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A Review on Design and Characteristics of Landmine Detection Robot

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Abstract: Landmines are underground explosive devices that explode when humans, vehicles, or animals pass them. Manual landmine detection is dangerous, time-consuming, and limited in difficult terrain. Mobility, flexibility to different terrains, precision, and real-time data processing are essential for landmine detection robots (LDR). Advanced sensor fusion and machine learning methods improve detection accuracy. Real-time data processing allows fast analysis and decision-making for mine detection and safe demining. Remote operation and autonomous functionalism improve these robots' productivity and safety, reducing human exposure to dangerous locations. The various kinds of LDR are described and illustrated in this article. The design considerations that render these robots appropriate for these duties have been prioritized. The necessary components and methods for autonomous navigation have been examined in light of the landmine detection mechanism and technologies.

Keywords: Landmine Detection Robot; Navigation; GPS; Vision Camera; All Terrain Robot.

1. Introduction

Landmines are hidden explosive charges strategically used in military operations to hinder enemy advancement by causing injuries rather than immediate fatalities. In times of war, buried landmines play a crucial role, posing significant threats even after the conflict's end, particularly for civilians. Landmines remain a persistent problem in 78 nations, presenting a formidable challenge for mobile autonomous robots designed for the tasks of detection and removal 1). These deadly devices not only endanger soldiers but also have severe implications for agricultural lands, water reservoirs, and the development of roads near borders. Landmines are triggered by various mechanisms, often relying on the weight of an object to set them off. Depending on the type, these explosives may require a minimum pressure of nine kilograms, buried at depths of 10 to 40 mm. Their strategic placement in patterns, such as the Zigzag pattern, aims to impede enemy movements and divert them into ambush zones 2). The process of clearing mines is extremely hazardous, with statistics showing that for every 5,000 mines removed, one person is killed, and two others are injured. Removing these mines can be exceptionally costly, as it may take 50 times the original mine's price to eliminate each one safely 3). Startling statistics from the United Nations reveal that over 100 million landmines are hidden underground across 60 countries, resulting in a tragic toll of 10,000 deaths and 20,000 injuries annually 4). Removing these landmines from affected areas traditionally involves extensive human labor, time, and effort. Trained animals have been utilized in the demining process to verify and clear affected regions. Mobile autonomous robots have emerged as a potential solution due to their lower error rates, resilience to environmental conditions, and higher accuracy compared to humans. Mobile robots for landmine detection have been developed and utilized in the last few decades. Such as HUMI a six-wheeled robot (HUMI – Robot for Humanitarian Demining) based on the Ackermann Geometry for movement in rough terrain, for landmine detection and removal. A comprehensive research survey has been conducted to explore various landmine detection technologies, including electromagnetic induction, ground-penetrating radar, nuclear quadrupole resonance, Infrared (IR), hyperspectral methods, and Electric impedance tomography [5].

2. Robot Design

Robot vehicles exhibit diverse characteristics that allow for their classification based on various parameters. These parameters include their type of locomotion, the mode of operation, and the terrain they navigate. In terms of locomotion, robots may be equipped with wheels, tracks, legs, or a combination of these, influencing their mobility and adaptability to different environments [6]. Many current designs incur high costs, but certain robot designs can be rendered cost-effective when tailored for small-scale applications and testing purposes [7].

The mode of operation further distinguishes robot vehicles, with a primary division into autonomous and non-autonomous categories. Autonomous robots operate independently, relying on sensors, algorithms, and artificial intelligence to make decisions and navigate their surroundings [8]. On the other hand, non-autonomous robots require external guidance or control from human operators.

2.1 All-Terrain Robots

Terrain adaptability is a crucial aspect of the design and functionality of robotic vehicles, referring to their ability to navigate and operate effectively across different types of landscapes and environmental conditions [9]. A robot's terrain adaptability is determined by its capacity to handle variations in surfaces, obstacles, and inclines that may be encountered during its tasks. Robots with high terrain adaptability are equipped with features such as specialized wheels, tracks, or legs, as well as advanced sensor systems for environmental perception [10]. This adaptability allows them to excel in diverse terrains, including rough, uneven, or challenging environments like mountains, forests, deserts, and urban landscapes.

Wheels play a crucial role in achieving traction on rough terrains. Off-road tires are commonly employed in many robots for enhanced performance in challenging environments. In contrast, applications such as flying robots, swarm robotics, and mobile robots often utilize omni-directional wheels to enable versatile and precise movement [11].

All-terrain robots embody an impressive fusion of technological innovation and adaptability, purpose-built to effortlessly traverse diverse landscapes. These versatile machines feature robust suspension systems and advanced sensor suites, including LiDAR and cameras, enabling them to navigate through rough, uneven, and challenging terrains with ease [12]. From rocky surfaces to dense forests, these robots showcase exceptional mobility and agility, proving indispensable in applications like search and rescue missions and planetary exploration. Their articulated chassis and adaptive features empower them to dynamically surmount obstacles, demonstrating resilience in the face of unpredictable environmental conditions. The versatility of all-terrain robots extends beyond conquering various landscapes; it lies in their capacity to operate autonomously, and efficiently executing tasks in environments where human access might be limited or hazardous. As technological advancements persist, these robots play a pivotal role in extending the reach of exploration, disaster response, and scientific research to new frontiers. Moreover, the independent suspension systems implemented in All-terrain robots can operate individually, providing adaptability when traversing uneven terrains, as discussed in [13].

Engineers and researchers employ Finite Element Analysis (FEA) for a detailed examination of the structural and mechanical behavior of all-terrain vehicles. FEA offers insights into stress distribution, deformation, and potential failure points, facilitating design optimization for robust performance across diverse terrains [14].

2.2 Mode of Operation

The mode of operator refers to how a robotic system is controlled or operated, delineating the level of human involvement in guiding or overseeing the machine's actions. There are two primary modes of operator control: autonomous, and teleoperated. Many roboticists leverage ROS (Robot Operating System) as middleware to achieve both autonomous and manual control, employing various control devices, including gaming consoles [15].

2.2.1 Autonomous

In autonomous mode, the robot functions independently without direct human intervention. It relies on a combination of pre-programmed algorithms and real-time sensor data to make decisions and navigate its environment. Autonomous robots are capable of performing tasks without continuous input from a human operator, making them well-suited for applications such as automated exploration, agriculture, and search and rescue.

The utilization of autonomous systems in Automated Guided Vehicles (AGVs) significantly diminishes labor intensities [16].

2.2.2 Teleoperated/ Manuel Operate

Teleoperated mode involves the remote control of the robot by a human operator. The operator uses a connected device to send commands to the robot, guiding its movements and actions in real-time. This mode is particularly useful in scenarios where human judgment and dexterity are essential, such as in hazardous environments [17].

2.3 Wheeled Robots

Robot vehicles can be classified according to their mobility, a classification primarily influenced by the type of wheels employed. The selection of wheels is contingent upon the particular demands of the robot's designated purpose and the nature of the terrain it is engineered to traverse. Below are various classifications of robot vehicles based on their wheel configurations. Wheeled robots are autonomous machines specifically crafted to navigate surfaces by employing motorized wheels as their primary mode of propulsion. The classification of a wheeled robot is based on the number of wheels it possesses, encompassing categories such as two-wheel, four-wheel, six-wheel, and so on.

2.3.1 Two-Wheel Robot

Due to its inherent ability to balance itself and adeptly navigate around holes and small obstacles, a two-wheel robot possesses a significant advantage when traversing on terrain.

2.3.2 Four-Wheel Robot

Four-wheel robots commonly referred to as a wheeled mobile robot (WMR), represents a robotic platform characterized by the use of four wheels for its mobility. These robots exhibit a diverse range in size, spanning from compact hobbyist platforms to larger and more advanced industrial or research-oriented robots. Four-wheel robots commonly feature a square or rectangular frame, incorporating two wheels on each side of the chassis. The wheels are typically powered by electric motors, which may be either brushed or brushless, depending on the specific application 18).

Numerous 4-wheel robots employ a differential drive system. They are allowing independent control of the wheels on each side. This facilitates turning by adjusting the speed of the wheels on either side.

2.3.3 Six-wheel Robot

A six-wheel robot, often referred to as a hexapod or hexarotor, is a robotic platform equipped with six wheels for mobility. This configuration provides enhanced stability 19) and adaptability, enabling these robots to navigate over uneven terrain, stairs, and obstacles. Similar to 4-wheel robots, hexapods may use a differential drive system, allowing them to turn by varying the speed of the wheels on each side.

2.4 Tracked Robots

Tracked robots are robotic vehicles equipped with continuous tracks instead of wheels for mobility. Tracks provide stability on uneven terrain and enhance traction, allowing tracked robots to navigate through mud, sand, snow, and other challenging environments.

Tracked robots are well-suited for outdoor and rough terrain applications, including rocky landscapes, construction sites, and disaster-stricken areas. Tracked robots can often carry heavier payloads compared to wheeled robots, making them suitable for tasks requiring equipment or sensors with substantial weight.

2.5 Hybrid Robots (wheel track)

Hybrid robots, integrating both wheel and track systems, present a distinctive fusion of benefits by merging the stability and efficiency associated with wheels and the terrain adaptability offered by tracks. This innovative design enables the robot to dynamically adjust its locomotion method in response to the encountered terrain. When navigating smooth surfaces, the robot can leverage wheels for optimal efficiency, while it seamlessly switches to tracks for negotiating rough or uneven terrains.

Equipped with an array of sensors including cameras, LiDAR, and proximity sensors, the robot can intelligently assess the terrain, facilitating the automatic determination of the optimal mode of locomotion. Wheeled mobile robots have become a preferred choice due to their significant advantages over alternative locomotion types like legged or tracked systems 20). The appeal of wheeled robots lies in their simple mechanical structure, which facilitates ease of design and maintenance. Furthermore, they are highly energy-efficient, conserving power and ensuring longer operational duration. Wheeled robots are known for their agility, achieving impressive speeds that enable swift and efficient traversal across a variety of terrains. Another notable advantage is their inherent stability, which contributes to smoother and safer navigation. This stability is precious when operating in unpredictable or challenging environments. Moreover, wheeled mobile robots offer a level of control simplicity that streamlines their operation and maintenance. As a result, these characteristics collectively position wheeled mobile robots as a practical and effective choice for various applications, including autonomous landmine detection.

The decision control system manages the robot's decision-making processes. However, the linchpin of the system's autonomous navigation is the sensor component, with LIDAR serving as the pivotal element for perceiving and comprehending the robot's environment. This sensory input is paramount for the robot's ability to navigate and respond intelligently to its surroundings 21). A bio-mimetic robot like the hexapod robot is an excellent choice for fulfilling complex movement requirements 22).

Table 1. Design and Mechanisms Overview

Author’s Name	Mechanisms for Locomotion	Advantages	Future Improvements
P. Kopacek et al. [1)]	Six-wheeled robot with Ackermann geometry	-Asymmetric wheelbase enables equal weight distribution. -Uniform weight distribution with individual wheel drive	-Need improvements in driving capability in dense vegetation.
A. Mohammad et al. [4)]	Combination of two bogie mechanisms with differential gear drive	-Suspension is use to improve stability of system -Uniform distribution of the load on each wheel	-Improvements in design of robot to enhanced durability
Z. Li et al. [6)]	The transformable track mechanism with driving wheels	-self-adaptive mechanism for locomotion -Overcoming obstacle of different height by wheels and track	-Future work related to the obstacle-negotiating performance of the robot
B. Hamed et al. [8)]	parallel wheeled-differential drive method with two driving wheels	-Minimum size of robot - Mechanism is capable for fast locomotion	-Changes in autonomy of robot and weight reduction is required
J. Zhao et al. [9)]	Wheel-legged hybrid robot	-Robot with wheel and leg combine structure -Vehicle adapts the variety of complex road conditions	-Improvements related to structural design as it requires high control ability
A. Verma et al. [10)]	Rocker bogie suspension and differential drive mechanism	-System with spring suspensions -Design is simpler and more reliable	-Design improvements needed aims to increase the payload
C. Kannan et al. [18)]	Four-wheel-drive transmission for all terrain vehicle	- Four-wheel driveline has high performance on rough terrain -Two drive modes such as four-wheel drive and two-wheel drive.	-Further innovations include the introduction of actuators to engage the shifting mechanism.
M. P. Mann et al. [19)]	Six-wheel robot with Rocker bogie mechanism	-Analysis of dynamic stability of rocker bogie vehicle -Dynamic stability measure used for the maximum allowable speed of the vehicle.	- Future analysis with complex tire-soil interaction model of robot
P. Santana et al. [20)]	Four-wheel robot with Ackermann steering method.	-Multiple locomoting modes -Characteristic of high mobility enables low friction	-Improvements in the all-terrain capability of robot
S. Pecolt et al. [23)]	Rocker bogie suspension and differential drive mechanism	-Efficient and cost-effective mechanical construction -Individual wheel drive	-Required Materials with high Strength
V.S. Panwar et al. [24)]	Four-wheeled drive for floor cleaning robot	-It has a simple mechanical structure. -Four-wheel drive with capability to move on wet and dry surfaces	-Further improvements can lead to compact design of robot.

3. Autonomous Navigation

The concept of autonomous navigation is fundamental to the success of robotics in a wide range of applications including landmine detection [25)]. Autonomous robots equipped with the ability to navigate independently without human intervention offer significant advantages in terms of efficiency and adaptability. Autonomous Mobile Robots (AMRs) have revolutionized various industries by their ability to autonomously create maps of their environments and navigate while efficiently avoiding obstacles [26)].

3.1 Sensors

In the realm of landmine detection, the application of autonomous navigation is particularly significant. A central challenge in the development of AMRs is the selection of appropriate sensors like GPS, LiDAR, Camera etc. for autonomous navigation. The sensors play a pivotal role in perceiving the robot's surroundings and providing real-time data for decision making. Designing a robot for outdoor environments presents unique challenges, as the mechanics of the robot must contend with environmental stresses and the unpredictable conditions inherent to outdoor settings. This reality necessitates a more complex mechanical design in comparison to robots built for indoor use. The ability to navigate autonomously in outdoor environments is a core challenge faced by developers in the field.

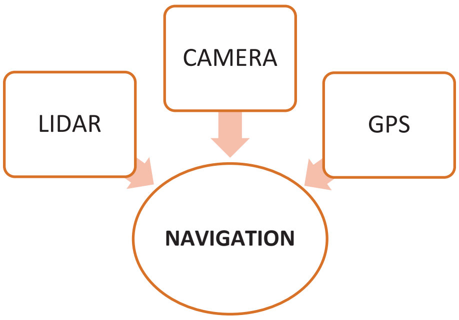

Fig. 1: Sensors used in Navigation System

3.1.1 LiDAR

LiDAR (Light Detection and Ranging) technology is a critical component in robotic navigation systems, providing invaluable information for accurate [27) and efficient movement in various environments. LiDAR sensors emit laser beams and measure the time it takes for the light to bounce back after hitting objects, creating detailed 3D maps of the surroundings 28). In terms of navigation, LiDAR enables the precise detection of obstacles, allowing robots to perceive and navigate through complex terrains with a high level of accuracy 29). These sensors excel in challenging environments, such as low-light conditions or situations with limited visibility. The 3D mapping capabilities of LiDAR contribute to obstacle avoidance 30)31), path planning, and localization, providing robots with a comprehensive understanding of their surroundings. This technology is particularly valuable for autonomous vehicles, drones, and robots operating in environments where visual information alone may be insufficient 32). LiDAR's ability to generate real-time, detailed maps enhances the safety and reliability of robotic navigation, making it an integral component in advancing the autonomy and adaptability of robotic systems.

3.1.2 Camera

Cameras play a pivotal role in robotic navigation by providing crucial visual information those aids in perceiving 33) and interpreting the surroundings. These sensors serve as the “eyes” of a robot, capturing real-time images or video feeds that are then processed by sophisticated computer vision algorithms 34). In the context of navigation, cameras contribute to tasks such as obstacle detection 35), terrain analysis, and path planning. High-resolution cameras enable the robot to identify and recognize objects, obstacles, and landmarks, empowering it to make informed decisions about its movement and trajectory. Depth-sensing cameras 36)37), utilizing technologies like stereoscopic vision or time-of-flight, enhance the robot's spatial awareness. This capability helps the robot gauge distances and navigate through three-dimensional spaces. Additionally, cameras can be instrumental in localization, aiding the robot in understanding its position relative to its surroundings. Whether it's an autonomous vehicle discerning road features or a planetary rover exploring unfamiliar terrain, the information gathered by cameras serves as a fundamental component for the successful navigation of robotic systems across diverse and dynamic environments 38).

3.1.3 GPS

Incorporating GPS technology into outdoor settings represents a crucial step forward in enhancing autonomous navigation capabilities 39). The integration of GPS stands as a significant advancement for robots operating in challenging terrains. By integrating GPS technology into the robot's toolkit, it gains highly precise localization allowing for the pinpointing of exact geographical coordinates 40). This level of accuracy is indispensable for critical operations such as landmine detection 41), and removal. Furthermore, GPS plays a pivotal role in accurately marking the locations of detected landmines 42), ensuring the safe and efficient execution of removal procedures. The seamless fusion of GPS technology with the robot's autonomous operation further fortifies its effectiveness, making it an indispensable tool in the ongoing mission to clear landmines from hazardous terrains. The Global Positioning System (GPS) serves as the preeminent global navigation satellite system (GNSS) 43), operating through a constellation of approximately 24 to 32 medium earth orbit (MEO) satellites. These satellites emit highly accurate microwave signals, facilitating the establishment of precise current location, time, and velocity of a GPS receiver 44). Operating at the speed of light, the receiver computes distance and position based on the arrival time of signals. While creating maps for high-speed vehicles necessitates costly, high-end sensors and substantial effort, low-speed applications often do not require detailed maps. Leveraging open-source software development kits (SDKs) and readily available satellite maps on the internet provides a practical and economical solution for guiding mobile vehicles through extensive, unfamiliar areas. In scenarios where high precision is essential, integrating consumer-grade GPS receivers with online maps offers a cost-effective alternative for navigating large-scale, uncharted terrains.

Table 2. Sensors used in navigation system by authors.

Authors	Sensor	Description
S. Pecolt et al. [23]	Camera	Camera is used for capturing images or videos of the surroundings, which can be useful for monitoring, exploration, or data collection purposes.
S. Pan et al. [29]	RPLIDAR-A1	LiDAR scan the environment and construct a point cloud map
A. Krishnan et al. [36]	Kinect depth camera	Depth camera provide rich and accurate 3D information about the environment
C. Marcu and L. Tamas [42]	Camera GPS	Camera images are used to identify key points on the robot track, such as landmarks or intersections and GPS provide the corresponding coordinates of those points.
C. M. Revanth et al. [45]	LiDAR	LiDAR scans the environment and SLAM creates a map.
J. Beck et al. [46]	LiDAR Camera	Lidar is used for scanning environment and camera capture visual data in the form of video or image
R. Krishnamoorthi et al. [47]	Camera LiDAR	Camera used to identify road features such as lanes, signs, and traffic lights. lidar is used to create accurate 3D maps of the environment and provide precise distance measurements.
J. Godoy et al. [48]	Camera LiDAR	Camera is used for tasks such as lane detection, traffic sign recognition, and object classification. lidar is used for collecting high-resolution, three-dimensional information about the surrounding environment.
S. Harapanahallia et al. [49]	Camera	Camera is used for obstacle detection and avoidance. Lidar is used for map creation.

3.2 Navigation Algorithms

Navigation algorithms in autonomous systems play a crucial role in enabling devices, robots, and vehicles to determine their position, motion [50], plan routes and navigate through environments without human intervention. These algorithms often rely on a combination of sensors, computational techniques, and decision-making processes to achieve their goals.

3.2.1 Mapping Algorithms

Mapping algorithms are pivotal in robotic and autonomous navigation, enabling robots to comprehend and maneuver through their surroundings effectively. Simultaneous Localization and Mapping (SLAM) is a foundational technique that facilitates the creation of maps in unknown [51], and known environments while simultaneously determining the robot's position within them [52] [53]. SLAM algorithms integrate data from diverse sensors like cameras, LIDAR, IMU, and wheel encoders, employing techniques such as feature extraction, matching, data association, and probabilistic filtering for trajectory estimation and map construction [54] [55]. Grid-based mapping divides environments into grids [56], maintaining probabilities or semantic information for each cell [57], while feature-based mapping focuses on extracting distinct features from sensor data to represent the environment. Topological mapping emphasizes topological relationships between regions or landmarks, while semantic mapping integrates semantic information like object categories or room labels. Deep learning-based mapping leverages techniques like CNNs [58], and RNNs to process sensor data directly [59] [60], extracting meaningful representations for mapping tasks. These algorithms continually evolve with technological advancements, with the choice of algorithm depending on the robot's sensing capabilities, computational resources, and application requirements.

3.2.2 Localization Algorithms

Localization algorithms are pivotal in robotic and autonomous navigation systems, allowing robots to determine their position within an environment. The Kalman Filter, a recursive estimation algorithm, combines noisy sensor measurements with a dynamic system model to estimate the system's state. Its extended version, the Extended Kalman Filter (EKF) [61], is adept at handling nonlinear systems, making it suitable for various robotic localization tasks. Particle Filter, also known as Monte Carlo Localization (MCL), represents the posterior probability distribution of the robot's pose using weighted particles, making it effective in non-Gaussian and nonlinear environments. Graph-Based SLAM (GraphSLAM) formulates localization as a graph optimization task, estimating the robot's trajectory and landmark positions by optimizing the graph structure based on sensor measurements. Scan Matching Techniques, such as the Iterative Closest Point (ICP) algorithm, align consecutive sensor scans to estimate the robot's motion and update its pose accurately. The choice of localization algorithm hinges on factors such as sensor suite, computational resources, accuracy requirements, and environmental conditions, emphasizing the need for selecting the most suitable algorithm for specific robotic navigation tasks.

3.2.3 Path Planning Algorithm

Path planning algorithms are pivotal in robotic and autonomous navigation, allowing robots to navigate from their current position to a desired destination while avoiding obstacles [62], and adhering to constraints. Dijkstra's Algorithm is a classic choice, efficiently finding the shortest path in weighted graphs, albeit it can be computationally expensive. Rapidly-exploring Random Tree (RRT) and Probabilistic Roadmap (PRM) are sampling-based algorithms, with RRT rapidly exploring high-dimensional spaces and PRM precomputing a graph of connectivity to quickly find feasible paths. Dynamic Programming algorithms, such as the Bellman-Ford algorithm, offer optimal solutions by breaking down problems into simpler subproblems. Potential Field Methods model robot motion as an interplay of attractive forces toward the goal and repulsive forces from obstacles, enabling reactive navigation in dynamic environments. A* Algorithm, on the other hand, combines the benefits of Dijkstra's Algorithm and greedy best-first search by using a heuristic function to guide the search towards the goal efficiently. The choice of path planning algorithm depends on factors like robot kinematics, environment complexity, computational resources, and real-time constraints, underscoring the need for selecting the most suitable algorithm for specific robotic navigation tasks.

3.2.4 Optimization Algorithm

Optimization algorithms are fundamental to robotic and autonomous navigation, providing solutions for optimal paths, efficient decision-making, and improved performance. Ant Colony Optimization (ACO), inspired by ant foraging behavior [63], is a metaheuristic algorithm applied to combinatorial optimization problems [64]. In robotic navigation, ACO aids in tasks like path planning, and trajectory optimization, simulating ants' pheromone trails to discover shorter paths over time. Differential Evolution (DE), another significant algorithm, is a population-based technique used for continuous and discrete optimization [65]. DE iteratively perturbs and combines candidate solutions within a population, converging towards global optima in robotic navigation tasks such as trajectory optimization and parameter tuning. Teaching-Learning-Based Optimization (TLBO), modeled after classroom teaching processes, refines candidate solutions by simulating knowledge transfer among learners and a teacher. TLBO is effective for path planning, trajectory optimization, and control parameter tuning in robotic navigation systems. Fuzzy Logic, an additional paradigm, handles imprecise or uncertain data in decision-making processes. It complements optimization algorithms by providing robust reasoning capabilities, particularly useful in navigating dynamic [66] and uncertain environments. These algorithms collectively empower robots to navigate complex environments efficiently, optimize trajectories, and make informed decisions [67], enhancing their ability to explore and interact effectively with surroundings. Optimization algorithms, such as the Genetic Algorithm, are employed to optimize the shortest route, showcasing their role as effective tools in route optimization [68].

Table 3. Algorithms used in navigation system by authors.

Authors	Algorithms	Description
A. Sabiha et al. [31]	Teaching–Learning-Based Optimization (TLBO) algorithm	TLBO is used for online path planning.
K. Tsiakas et al. [51]	Normal Distributions Transform (NDT) SLAM, OpenStreetMap	NDT-SLAM is used for map generation and OpenStreetMap is used for global path planning.
O. Khan et al. [53]	SLAM, Z-Number-Based Fuzzy Logic	SLAM is used for creating map of environment and Z-Number-Based Fuzzy Logic is used for path planning, obstacle avoidance, and decision-making.
T. Kim et al. [56]	RTAB-Map A* algorithm	RTAB-Map is used for mapping and localization simultaneously with RGB-D camera data. Modified A* algorithm is used for path planning.
B. Guerreiro [61]	SLAM	In this article SLAM algorithm is used for creating map in GPS-denied environments.
E. Martinez-Soltero and J. Hernandez-Barragan [65]	Differential Evolution (DE) algorithm	DE is used for finding the best path in a complex environment based on sensor data.
Q. Zou et al. [69]	SLAM, Gmapping, Cartographer.	In this article SLAM is used for mapping. Gmapping and Cartographer both are used for localization.
M. Munoz-Banon et al. [70]	Naive-Valley-Path (NVP), OpenStreetMap (OSM).	NVP is used for local path planning and obstacle avoidance and OSM is used for global path planning.
F. Rovira-Mas et al. [71]	Augmented Perception Obstacle	This algorithm is used to map using lidar and ultrasonics.

	Map (APOM)	
Q. Xu et al. 72)	SLAM_GMapping, A* algorithm	SLAM_GMapping algorithm is used for creating environment map. A* algorithm is used for path planning.
V. Panwar et al. 73)	Generalised Regression Neural Network (GRNN)	GRNN is used for motion planning and control of an E-puck robot among scattered obstacles.
V. Panwar et al. 74)	Multi-Objective Genetic Algorithm	Multi-Objective GA used to control the velocity of a two-wheeled robot. This approach allows the robot to navigate smoothly while avoiding obstacles.
S. Singh et al. 75)	The Sunflower Optimization Algorithm (SFO)	The Sunflower Optimization Algorithm (SFO) is used for motion control and planning of a wheeled robot. SFO is inspired by sunflowers capturing solar radiation.
A. Pandey et al. 76)	Particle Swarm Optimization (PSO), Feedforward Neural Network (FNN)	PSO is used to optimize and fine-tune the feedforward neural network (FNN) for obstacle avoidance FNN used to controls the differential drive of the Pioneer P3-DX wheeled robot.
V. Panwar et al. 77)	Multi-Objective Particle Swarm Optimization (MPSO) algorithm	The MPSO algorithm minimizes wheel velocities, allowing the robot to cover less distance and reach its goal faster.

4. Landmine Detection

The accurate landmine detection and precise localization of landmines are the core of any effective landmine detection and removal strategy. A multitude of techniques are currently employed in the field of landmine detection, each offering unique advantages and challenges.

These include methods such as electromagnetic induction, ground penetrating radar (GPR), nuclear quadrupole resonance, infrared (IR) imaging, hyperspectral methods, and electric impedance tomography. Among these, the use of electromagnetic induction sensors has gained prominence due to their accessibility and cost-effectiveness. The critical factor that significantly influences the performance of a metal detector for landmine detection is the distance between the sensor head and the ground. By precisely adjusting this gap between the landmine and the sensor head, it becomes possible to enhance the metal detector's detection capabilities and overall performance. Ground Penetrating Radar (GPR) undoubtedly excels in landmine detection, providing a robust means of identifying buried objects with precision. Some advanced landmine detection systems employ a dual-sensor approach, with the metal detector as the primary sensor for detecting metal-containing objects, typically associated with landmines, and the GPR as the secondary sensor for target identification. However, the challenge of unwanted scattered waves presents itself in this configuration, potentially degrading the quality of GPR data and complicating its analysis. Mitigating this interference is pivotal for achieving accurate and reliable landmine detection results, prompting ongoing research into advanced signal processing techniques to optimize the performance of these dual-sensor systems 78). Enhancing the accuracy of landmine detection involves sensor fusion, the integration of multiple sensor techniques to achieve improved detection rates, reduced false alarms, enhanced discrimination capabilities, and robust algorithms, with a particular focus on anti-personnel landmine (APL) detection. Various sensor fusion algorithms, both decision level and feature-based, are employed to combine data from different sensors, ultimately leading to a more effective and reliable landmine detection system. Feature-fusion techniques, exemplified by the depth-fusion approach, leverage features and confidence values from sensors to optimize algorithm settings, contributing to the system's ability to perform well in real minefields and controlled environments 79). In its highly sensitive mode, the MD-3003B1 landmine detector exhibits an impressive level of sensitivity, capable of detecting even tiny metallic pins as small as 15 mm in size. This heightened sensitivity is particularly valuable when used for the detection of landmines, as it ensures that even the smallest metallic components do not go unnoticed. However, it's worth noting that in its low sensitivity mode, the detector is optimized to respond primarily to larger metal objects, making it adaptable to various detection requirements. Nonetheless, when the mission involves landmine detection, the highly sensitive mode proves to be the most suitable and effective choice 80). A number of researchers have endeavored to address the issue of limited sensor range by developing systems to effectively control the range of landmine detectors. These efforts aim to overcome the challenges associated with short detection distances, enhancing the overall performance and effectiveness of the detection technology 81).

In the realm of landmine detection, a new generation metal detector has emerged— the “Beat Balance” (bb). This innovative detector combines Beat Frequency Operation (BFO) and Induction Balance (IB) principles, creating a hybrid solution for enhanced sensitivity. By integrating the strengths of both BFO and IB, the “Beat Balance” detector proves effective in identifying both metallic and non-metallic landmines [82]. Figure 2 displays the distribution of landmine detection technologies used in research studies.

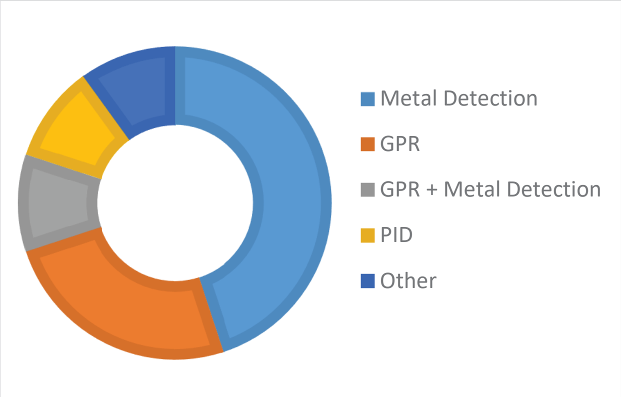

Fig. 2: Landmine detection technology usage in landmine detection robots

Table 4. Landmine detection technologies overview.

Author’s	Approach	Pros	Drawbacks	Surface contact requirement
P. Kopacek et al. [1] L. Robledo et al. [5] A. Kunaraj et al. [33] F. Albert et al. [83]	Electromagnetic induction (metal detector)	Effective for metallic mines. Interfacing with Wideband frequency domain sensors can improve detection by 60%. Cost effective compare to other technologies.	False alarm rate due to large number of metallic particles. Limited for metallic mines.	Not required
K. Nandakumar et al. [2]	Inductive proximity sensor	Non-invasive and effective metal object detection.	Limited for metallic mines.	Not required
L. Robledo et al. [5] L. Bossi et al. [37] N. Nambiar et al. [84]	Ground penetrating radar (GPR)	Detection of plastic landmines possible.	Inhomogeneous subsoil may cause a great number of false alarms	Not required
L. Robledo et al. [5]	Nuclear quadrupole resonance	No static magnetic field is needed	Radio frequency interference may reduce efficiency	Not required
	Infrared and hyperspectral methods	Fast detection	Performance is depended on environmental conditions	Not required
	Electric impedance tomography (EIT)	Allows detection of metallic and non-metallic mines	Conductivity affects the working in dry soil or rocky surfaces.	Required
	X-ray backscatter (XBT)	Scatter signal tied to material density, requires single-sided access.	Limited to the depth of mines.	Not required
	Acoustic and seismic systems	Low false alarm rate, suitable for antitank mine detection	Low Speed and less detection range.	Not required
B. Hamed et al. [8]	Pulse Induction Detection (PID)	Two side coils enhance the mine scanning area. Less expensive.	Limited to metallic mines.	Not required
M. Neela et al. [78]	GPR with metal detector.	Enhances target identification while also detecting both metallic and non-metallic mines.	The sensor should be in close proximity to the mine.	Not required
A. Ebada et al. [85]	Biological methods	Possesses the potential to effectively lower the false alarm rate, enhancing the reliability of the system in minimizing erroneous alerts.	Understanding the chemical and physical principles that govern the sensor is essential.	Not required.

5. Conclusion

This review study provides an overview of landmine detection robots, supported by Table 1's designs and processes and Table 2's navigation system sensors. A review of the algorithms that were investigated by the authors may be found in Table 3. Whereas, in Table 4, authors list landmine detection devices studied. Landmines' extensive impact on humans and the environment necessitates urgent research and development. Automated navigation, sensor integration, and machine learning can improve landmine detection efficiency, safety, and precision. Landmine detection robots are being improved to make demining safer and more efficient through advances in materials, sensing technologies, and artificial intelligence.

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