of communication packet losses, and Table 3 shows varying mine density.

Table 1. Summary over three team sizes (medium mine density = 100 mines, p_loss = 0.0)

Team size	Precision ± std	F1 ± std	Area coverage (%) ± std	Avg detection time (s) ± std	Messages per agent ± std
5	0.86 ± 0.05	0.87 ± 0.03	94.2 ± 2.1	520 ± 60	450 ± 40
10	0.91 ± 0.04	0.92 ± 0.02	98.0 ± 1.0	320 ± 45	860 ± 70
20	0.95 ± 0.03	0.95 ± 0.02	99.6 ± 0.3	195 ± 30	1900 ± 150

Source: created by the authors

Table 2. Effect of communication packet loss (team size = 10, medium density)

p_loss	Precision ± std	Avg detection time (s) ± std	Messages per agent ± std
0.0	0.91 ± 0.04	320 ± 45	860 ± 70
0.10	0.86 ± 0.06	410 ± 55	780 ± 90

Source: created by the authors

Table 3. Varying mine density (team size = 10, p_loss = 0.0)

Density	Mines	Avg detection time (s) ± std	FP rate (FP per run) ± std
Low	50	210 ± 35	3.2 ± 1.5
Medium	100	320 ± 45	6.8 ± 2.2
High	200	480 ± 70	14.4 ± 3.8

Source: created by the authors

9 Testing a Multi-Agent System for Mine Detection

The developed system underwent extensive testing and performed as intended under various testing conditions. Suitable assessment procedures were used to evaluate the performance of each robot in the MAS for robotic mine detection. The testing process spanned several simulations of a real-world mine detection setting, where multiple robots with sensors and communication capabilities were coordinated and operated in a virtual minefield. The parameters evaluated during the testing largely revolved around the robots' capability to individually communicate and share information in real-time to help achieve a common goal, namely mine detection.

In addition to pilot tests for evaluating the means of exchanging communications, the embedded AI programmed in each agent was assessed. These programs process sensor data, interpret images, and determine the potential threat level based on predefined decisions (also learned), assessment of mines, in which the robots are tasked with locating and detecting. To provoke alternate decision heuristics, different feature tests were conducted to increase or decrease the robot's capacity to adapt to changing conditions of the scenario in the testing area, as well as to alter the conditions (i.e., terrain type, density of mines) considered in the assessment. This adaptability is typically encountered in real-world mine detection operations.

As the robots worked through simulated scenarios, they utilized sensor data fusion, image processing, and AI-based decision-making to interpret, evaluate, detect, and classify mine-based threat levels. The performance of each agent was determined using the following factors: detection accuracy, false positive rates, percentage area coverage, and speed of detection. A form of stress testing was also applied to evaluate the system's robustness and scalability based on simulating scenarios with a high agent load of activity within complex environments with multiple agents.

The test results obtained from the process yielded even more data to analyze the MAS architecture and agents' functions and see if they require certain changes. Importantly, the results obtained from the real-world scenarios advance the understanding of the capabilities and limitations of MAS-based mine detection systems.

Overall, the summarized simulation results demonstrate that larger agent teams substantially improve detection accuracy, mine coverage, and reduce detection time, although they generate significantly higher communication loads. The system maintains good performance under low communication loss, but accuracy and speed decline when packet loss reaches 10%, highlighting the importance of communication reliability. Higher mine densities increase the computational and communication burden, resulting in slower detection and more false positives. These experiments confirm that the proposed MAS architecture is scalable, adaptive, and robust under realistic operational conditions, making it a strong candidate for real minefield detection.

10 Conclusion

Implementing a MAS within robotic platforms represents a significant progression in the mine detection field, bringing value to systems that are safer for working in potentially dangerous environments while being more cost- and time-efficient with regard to the mission. This key advantage is the result of the autonomous, communicative, and collaborative efforts of MAS robots, which work seamlessly to collectively detect mines. Importantly, robots can share data/sensor information using recognized data protocols over a common wireless medium, where robots pass messages to other agents coordinating and controlling an effort to fulfil a mission to detect mines. The use of a publish-subscribe architecture for message passing also adds automation and ultimately reduces the overhead cost of excessive messaging to exchange information through agents. Each part can autonomously adapt actions and responses, and the MAS utilizes decentralized decision-making, where agents use local observations and defined instructions to perform behavior adaptively in dynamic environments. For example, adaptive communication protocols can adapt transmission protocols to effectively share data in challenging environmental conditions. Testing MAS under robotic mine detection operations demonstrated great potential for improvements through traditional detection tools and processes by reducing the characteristics of detection error, area of coverage, and speeding up overall operational effectiveness for mine clearance and safety for communities affected by mines.

Acknowledgement:
The authors would like to express their sincere appreciation to Tafila Technical University for its valuable support in conducting this research and providing the opportunity to develop and present this work. The continuous encouragement and facilitation offered by the University played a significant role in the successful completion of this study.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

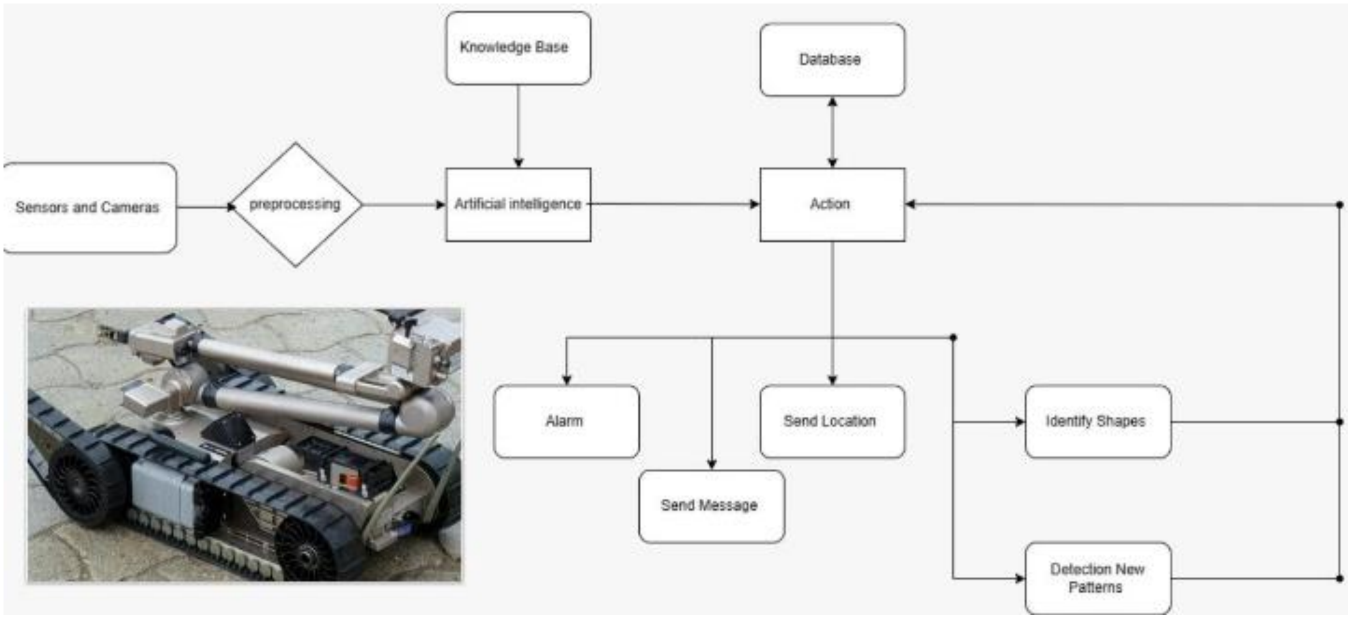

Fig. 1: The microprocessor control system of the mobile robot.
Source: created by the authors

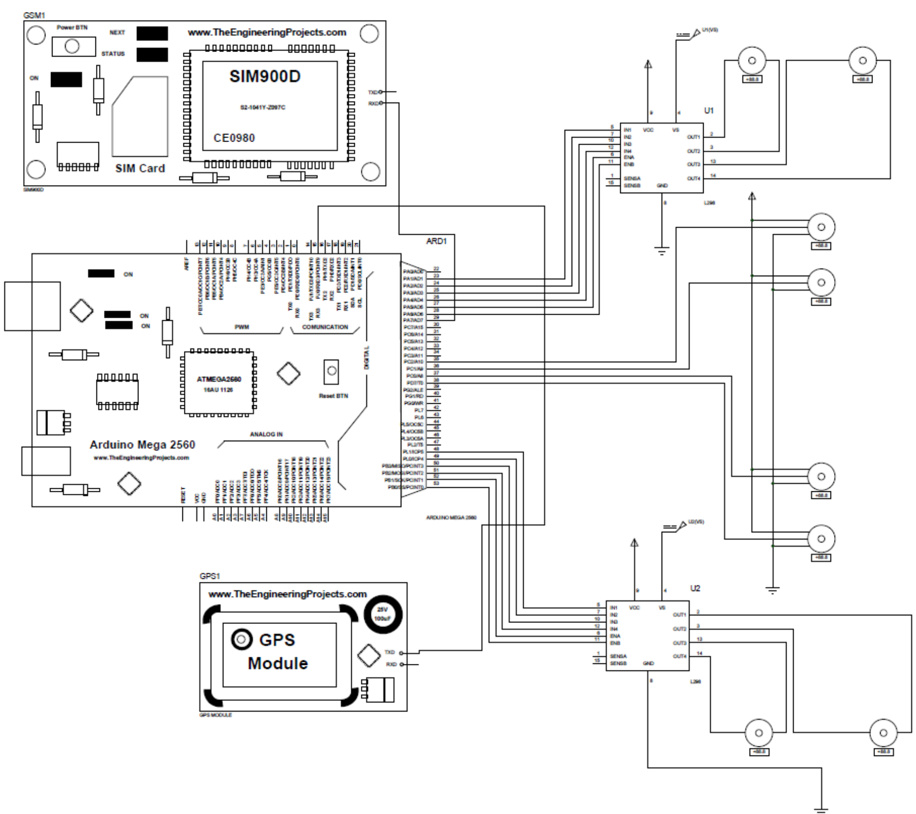

Fig. 2: Circuit schematics of the mobile robot.
Source: created by the authors

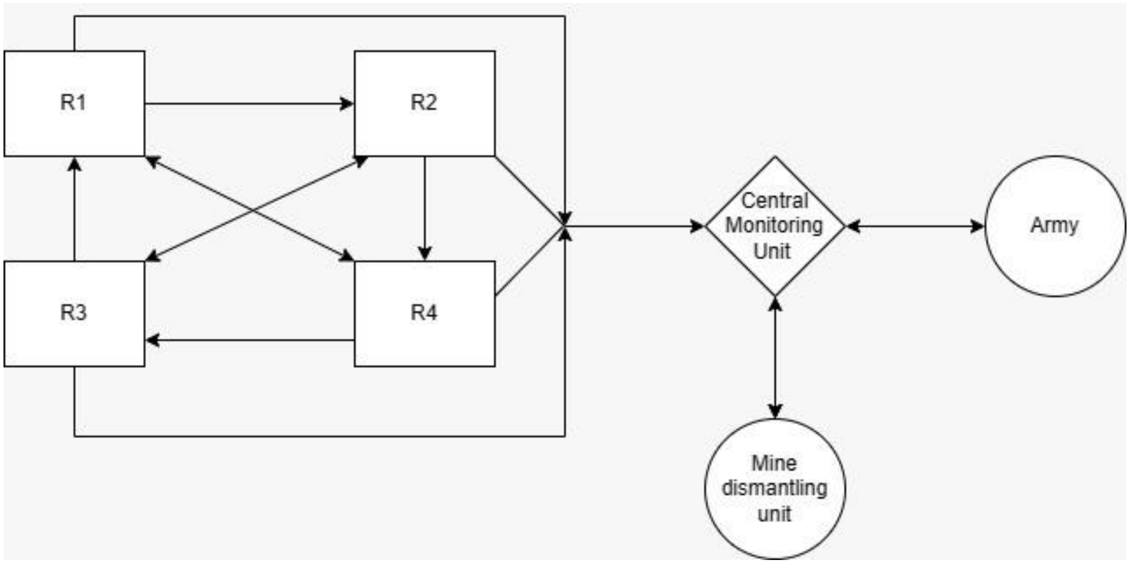

Fig. 3: Multi-Agent System for Mine Detection.
Source: created by the authors