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Review

A Survey on Swarm Robotics for Area Coverage Problem

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Abstract: The area coverage problem solution is one of the vital research areas which can benefit from swarm robotics. The greatest challenge to the swarm robotics system is to complete the task of covering an area effectively. Many domains where area coverage is essential include exploration, surveillance, mapping, foraging, and several other applications. This paper introduces a survey of swarm robotics in area coverage research papers from 2015 to 2022 regarding the algorithms and methods used, hardware, and applications in this domain. Different types of algorithms and hardware were dealt with and analysed; according to the analysis, the characteristics and advantages of each of them were identified, and we determined their suitability for different applications in covering the area for many goals. This study demonstrates that naturally inspired algorithms have the most significant role in swarm robotics for area coverage compared to other techniques. In addition, modern hardware has more capabilities suitable for supporting swarm robotics to cover an area, even if the environment is complex and contains static or dynamic obstacles.

Keywords: swarm robotics; area coverage; hardware architecture; swarm robotics algorithms

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1. Introduction

Area coverage is one of the essential and attractive topics that has been studied in the last few years. This term is used in specific spatial area robotics to gain or update information in the robotic domain. Area coverage is a critical concept in different significant applications comprising the exploration of planetary, detection and demining of mines, wildfire fighting, and surveillance. Generally, the set of coverage behaviours required and the performance metrics used depend on the application [1]. Area coverage is a field of multi-robot systems called swarm robots. A swarm robot is one swarm intelligence application, including mobile robots responsible for completing a particular task [2]. Many distributed algorithms have been proposed and used for coordinating sets of robots to maximise the sensing coverage of a given environment area.

Swarm robotics is bio-inspired; the behaviour stems from observing common behaviours of animals, where each individual in the group acts autonomously similarly [3]. The basic idea for this swarm robotics is that each robot undergoing simple rules depends on local sensory inputs and communication with their neighbours locally [4]. Swarm robotics has possibilities to enable the use of practices in different problem solutions because of their characteristics: synergistic, distributed, robust, operating in real-time, universal, practical, optimality, reliability, and scalability. Swarm robotics research encompasses aggregation, area coverage, the search for a target, and cooperative handling [5]. This paper aims to survey the research which poses a problem of area coverage that benefits from a swarm robotics-based approach.

This paper is outlined as follows, Section 2 introduces the Methodology used for this study. Section 3 submits the algorithms and methods used in swarm robotics for area coverage problems. Section 4 encompasses the analysis and discussion of these algorithms and techniques used. Section 5 shows the hardware architecture used. Section 6 introduces the applications of swarm robots in this domain. Section 7 is the discussion. The last section is a conclusion.

2. Methodology

For area coverage problems involving swarm robots, this survey's methodology presents an open and systematic way of selecting and categorising studies. Here are the specifics regarding the paper selection criteria, classification method, and anything else that might be pertinent. This review includes articles that were published in journals from 2015 to 2022, covering the most current trends and advancements in swarm robots for coverage areas.

2.1. The Rationale for the Time Frame

A period of tremendous technical developments occurred between 2015 and 2022, and this is why that is that time range was selected. During this time, swarm robotics controllers became more robust, and advancements in sensing technologies and hardware capabilities were substantial. Swarm robotics was widely acknowledged as an exciting new study area. During this time, swarm robotics emerged as a separate and significant field within robotics study.

Advancements in swarm robotics algorithmic frameworks occurred between 2015 and 2022. Optimisation methods, coordination strategies, swarm intelligence system developments, and swarm robots are becoming more effective at tackling area coverage issues. During this time, swarm robotics moved from a theoretical study field to one with real-world applications. The practical applications of swarm robotics in agriculture, exploration, surveillance, and industry have recently attracted much attention from researchers and practitioners.

Swarm robotics has recently seen an upsurge in academic publications, conferences, and group projects, all coinciding with the chosen time range. The survey covers all essential and relevant contributions by focusing on this time frame. During 2015–2022, swarm robotics reached a point of maturity. Scientists might improve previous efforts, test new approaches, and expand existing knowledge. The variety and depth of the surveyed papers demonstrate this level of development.

The selected period captures foundational works and contemporary achievements while considering the historical context. This way, we know that the articles we are looking at are up-to-date and relevant to where swarm robotics is to ensure consistency when reviewing and comparing the selected publications; thus, the survey should be limited to 2015 to 2022. This makes it possible to concentrate on the most current trends and developments within the given period. Using this era as a starting point, the survey explores the history, development, and current uses of swarm robotics for coverage areas. This way, we may be sure that the chosen papers advance our knowledge of swarm robotics in the given setting. The conceptual framework of the work is shown in Figure 1.

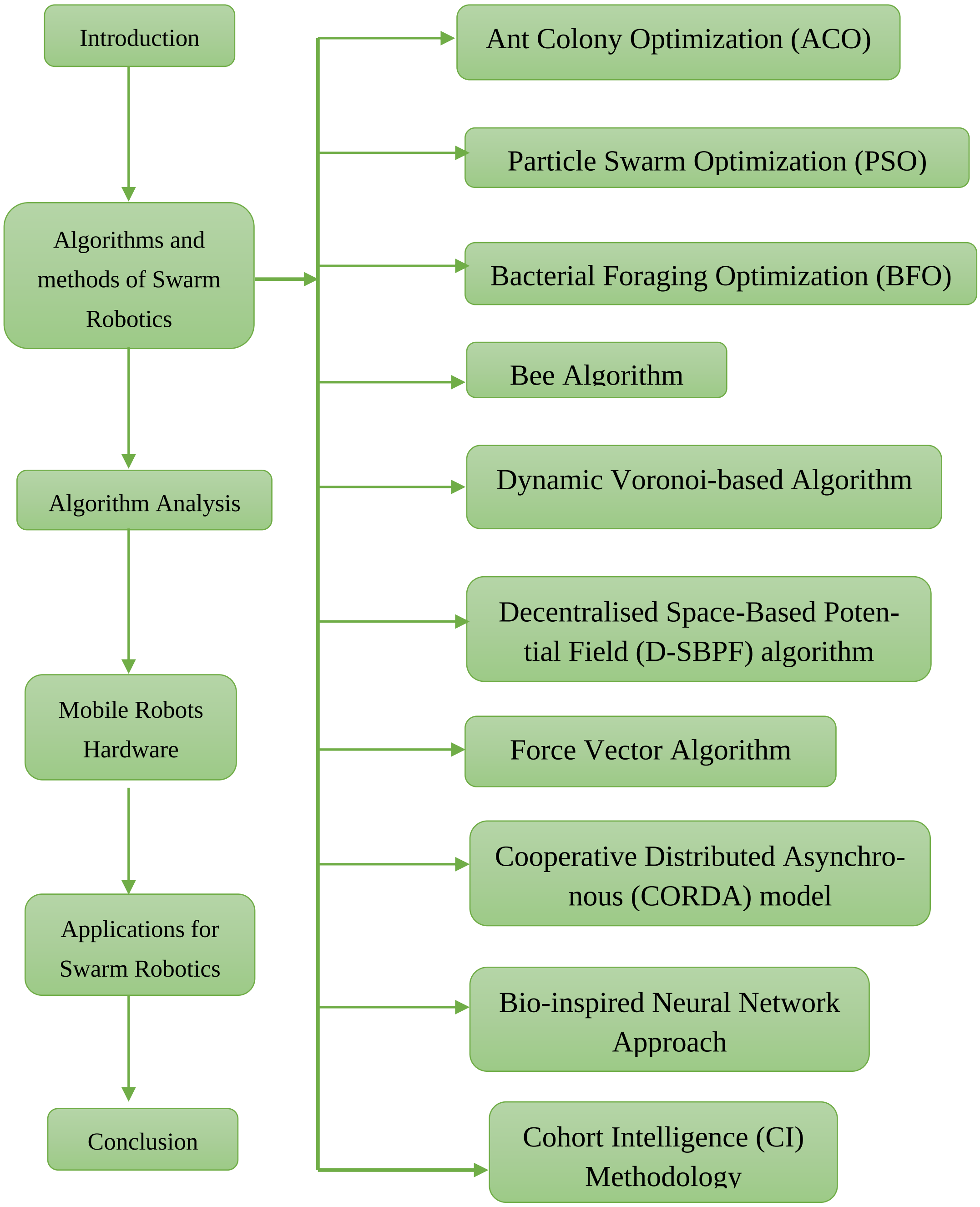

Figure 1. Conceptual framework of the work.

2.2. Search Criteria

Google Scholar, IEEE Xplore, PubMed, and ScienceDirect were among the credible academic databases queried in a thorough literature search. "Swarm robotics", "area coverage", and similar topics were among the search queries. Publications published between 2015 and 2022 were eligible for inclusion in this review. We aimed to cover the most recent trends and advancements in swarm robots within this period. Swarm robotics-based area coverage difficulties are the focus of a few articles. The main focus areas are exploration, monitoring, mapping, foraging, and similar activities. Publications in high-quality robotics-related peer-reviewed journals and conferences were given priority. This guaranteed that only works that have passed thorough academic evaluations were included. For reader accessibility and transparency, we included only papers whose entire texts were freely available online. The papers used from the journals are illustrated in Figure 2.

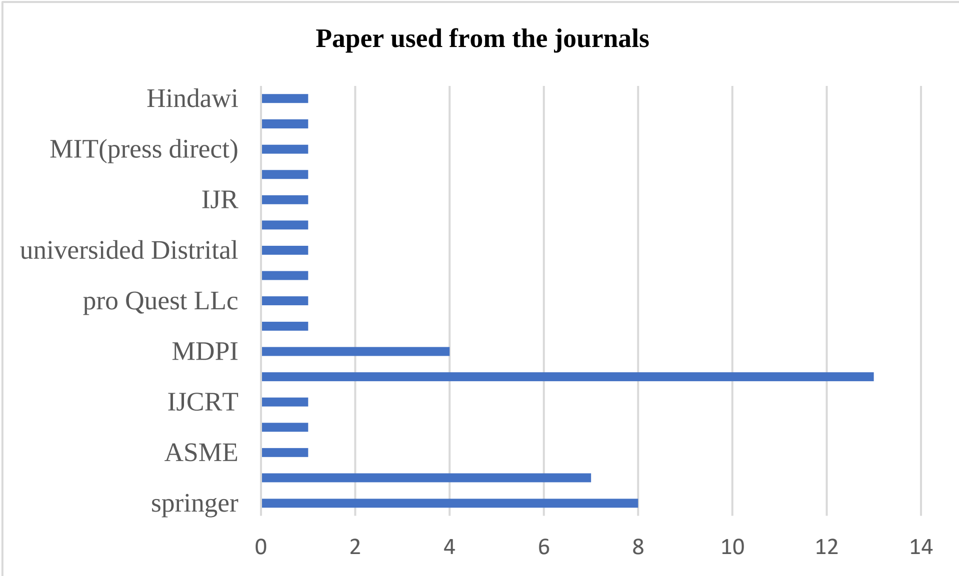

Figure 2. No. of papers used for journals.

Articles were considered for inclusion if they pertained to area coverage applications using swarm robotics. Novel algorithms, techniques, and their applications across fields were the primary focus of the selected studies. We did not include papers published after the specified time or that did not add significantly to our knowledge of swarm robotics for area coverage.

2.3. Classification Process

We sorted the cut articles according to their major use case, algorithmic methods, robot coordination, centralisation, obstacle handling, and hardware requirements. Categories such as exploration, task allocation, coordination, and specialised applications (such as agricultural, surveillance, and industrial tasks) were used to classify the selected studies. Additional paper classifications were made according to the sensors, processors, and algorithms utilised for swarm coordination in the robotic platforms. To help readers better understand the many facets of swarm robotics, each work was assessed for its merits, shortcomings, and overall impact. Our classification of the reviewed articles is based on significant themes, areas of application, and the methodology used.

2.3.1. Thematic Classification

We focused on studies that examined the use of swarm robotics to survey large areas. Problems with effectively uncovering unknown environments are a common focus of these investigations. The research articles highlighting swarm robots' task allocation procedures. One aspect of this is determining how to best cover a particular region by allocating duties to robotic agents. To achieve coordinated and efficient coverage of areas, papers focused on the coordination mechanisms used in swarm robotics.

2.3.2. Application Domain Classification

Agricultural robotics papers cover precision farming, pest management, and sustainable broad-acre farming. A collection of the articles detailed using swarm robotics for surveillance tasks, including keeping tabs on expansive regions for intelligence gathering or security reasons. Various papers were about using swarm robots in manufacturing, including logistics, cleaning, and maintenance.

2.3.3. Methodological Classification

Various papers are organised according to the algorithmic approaches used in swarm robotics, including Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO). Some articles discussed the various setups and parts of the sensors, CPUs, and communication modules used in swarm robotic platforms. Readers will find a comprehensive and organised synopsis of the many facets of swarm robotics in the reviewed literature according to this categorisation.

For the survey, we retrieved the following data from each chosen paper: title, authors, publication year, essential algorithms, application domain, coordination mechanisms, hardware details, strengths/limitations, and presentation of the results. Each paper's impact on swarm robotics for coverage area was considered while making a final decision. Emphasis was placed on works with noteworthy methodology, experimental validations, or practical applications.

3. Algorithms and Methods for Swarm Robotics

Most algorithms applied for swarm robotics in area coverage are inspired by coordination among biological entities [6]. The algorithms used in swarm robots are classified into stochastic and deterministic [7]. By definition, deterministic approaches use mathematical models that rely on local optimum and gradient to solve problems [8]. In contrast, stochastic techniques rely on mathematical properties to perform a given function, but with minimal dependency on the gradient and local optimums when solving specific problems [9]. Experts argue that the stochastic technique is more user-friendly than the latter in optimising robots to work independently or simultaneously in a swarm [10]. The type of algorithm applied in swarm robots is mainly dependent on the nature or type of problem being solved by the robot [11]. Researchers and developers of the optimisation domain have designed stochastic algorithms that mimic natural processes that are synonymous with various types of animals and flies, such as fish, birds, and bees. The notable algorithms developed from such observations include Particle Swarm Optimisation (PSO) and Honey Bee Optimization (MBO) [12,13]. And, lately, algorithms are based on bacteria colony behaviours [14]. The algorithms mentioned above are commonly used in swarm robots for area coverage. Many algorithms and methods have been used in swarm robots for area coverage in the last seven years, as follows.

The algorithms are divided into sections such as metaheuristic algorithms–swarm intelligence and classical algorithms.

3.1. Metaheuristic Algorithms–Swarm Intelligence

In the field of swarm robotics, metaheuristic algorithms, especially those based on swarm intelligence, are crucial for covering large areas, and they have recently become powerful instruments for solving complicated issues. In order to create effective and adaptable tactics for robotic swarms, these algorithms take cues from the cooperative behaviour seen in natural systems, like ant colonies, beehives, and bird flocks. By encouraging decentralised decision making, the metaheuristic method allows swarm robots to jointly traverse large areas.

3.1.1. Ant Colony Optimization (ACO)

The ACO algorithm is one of the swarm intelligence algorithms [15]. The movement of ants is influenced by their need to search for food. When ants move from one point to another in search of food, they produce organic compounds called pheromones in the form of deposits in their footpath [16,17]. Pheromone paths enable ants to reach the food source and bring it to deposit in their colonies [18]. The ants will follow the trail with the highest quality and quantity of food [19]. Many researchers designed an ant-based algorithm applicable to swarm robots. The algorithm uses artificial intelligence robot-to-robot communication as a substitute for nature-based communication [20].

Ref. [21] introduced the design of control laws used by swarm robots to enable them to work cooperatively. Ant colonies are used for this purpose through pheromones to control individual robot behaviour. The decentralised control law is formed using many reaction-diffusion equations, leading to area coverage. Analysis was made in this work for the effect of pheromone diffusion and evaporation on the environment and measuring the performance of area coverage. Adding noise to the control law has the greatest effect on the algorithm for covering an area, and these parameters significantly influence the performance of the area coverage. The global concept is achieved by finding the most critical parameter to be the magnitude of the noise applied. Meanwhile, the local image is also achieved by adding noise depending on the importance of the other parameters: diffusion and evaporation.

Ref. [22] proposed a Cellular Automata Ant Memory Model (CAAM), which is used for swarm robots to perform foraging search tasks in a known environment with nests. Robots communicate with each other through the inverted pheromone. The swarm robot deposits the pheromone in each step, leading to a repulsive force among the team's individuals. In addition, to remember the robot's last positions and to avoid unnecessary explorations, I used a short-term memory inspired by Tabu Search. The forage robot has two operations, one for searching and another for homing, which is getting the food to the collection point named nest. The simulation results show that the newly proposed method can implement the foraging task competitively by covering the area effectively in searching and detecting adequate nests in homing operation.

Ref. [23] proposed a control law for area coverage using swarm robots in a 2D region inspired by the ant foraging dynamical features. The basic idea is to increase the search efficiency of that dynamic, adaptive switching between Brownian motion and Levy flight in the stochastic component of the search. The area of 100×100 square units was used for the simulations with a 10-robot swarm. The simulation results refer to enhanced performance for area coverage through swarm robots by this method in a particular threshold value.

Ref. [24] proposed a new hybrid method that combines natural and evolutionary computing methods, using genetic algorithms, inverted ant pheromones, and Tabu Search to implement the swarm robots in surveillance tasks. The new model is named Genetic Shared Tabu Inverted Ant Cellular. An inverted pheromone indicates that when the insects are at risk, they tend to drift away from each other and increase the coverage area; in construct, when ants are in a foraging case, they tend to cluster along particular paths that lead to the food source. The simulation experiments used e-puck architecture within the Webots simulator and Python programming language.

3.1.2. Particle Swarm Optimisation (PSO)

Particle Swarm Optimisation is one of the swarm algorithms in artificial intelligence developed by Kennedy and Eberhart to simulate birds' flocking behaviour [25] graphically. It is a stochastic technique that facilitates robot movement in a swarm [26]. The Particle Swarm Optimisation algorithm differs from others because its functionality solely depends on the objective function. It does not rely on differential objectives or gradients in flying formation [27]. A flock of birds that move in groups benefits from the experience of each flock member. For instance, when a flock of birds flies randomly in search of food, they increase the chances of each bird in the community getting the best hunt [28,29]. The Particle Swarm Optimisation algorithm was designed to assist in solving optimisation problems in both the local and global space [30,31]. However, each robot utilises the Particle Swarm Optimisation algorithm to navigate the terrain or area in a semi-autonomous manner that is distinct from other robots in the swarm. This allows the robot to solve the problem and navigate independently while functioning as a swarm [32,33].

PSO is a control strategy for a swarm robotic system. Many developed PSO algorithms have been presented and proposed for this purpose and used for area coverage problems as follows:

Ref. [34] presented five robots with an XBee module for the problem of seeking electromagnetic sources by area coverage by modifying and implementing the PSO algorithm on mobile robots according to the physical constraints presented by both robots and the environment. Three different PSOs were evaluated by simulations encompassing PSO with Inertia Weight, PSO with Constriction Factor, and Standard Particle Swarm Optimization (SPSO). The area covered was 5×5 m^2, and applying the Vicon tracking system gave the information of each robot's precise position via the support of an indoor GPS system to recognise markers on the robots. The type of robots used with an XBee module in experiments improved from the Parallax Shield-Bot, which Arduino controls. These robots search for the target source, a module of XBee hanging above a floor at a height of 20 cm in the middle of the area, to avoid a probability collision with the Robot. Also, the avoidance strategies for static and dynamic obstacles occurred in PSO in this experiment. The results proved that the best and most convenient diversity of PSO is the Inertia Weight PSO for this work.

Ref. [35] presented a novel method approach that depends on Robotic Darwinian Particle Swarm Optimization (RDPSO), Probabilistic Finite State Machine (PFSM), and Depth First Search (DFS). This new approach was proven to decrease the time needed by the AntBOT swarm to explore the area coverage environment. The simulator is V-REP, with different layouts, and three various environment areas are used (25 m^2, 100 m^2, and 400 m^2). The results indicated that the speed of exploration increases with a combination between RDPSO and PFSM by at least 1.4x the rate of the individual algorithms. In addition, it enhances the motion of robots in the environment by allowing smaller sizes for swarm robots to process exploration and rescue at a minimum cost.

Ref. [28] dwelled upon the description of implementing Robotic Darwinian Particle Swarm Optimization (RDPSO) for search and rescue in a particular area coverage. A Robot Operating System (ROS) and Gazebo simulator with Rviz were used. Rviz is a ROS visualisation tool for visualising sensory data, such as camera data, distance measuring device data, GPS information, etc. The experiments were performed for the rescue operation in two cases, one for two static victims by four robots and another for four static victims, using eight robots, with 30 trials for each patient. The simulation results indicated that RDPSO, compared to RPSO, performs better for multiple target search and rescue (SAR) operations.

Ref. [36] described the significance of fitness functions in the swarm robotics performance. Two maps, one for simulating an open area containing obstacles and another map with features of an apartment, were presented and used to assess a the PSO-based algorithm's performance. These maps have an area of 25 square meters, including walls and static targets. Three flexible fitness function types were used: standard (stand) and random target (rand_tar), using Euclidean distance to the nearest target and distance from the base (dist_base), which computes the Euclidean distance to the ground (launch point). It was noticed that the results of rand_tar and dist_base commands were better than the stand function. In total, 80% of the coverage area was achieved by the swarm robot after 1000 iterations through V-REP PRO EDU Platform.

Ref. [37] proposed an exploration-enhanced RPSO (E2RPSO) swarm robotic algorithm, searching for multitargets via extra exploration and extensive area coverage. Avoiding obstacles in the area enhanced the exploration capability by adjusting the dynamic Inertia Weight. Two diversities of the swarm were added, one named top-down diversity and another called the bottom-up diversity of the original PSO, which used adaptive dynamic Inertia Weight. The swarm robot detects all the targets in the covered area to handle the problem of searching for multitargets. The findings showed that this approach can balance exploration and exploitation and see more marks in a particular area without increasing time costs.

Ref. [38] proposed an effective target function method by the PSO algorithm with the inverse of the perspective approach, which led to a growing speed and a decrease in the size of input information. The primary aim is to find the positions of soccer robots with their Cartesian coordinates at a precision of 5 cm without the need for a global positioning system (GPS) in a specified area. The playground has a dimension of 9 × 6 m, with an extra 70 cm of margin around the ground. The implementation of the algorithm was performed through the MATLAB platform, and the simulation results showed that the number of function computations was reduced for each positioning, using the PSO algorithm. A better solution results from 50 particles (robots) randomly distributed over the whole area coverage.

Ref. [39] proposed an adaptive exploration robotic PSO (AERPSO) to detect multiple static or dynamic targets quickly through cooperation between swarm robots in a particular area. The exploration was performed by avoiding local minima while exploring unexplored regions. At the same time, avoiding obstacles using evolutionary speed and the aggregation degree assists the velocity and position of the swarm robots exploring new areas to detect targets. I also used adaptive Inertia Weight to help in improving the exploration. Compared with existing methods, the simulation findings show that the AERPSO algorithm enhances search time by approximately 40% and the detection rate by 25%. It is an excellent method for multitarget searching by providing a balance between exploration and exploitation.

3.1.3. Bacterial Foraging Optimisation (BFO) Algorithm

The BFO was proposed to mimic the E. coli bacteria's foraging behaviours in the intestine [40]. The algorithm became popular due to its high ability to escape from the local optimum, and when compared with other heuristic methods, it has faster convergence [41]. Some researchers are working to improve the BFO, which is used for area coverage as follows:

Ref. [41] proposed a bacterial chemotaxis optimisation (B.C.) algorithm. The B.C. is a decentralized algorithm used in swarm robots inspired by bacteria chemotaxis for target search and trapping within area coverage. This algorithm was adapted from the original bacterial foraging optimisation (BFO), and it considered each robot to be a bacterium and applied the mechanism of bacteria chemotaxis to solve problems of distributed controlling for swarm robots in area coverage. The B.C. set the target's position to a significant value, divided the area by the Voronoi method, computed the gradient for the robots' chemotaxis direction, and approached the target's position by bacteria swimming through the law in each Voronoi cell. Twenty-six robots can avoid six obstacles by moving robots in the direction to avoid these obstacles. The problem of detecting targets and surrounding them in a particular area was solved in this work. Simulation results have presented B.C. as having a good performance, robustness, and algorithm calculation complexity compared to several methods for swarm robots' distribution.

Ref. [42] introduced a new proposal for a swarm robotic system called a bacterial chemotaxis-inspired coordination strategy (BCCS) for coverage and aggregation. Chaotic preprocessing is used to initialise the starting positions of the robots. Then, the area covered by the robot is computed as a fitness function value to compare with previous ones. Based on BCCS, every robot makes an action, running or rotating. The process continues until the maximum number of iterations is met or the number of covered cells satisfies the termination conditions. In addition, it has presented a random factor to guide robots to rendezvous at an undefined point to overcome aggregation. The simulation results showed the supremacy performance of the proposed strategy compared with other controllers in both success rate and iteration average number. BCCS has a high exploration ability for area coverage.

3.1.4. Bee Algorithm

The bee algorithm is inspired by observing how honey bees breed, mate, and forage. Their behaviours form the basis of bee optimisation algorithms [43,44]. The Honey Bee Optimization (MBO) is among the main algorithms based on the breeding and mating activities associated with honey bees and depends on swarm intelligence [45,46]. There are several algorithms based on the Honey Bee Optimization (MBO), including Fast Marriage in Honey Bee Optimization (FMHBO), Honey Bees Mating Optimization (HBMO), and Honey

Bee Optimization (HBO) [47,48]. As mentioned earlier, the algorithm uses evolutionary behaviours, such as the random explorative behaviour of the bees, to solve problems or achieve set objectives. The principal functionality of the bee algorithm commences from a single source, typically referred to as the queen, and flows to other bees (or robots) in the colony (swarm) [49]. The principle is based on the forward pass concept, which implies that information is sent from a single source as it flows to other colony members [50]. Like the queen, a single robot in a swarm is used as the source of information to guide other robots as they move in the area [51]. The algorithm's objective is to allow swarm robots to be attracted to a goal with the highest solution when deployed to survey a large expanse [52].

Ref. [53] proposed a novel concept of surveillance robotics that is based on honey bees and with the integration of an autonomous telepresence robot. The telepresence robot means considering human control in the loop, as doing so is essential to improve robotic swarm efficiency and speed up convergence. Experiments used Turtlebot robots for performing a foraging task, beginning at the hive location and randomly exploring in a specific area for a particular food location. The experiments assessing a proposed swarm coordination system in an unknown environment were performed via a simulation and on real robots. The simulation was performed for three settings: 5×5 m^2 shaped, 10×10 m^2 shaped, and 10×10 m^2 L-shaped. When Turtlebots find a food source, they take it and drive it to the hive, where they put food until they run out of food or detect another source. The telepresence represents a leader who sends related information about the location to the Turtlebots. The findings show the telepresence robot's role in increasing the operation's efficiency, chiefly in dynamic and complex scenarios where the sources of food change over time.

Ref. [54] focused on complex area coverage problems with special task areas such as forbidden regions or threat regions. At the beginning of the work, the adjusted area of the task was specified, and the grid was discretisation. Then, it was inspired by the labour division phenomenon of typical biological sets, such as colonies for bees and ants. The features analysis of the performance is made of both algorithms' labour division model for the ant colony (threshold model) and labour division model for the bee colony (activation–inhibition model) from the concept of individual and environment, individual and individual, and a novel swarm intelligence labour division method to solve the problem of complex area coverage in swarm robots. Three experiments are implemented by encompassing area coverage problems for the non-threat region, established threat region, and sudden threat region. The results show the capability of the proposed algorithm to solve area coverage and the dynamic environment. The algorithm can respond effectively to the sudden threat.

Ref. [55] referred to a set of autonomous cyber–physical robotic cleaners that have been controllers for wet-cleaning rooms in large public or commercial buildings. It introduces different control strategies for the movements of a robot set or those of robots within a set and the influential factors on the intragroup behaviour of swarm robots. It presented an approach to building formations for robots depending on the leading robot by the wet trails. The groups of cyber–physical robotic cleaners are controlled by using two strategies: one is a global strategy that depends on the bee's search algorithm, including swarm intelligence elements, and another related to orientation for leading the robot and its neighbours is a local formation-building approach. NetLogo carries out experiments for some robots set through tasks of control and formation. Simulation results can be exploited for similar problem solutions, such as harvesting, deactivating the area from radioactive substances, disinfecting the area from viruses, and others.

3.1.5. A Bio-Inspired Neural Network Approach

Artificial intelligence methods especially have more significance in swarm robots for area coverage. Several robots cooperate to complete coverage tasks efficiently. A neural dynamics method is proposed for this purpose and guides the group of robots in a dynamic environment for complete area coverage (CAC). Every robot considers other robots to be moving obstacles. The mobile robot's path is generated from the landscape of the neural network and the previous position of the robot. Many cases used this method and showed effective results to enable the robots to cover an area. The computations of the model are easy, and the path of the robot is created without searching over the global free workspace or any global cost functions [56].

3.1.6. Cohort Intelligence (CI) Methodology

Cohort Intelligence (CI) methodology is used to model the behaviour of candidates depending on the interaction among them to perform a common goal. The behaviour of each candidate is improved by looking at all other candidates in the cohort. The CI is used for coverage area in the operation of search and rescue by swarm robots, the roulette wheel selection method, and the median method. Also, a perturbation technique is used to solve the problem of getting stuck in non-convex obstacles by robots. Many cases were achieved, such as the No Obstacle Case (NOC), Stationary Obstacles Case (SOC), Single Dynamic Obstacle Case (SDOC), Multiple Dynamic Obstacles Case with the Same Velocity (MDOC-SV), and Multiple Dynamic Obstacles Case with Different Velocities (MDOCDV) [57].

3.2. Classical Algorithms

When it comes to solving area coverage problems in swarm robotics, classical methods provide a solid basis. When directing the actions of a swarm of robots, these algorithms frequently use deterministic methods and set parameters. Using more organised decision-making procedures and perhaps involving centralised control systems, classical algorithms differ from metaheuristic algorithms. We take a look at a wide variety of classical algorithms used in swarm robotics here, many of which have been fine-tuned for different tasks and settings.

3.2.1. Dynamic Voronoi-Based Algorithm

It is a mathematical model generally used in area division in some regions. These regions are based on the seeds given in the first. Every part has a corresponding region encompassing all points in space closer to itself than others. In this case, the region is called Voronoi cells [58]. The Voronoi algorithm controls swarm robots; each robot acts as a seed and divides the target area into Voronoi cells. Every robot must cover its own Voronoi cell, guaranteeing that each target point is closer to its corresponding robot [59].

Ref. [60] proposed a dynamic Voronoi-based algorithm, which is used for the area coverage problem; it divides the target area into Voronoi cells dynamically through the moving of robots rather than using a static algorithm and to improve the efficiency of modified bacterial foraging optimisation (MBFO) by using swarm robots in searching. The MBFO is also used to coordinate between robot positions and the swarm robot target area. The MBFO algorithm considers each robot to be a bacterium. Then, it applies the mechanism of bacteria chemotaxis to solve problems of decentralised controlling for swarm robots in experiments, using these two algorithms to the process of area coverage by 26 swarm robots in random locations on a 300×300 m^2 area by MBFO. The moving of robots depends on following the concentration gradient in the target area and using the sensor control the reaction between them. Also, after using 10, 20, and 30 robots to validate the efficiency of the new dynamic Voronoi bade on MBFO, the results showed the effectiveness of the dynamic Voronoi method.

3.2.2. The Decentralised Space-Based Potential Field (D-SBPF) Algorithm

D-SBPF is a simple decentralised method for dispersing a robot team to quickly explore and cover an area. The algorithm is considered a potential control method that supports knowledge of the area bounds to be explored. The basic idea is to solve the problem of deploying many robots in an unknown environment (buildings) to examine and collect information about the environment, using an effective method. The experiments were carried out using three maps, each 10×10 m^2, and a grid representation of 30×30. The approach uses an extended occupancy grid to represent the space where each cell can be attractive (if undiscovered) or repulsive (if discovered). A non-monotonic field scale factor proportional to coverage is also used to improve the searching of corners and niches and to assist in moving robots out of potential minima. The main characteristic of this method is that the robot, at any stage, can leave/join/rejoin the team. The simulation results show that using more robots at the beginning of exploration leads to more area coverage [61].

3.2.3. The Force Vector Algorithm

The general force vector algorithm was designed for most swarm robotics applications with few requirements to solve area coverage problems. This algorithm works efficiently and gets good results; it is considered an alternative to many complex algorithms for effectively covering an environment. Many simple robots are required for implementation with more capabilities, enabling the algorithm to cover specific areas [62].

3.2.4. Operative Distributed Asynchronous (CORDA) Model

Asynchronous CORDA is the primary computational model in the domain of swarm robots. It has a closer approximation to real-life situations when compared to other algorithms. The algorithms developed using the CORDA model view robots as consisting of four sequential cycles: wait, observe, compute, and move. All the cycles do not overlap. The primary objective of the research is to prove the CORDA model is popular and suitable compared to other available computational models for area coverage problems. Many solutions for area coverage have been discussed comprehensively by using this model. Two situations are applied. The first one is when covering the area without an obstacle; in this case, the robot starts to compute the boundaries of the strip that will be covered by itself depending on its closest horizontal neighbours. In the second case, when covering the area with obstacles, the robots start by being deployed randomly in the area and then collect on the left boundary. The robots divide the space into several blocks and draw the size of the blocks. In the beginning, the robot verifies if the region contains an obstacle (another robot or any object); if it has not found an obstacle, it travels directly to the entry point of the next block for exploration. On the contrary, it begins to paint the present block, a region above the horizontal line passing through its current position [63].

3.2.5. Deployment Entropy with Potential Fields Strategy

Deployment entropy was presented to cover persistent areas, using many sensing swarm robots, which depend on partitioning the area into many regions. Deployment means the uniformity of agents per region across all regions when covering an area. The study showed that a good spread of agents and growing sensor coverage resulted when compared with previous results, which did not use potential fields with deployment entropy. Fifty-agent deployment was used for the simulation. Two redeployments are global, which happens in partition regions, and local, which occurs in subregions. As a result, the robots cluster together more in corners at the end. The attractive and repulsive fields are applied receptively between robots, leading to the greater spread of robots to achieve area coverage. Deployment entropy is suitable because of its scalability and potential for robot system implementation that uses a decentralised control type. The simulation results show that the potential field approach is more effective than the non-potential field approach in generating a uniform group of distributed robots [64].

3.2.6. A Self-Organising Area Coverage Based on Gradient and Grouping (GGC)

A new method depending on gradient and grouping was proposed for area coverage called shortly (GGC), using simple robots without computing or storage space. The rise of a robot led to the system of swarm robots with accessible functions that enable self-organisation to cover the area of the unknown task. In a grouping operation, each group can cover the task area in parallel, improving the coverage speed. The simulation results show superior gradient and grouping methods on the other techniques in coverage concepts, coverage completion time, robustness, and other sides. Simultaneously, this method is beneficial for the system of submillimetre swarm robots, which will be considered basically for micro-medicine [65].

3.2.7. Frontier-Led Swarming Algorithm

A Frontier-Led Swarming algorithm was proposed for the exploration and coverage of the area of unknown environments while controlling a formation that allows for short-range communication. The algorithm includes two components: swarm rules to save a closeknit appearance and frontier search for maintaining exploration and coverage. Three experiments were conducted in various environments, using heterogeneous and homogeneous groups of mobile robots to test the algorithm. The first experiment used real heterogeneous swarm robots, the TurtleBot Burger and Pioneer UGVs, and the second used real robots in an environment containing unknown static obstacles. The third experiment used a simulation in a 2D large-scale urban-like environment with obstacles through a virtual Gazebo. The results demonstrate that the proposed algorithm performs better than the current map coverage approaches [66].

4. Algorithms Analysis

The algorithms and methods discussed in this survey point to using swarm robotics to cover specific areas. These algorithms are either metaheuristic or classical algorithms. Each of these algorithms is adopted and integrated into swarm robots based on the need and the type of problem being solved in an extensive coverage. The successful usage of swarm robots is not solely associated with the algorithm used but with the existing hardware infrastructure. The area environment is an essential factor in achieving coverage; it may be known components or unknown. In unfamiliar territory, they face difficulties handling it due to needing more information about obstacles available and their type (static or dynamic).

Earlier algorithms were based on teams to mimic the swarm behaviours of biological entities. The primary challenge of team-based algorithms was encountering obstacles, and complete synchrony was required for effective communication among team members. Individual coverage is an emerging trend in recent surveys where a robot communicates with the rest of the swarm and updates the area covered. Regardless, there are gaps in adequate area coverage, although the current algorithms are relatively better than earlier algorithms. Another takeaway from this survey is that modern algorithms rely less on computations than earlier algorithms with elaborate mathematical models. Table 1 shows the specifications of each algorithm or method.

Table 1 provides a thorough summary of several metaheuristic algorithms, from those with their origins in swarm intelligence to the classical algorithms used in swarm robotics to cover areas. A wide range of tasks, environments, and applications can be handled by these algorithms. You can learn a lot about the algorithms' strengths and weaknesses, as well as their possible difficulties, from this. Researchers and practitioners interested in the state of area coverage algorithms for swarm robotics will find the table to be an invaluable resource. The ant algorithm, which exemplifies swarm intelligence with its decentralised chemotactic control law, is a renowned example of a metaheuristic algorithm. Incorporating noise to enhance area coverage performance, this algorithm showcases both global and local ideas. However, there are problems with iterative modifications to the probability distribution and uncertainty in the convergence time. The Cellular Automata Ant Memory model with Tabu Search is another notable technique that deals with foraging activities and dynamic applications. While the algorithm's usage of Tabu Search-inspired short-term memory is effective, it has computational hurdles when dealing with robot movement.

Table 1. The specifications of each algorithm or method.

Algorithm or Method	Application	Environment	Environment Complexity	Task	Obstacle	Type	Classification	Strength	Limitations	Ref.	Year
Ant algorithm + decentralised chemotactic control law	Area coverage	Known	Low	Simple	No obstacle	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Global and local concepts are achieved - Adding noise based on the magnitude to control law significantly influences and improves the performance of area coverage - Using noise is an important step to provide abilities to improve many algorithms, such as the Particle Swarm Optimisation (PSO), grey wolf algorithm, or cuckoo search algorithm	- Uncertainty in convergence time - Probability distribution changes by iteration	[21]	2016
A Cellular Automata Ant Memory Model (CAAM) + Tabu Search	Area coverage to perform foraging tasks: - Dynamic applications (changes in terrain) - Travelling salesperson problem	Known	Low	Simple	Static	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Avoid unnecessary explorations by using a short-term memory inspired by Tabu Search - A better distribution for the robot team - Transition rules of C.A. used that provide local control for obstacles, which leads to non-use obstacle avoidance algorithms - Efficient solution	- Sequences of random decisions. - Consuming for computation time through the moving robots	[22]	2017
Ant foraging + adaptive Brownian Levy flight transitions + control law	Area coverage to perform foraging tasks in 2D domain	Known	Mid	Moderate	No obstacle	Stochastic alg.	Metaheuristic alg.–swarm intelligence + classical algorithm (random walk)	- Improve area coverage performance by using this method - Using Levy led to lowering the constraints of communication and sensing of robots - Increase area coverage up to a specific value of threshold by transitions from Brownian motion to Levy flights	- There is no detailed analysis for parameter variations such as pheromone diffusion coefficient, evaporation rates, Levy index, and noise intensity and does not determine which is better	[23]	2017

Table 1. *Cont.*

Algorithm or Method	Application	Environment	Environment Complexity	Task	Obstacle	Type	Classification	Strength	Limitations	Ref.	Year
Genetic Shared Tabu Inverted Ant Cellular Automata (GSTIACA)	Area coverage for surveillance tasks	Known	Mid	Simple	Static	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Provide advanced surrogate techniques for swarm robotic surveillance tasks, especially in science and engineering - Transition rules of C.A. used that provide local control for obstacles, which leads to non-use obstacle avoidance algorithms - GA optimises the control parameters of a robotic - The approach of integrating the various techniques of artificial intelligence with natural computing, which was not used in the previous research	- Not be applied to real robots yet	[24]	2022
- Particle Swarm Optimisation with Inertia Weight - Particle Swarm Optimisation with Constriction Factor - Standard Particle Swarm Optimisation (SPSO)	area coverage for Source-seeking	Unknown	High	Hard	Static and dynamic	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Relatively simple to implement - Few parameters to vary - Fast and inexpensive computations - Robust - Escape from local optimal solutions - Work well without a centralised unit if the robots can reach their positions	- More powerful robots are required for areas with obstacles - Increased the swarm size based on each environment/area	[34]	2015
Robotic Darwinian Particle Swarm Optimization (RDPSO) + Probabilistic Finite Sate Machine (PFSM) + Depth First Search (DFS)	Area coverage through robots' exploration and navigation	Unknown	Mid	Moderate	Static	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- The proposed method proved to have good navigation in optimal time, about a 40% higher success range, with a speed of 1.4× for exploration compared to other methods. - The consumed time decreases when the size of the swarm increases - The swarm of simple robots is faster than that of a single complex robot	- Increasing the size of the hive above a particular level leads to the saturation of the RDPSO algorithm and not obtaining the optimal time and cost for each task	[35]	2017

Table 1. *Cont.*

Algorithm or Method	Application	Environment	Environment Complexity	Task	Obstacle	Type	Classification	Strength	Limitations	Ref.	Year
Robotic Darwinian Particle Swarm Optimisation (RDPSO)	Area coverage for search and rescue	Unknown	High	Moderate	Static	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Reduce the computational cost - Improve the efficiency of navigation - RDPSO permits the robot not to get suboptimal solutions - The ability to determine the positions of multiple targets and collisions - The distribution of the actual target positions does not influence the work of the algorithm	- Increasing the size of the swarm above a particular level leads to the saturation of the RDPSO algorithm and not obtaining the optimal time and cost for each task	[28]	2017
Particle Swarm Optimisation-Based Algorithm	Area coverage and swarm robot coordination	Unknown	High	Moderate	Static	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Increasing area coverage and the ratio of detecting more targets by storing the information for one robot when locating a target and starting a search for another - Produces many flexible fitness functions which can be used in various maps and affect the performance of swarm robots	- The algorithm does not focus on robot aggregation because the objective is to explore the area - The positions of robots not known; a particular function was used which returns these locations (like GPS work)	[36]	2018
Exploration-enhanced RPSO (E2RPSO)	Area coverage to find multiple targets	Unknown	High	Moderate	Static and dynamic	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Avoid falling into local optimums - Comprehensive search area coverage - It is vital in applications of the search for multitarget due to making a good balance between exploration and exploitation	-Does not detect all targets in the search area	[37]	2020
Particle Swarm Optimisation algorithm+ Inverse Perspective Map (IPM) transformation	Area coverage for positioning of soccer robots	Known	Low	Simple	No obstacle	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Implementation simplicity - Reduced computational and memory consumption of its design - Increases speed and decreases size of input information - Eliminate perspective effects - High accuracy in determining the robot location	- The possibility that it might get stuck at local optima, and robots will never be aware that other solutions might exist	[38]	2021

Table 1. *Cont.*

Algorithm or Method	Application	Environment	Environment Complexity	Task	Obstacle	Type	Classification	Strength	Limitations	Ref.	Year
An adaptive exploration robotic PSO (AERPSO)	Area coverage to find multiple targets	Unknown	High	Moderate	Static and dynamic	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Avoids local minima - Detecting all targets in the search area - Explores unexplored regions and helps with obstacle avoidance, using evolutionary speed and aggregation degree - Improves the search time - It balances between exploration and exploitation	- Not be applied to real robots yet	[39]	2022
Bacterial chemotaxis optimisation (B.C.) + Voronoi-based algorithm	- Search for target and trapping within area coverage distributed control for swarm robots in the area	Unknown	High	Hard	Static and dynamic	Stochastic alg. + deterministic	Metaheuristic alg.–swarm intelligence + classical algorithm (motion planning)	- Less vulnerability to a local optimum - Robustness to unexpected failure for a robot - Effectiveness	- Time consumption is based on randomly initialising the population of swarm robots and the target - Does not depend on physical robots to verify the performance	[41]	2015
Bacterial chemotaxis-inspired coordination strategy (BCCS)	Swarm robotic systems for coverage and aggregation	Known	Low	Simple	No obstacle	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Better coverage through preprocessing - Better exploration capability - In most cases, BCCS has fewer iterations and a higher success rate - Distributed system	- Uncertainty in irregular environment	[42]	2021
Honey bee algorithm	Area coverage to perform foraging tasks, robot coordination and surveillance robotics by using a human telepresence robot in the system	Unknown	Low	Simple	No obstacle	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Low computation - Robustness - Scalability - Adaptability - Simple and flexible - Broad applications, even in complex functions - Popular - Ease of implementations - The human operator controlling the telepresence robot speeds up the convergence of the swarm	- New algorithms require new fitness tests - Slow in sequential processing - Large objective function evaluation	[53]	2016

Table 1. *Cont.*

Algorithm or Method	Application	Environment	Environment Complexity	Task	Obstacle	Type	Classification	Strength	Limitations	Ref.	Year
Labour division phenomenon approach for the bee colony algorithm and ant colony algorithm	Complex area coverage of swarm robots (- Coverage monitoring for forest fire - Task allocation for UAV - Detection for nuclear and biochemical disaster - Search and rescue in an area - Searching for anti-terrorism explosives)	Unknown	High	Hard	Static and dynamic	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- High ability to solve area coverage and dynamic environment - The algorithm can respond effectively to the sudden threat - Low computation - Robustness - scalability	- Lack of global communication. Between robots - May not apply to some situations	[54]	2020
Bee search algorithm + local formation-building approach	- Area coverage for cleaning robots - Harvesting - Deactivating the area from radioactive substances - Disinfecting the area from viruses	Unknown	High	Hard	Static and dynamic	Stochastic alg.	Metaheuristic alg.–swarm intelligence	- Global solutions - A high ability to solve area coverage - Scalability - Simple and flexible - Low computation - Robustness - Use for orientation by leading robot and its neighbours	- It requires several strategies to provide controllers for the motion of robots	[55]	2021
A bio-inspired neural network approach	Area coverage by swarm robot	Unknown	High	Simple	Dynamic	Stochastic alg.	Heuristic alg. and bioinspired alg.	- Reducing completion time - Robustness - Fault-tolerant	Not perfectly accurate	[56]	2018
Cohort Intelligence (CI) methodology + perturbation technique	Area coverage for search and rescue by swarm robots	Unknown	High	Hard	Static and dynamic	Stochastic alg.	Nature-inspired Swarm Intelligence	- Robots will not get stuck in the non-convex region by using the perturbation technique	- In some situations, it needs many techniques to support it	[57]	2020

Table 1. *Cont.*

Algorithm or Method	Application	Environment	Environment Complexity	Task	Obstacle	Type	Classification	Strength	Limitations	Ref.	Year
Dynamic Voronoi-based algorithm + modified bacterial foraging optimisation (MBFO)	Area coverage searching problem in decentralised control of sensors of swarm robots	Known	Low	Simple	No obstacle	Deterministic + stochastic alg. (MBFO)	Classical algorithm (motion planning) + metaheuristic alg.–swarm intelligence	- Escape from local optimum - Quick search and saves energy for robots - Robots motion by following the gradient in the target area and the sensor range control on reactions between robots	- Consuming for computation time through the moving robots - Does not depend on physical robots to verify the performance	[60]	2015
Decentralised Space-Based Potential Field (D-SBPF) algorithm	Area coverage for exploration by swarm robots - Motion planning for swarm robot	Unknown	Moderate	Simple	Static	Deterministic	Classical algorithm + (motion planning)	- Simple - Uniform - Decentralised - Disperse the group of robots to perform a quick search, using an effective method - The area was represented by a grid that was either attractive (if unexplored) or repulsive (if discovered), which led to enhancing the searching - The robots can leave/join/rejoin the group at any stage	- Decrease in the efficiency of coverage and speed when a few robots are used - Lower exploration performance for maps with complex geometry	[61]	2015
The force vector algorithm	Area coverage by swarm robot	Known	Low	Simple	No obstacle	Deterministic	Classical algorithm	- Applies well to robot swarms with few requirements. - Effective area coverage - General solution - Simple to implement	- There are some constraints on used robots - It is not reliable like other algorithms - A secondary solution	[62]	2016
The Cooperative Distributed Asynchronous (CORDA) model	Area coverage by swarm robot	Known	Low	Simple	Static/ no obstacle	Deterministic	Classical algorithm	- Famous and suitable compared to other available computational models for area coverage - Reduces system cost - Fault-tolerant	- Robot velocities affect this model under limited visibility - More powerful robots are required for areas with obstacles	[63]	2017
Deployment Entropy with Potential Fields Strategy	Covers persistent areas by swarm robots for surveillance applications	Known	Low	Simple	Static	Deterministic	Classical algorithm	- A good spread of agents - Growing sensor coverage - Scalability - Decentralized system (more security) - More effective at generating a uniform group of distributed robots - Low computational complexity	- Lack of persistence results - The robot knows its position but does not know other robots' positions in the group	[64]	2020

Table 1. *Cont.*

Algorithm or Method	Application	Environment	Environment Complexity	Task	Obstacle	Type	Classification	Strength	Limitations	Ref.	Year
ASelf-Organizing Area Coverage Method + Gradient and Grouping	Area coverage By swarm robot	Unknown	High	Hard	No obstacle	Deterministic	Classical algorithm	- Less completion time for coverage - Low computational cost - Robustness - Its parallel coverage led to speed covering an area - Very useful for the system of submillimetre swarm robots, which will be considered basically for micro-medicine	- The number of teams must be a manageable size - The robot coverage distance must be a reasonable value	[65]	2021
Frontier-Led Swarming algorithm	Area coverage by swarm robot for exploration	Unknown	High	Hard	Static	Deterministic	Classical algorithm	- High performance for area coverage - Re-tuning of parameters of algorithm not needed to move the system to another environment - Covering an area, even if in cluttered environments and including unknown obstacles	- Not able to track changes in the environment (avoiding moving obstacles) - Does not search for optimal parameters of swarm robots	[66]	2022

One notable metaheuristic algorithm with applications in surveillance jobs is the Genetic Shared Tabu Inverted Ant Cellular Automata (GSTIACA). The control settings are optimized using genetic algorithms (GAs), and it incorporates multiple AI approaches. Despite its potential, GSTIACA has not yet been implemented on actual robots, which emphasizes the importance of doing practical validation. Numerous source-seeking applications have made use of the Particle Swarm Optimization (PSO) family, which includes variations such as Inertia Weight PSO and Constriction Factor PSO. Although these algorithms are simple, resilient, and scalable, how well they perform is conditional on the surrounding conditions and the size of the swarm. With the introduction of depth-first search and a probabilistic finite-state machine, Robotic Darwinian Particle Swarm Optimization (RDPSO) demonstrates faster and more efficient navigation in exploratory tasks. Concerns with optimal time and cost arise, however, when swarm sizes are large and RDPSO becomes saturated. An essential tool for multitarget search applications, the Exploration-Enhanced RPSO (E2RPSO) helps avoid local optima by striking a balance between the two. The techniques used here demonstrate the costs and benefits of increasing swarm size in terms of computing efficiency. By way of comparison, one traditional algorithm, D-SBPF, makes use of a grid-based environment representation, attractive and repulsive forces, and decentralized robot dispersion. Despite its simplicity and uniformity, it struggles with complex geometric maps and shows diminishing efficiency and speed with fewer robots. Although the Frontier-Led Swarming algorithm does a great job with exploratory tasks, it cannot monitor environmental changes or tune swarm settings for best performance.

When combined with a Voronoi-based algorithm, Bacterial Chemotaxis Optimization (B.C.) offers benefits such as effectiveness and robustness, particularly in situations that are unknown or constantly changing. Nevertheless, there are worries about the amount of time it takes to initialize a population. The Honey Bee Algorithm has received praise for its scalability, resilience, and minimal computation, which were all influenced by the labour-division phenomenon. Still, there are situations where its sequential processing speed and evaluation of huge objective functions are a hindrance to its performance. All of the methods that were looked at show how swarm robotics has progressed to solve problems with area coverage. The efficiency of algorithms, the integration of hardware, and the practical applications have all seen these developments. The continuous difficulties of scalability, context adaptation, and coordination strategies are well known. Hardware concerns, such as advanced control systems and sensors, improve the capabilities of swarm robots. This is demonstrated by GRITSBot, TurtleBot3, and e-puck 2. Possible directions for further study and improvement are laid out in the table's discussions. Emerging as possible avenues for investigation include adaptive algorithms, dynamic obstacle avoidance, and integration with new technology. According to the editor's remarks, experienced reviewers have stressed the need for a critical literature study, methodical discussions, and considerable improvements despite the progress. To lay the groundwork for future developments in this area, this extensive study of swarm robotics algorithms for area coverage explains their advantages, disadvantages, and possible uses in various sectors.

5. Mobile Robots Hardware Used for Swarm Robotics

The type of hardware used in swarm robots varies based on the coverage needs. The various types of hardware include cameras, controllers, actuators, and sensors [67,68]. Each component in the hardware is used to perform a specific task that assists in the functionality of each robot in the swarm [69]. Sensors are essential in facilitating information or data about the surrounding environment; mapping is called mapping. Swarm robots use sensors to analyse the topography of a domain by detecting key features, like land, roads, paths, and obstacles, among other feasible features [70]. The I.R. Proximity Sensor is the standard type of sensor that detects obstacles in swarm robots [71]. Controllers are essential to the swarm robot hardware [72]. Two approaches are used in controlling swarm robots, which include a centralised and decentralised control system [73]. Centralised control is a situation where a lead robot is responsible for dictating the movement of all robots in the swarm [74].

In contrast, a distributed approach is used where each robot in the swarm plans and dictates its movement [75]. The controllers are fused with communication devices to enhance efficiency in covering a large area. Wireless devices like the Internet, Bluetooth, infrared, and LED lights are examples of communication devices that improve the functionality and movement of swarm robots [76]. The selection and application of each controller or communication device depend on the swarm device's type and function.

Moreover, power is essential hardware in the swarm robot. Ideally, swarm robots are small; hence, ample power is needed to ensure that the device functions appropriately [77]. It is the role of the power supply unit to ensure that there is an optimal supply of power for the swarm robots. Most swarm robots use lithium batteries with a power voltage capacity of between five and twenty-five of direct current [78]. The batteries provide consistent and high-density voltage in small batteries that can be fitted in small swarm robots. They are some of the robot platforms that are developed and used for swarm robotics as follows:

Ref. [79] proposed GRITSBot. It is an inexpensive microrobot used for swarm robotics. It allows the user to manage giant cooperative robots and has features encompassing automatic sensors, autonomous recharging, wireless robot reprogramming, and multiple robots. GRITSBot was presented to decrease various robot testbeds to fit on a table and achieve experiments available to many users. GRITSBot is used for an R-shaped area of coverage in the testbed, using thirteen GRITSBot robots distributed in this shape [80].

Ref. [81] proposed milli-robot-Toronto (mROBerTO) has become more prevalent in recent years, particularly for swarm robotics studies, enabling researchers to perform many experiments through many robots in limited areas. Roberto is a new open-source modular design of millirobot) with a 16×16 mm^2 design, including various sensors such as proximity, IMU, compass, ambient light, and a camera. Roberto is capable of formation control, using an I.R. emitter and detector add-on. It has communication through Bluetooth, ANT+, or both simultaneously. It uses an ARM processor with 256 KB of memory and has the ability to program over the air to handle complex tasks. Roberto robots monitor and explore unknown area coverage via collective behaviour. Also, it is used for robot aggregation in an exciting area [82].

Ref. [83] developed a TurtleBot3 burgers which is the development of TurtleBot2, TurtleBot1, and iRobot's Roomba, respectively. ROS has managed all of these versions (Robot Operating System: a framework for research in robotics). TurtleBot3 is general hardware in a lot of robotics research, as it can solve the shortcomings of old versions. It is a low-cost platform, easily adaptable to particular needs, programmable in MATLAB and Python, and has 360-degree LiDAR (Light Detection and Ranging) sensor. These features make it suitable for motion-planning applications [84]. Also, TurtleBot3 was used to cover a cluttered area that contained unknown obstacles; for example, some experiments used a swarm of TurtleBot Burger to cover different regions [66].

According to [85], e-puck 2 is the hardware extension of the e-puck. E-puck 2 is a Raspberry Pi-suitable platform and has high features used by swarm robotics. It is characterised by more powerful and better-equipped sensors containing WiFi, USB, RGB LED, and a long-distance sensor [86]. E-puck 2 is used for swarm robots in area coverage as an entrapping approach without a communication environment, like a battlefield, depending on the environment information, and the communication made indirectly by the sensors of the camera and laser sensors. Two models were used: GRN (Gene Regulation Network) for entrapping the target pattern and FSM (Finite-State Machine) for moving to the target and, at the same time, avoiding obstacles. Then, these e-puck 2 robots surround the target environment [87]. Many extensions of e-puck, such as Pi-puck, which is an extension for the e-puck and e-puck 2, allow a Raspberry Pi Zero single-board computer to be attached to the robot [88].

Ref. [89] developed Colias IV for studying models of intensive computational embedded, which is a good platform for presenting visuals in algorithms of swarm robotics. It is a micro-ground mobile robot that occupies a diameter of 4 cm. It is characterised by a strong-ARM processor, has a set of various sensors comprising a small camera and two digital microphones, and has massive possibilities for connectivity. This miniature robot can sense and visually detect bio-inspired models. The benefits of this robot are its small size and depressed cost. The developed Robot Colias IV has revealed the potential for more research depending on multi-agent experiments, such as the aggregation behaviours in robot swarms for the coverage of a particular area.

Ref. [90] proposed the WsBot, a tiny swarm robot with little cost used in many domains, especially in smart factories. It introduces characteristics like intelligent agents and industrial teams to perform a global task—the communication method with others for WsBot by Wi-Fi. WsBot can contribute fundamentally to smart factories through area coverage by many swarm robots. These robots have been used in many experiments to enhance manufacturing productivity by using ARENA (platform for small-scale warehouse logistics) to achieve the behaviours of intelligent agents inside it. In addition, it avoids environmental obstacles and improves brilliant manufacturing experiments without using an actual warehouse [91].

According to [92], HeRo 2.0 (Heathkit Educational Robot) is a newer version of the first, simpler version of the HeRo platform. It is a low-cost robot containing a 3D-printed body and off-the-shelf ingredients. This robot is used with swarm robots, according to convenience, for a wide range of applications. It is completely open-source and has various sensors. An Espressif ESP8266 (32-bits160 MHz) microcontroller is used in its main board to accomplish the motors' control and get and process data from the sensor [93]. Robust and reliable communication between robots occurs using built-in Wi-Fi in its microcontroller module. HeRo 2.0 uses a TCP/IP protocol connection to execute the ROS Robot Operating System) with a remote computer. It has two wheels with a maximum speed of 25 cm/s and eight I.R. sensors, which prepare light and proximity metrics for obstacle detection. The modular main board allows the user to include many other components for communication or localisation, like a camera, motors, displays, and transistors. It provides the feature of long-time autonomy for a robot through a powerful Li-Po battery. Many experiments use HeRo 2.0 robots to achieve area coverage tasks by avoiding local collisions with other robots and obstacles. Table 2 shows the specifications of each hardware model.

Table 2. The specifications of each hardware model.

Hardware	Memory	Processer	Communication	Size	Applications	Strength	Limitation	Sensor	Application Environment	Cost	Ref.	Year
GRITSBot	- ESP8266 chip contains an SPI-controlled EEPROM chip - New version has 4 MB (32 MBit) of flash memory	- 8 MHz, - An Atmega 168 chip on the motor board - An Atmega 328 chip on the main board	Wi-Fi 802.11 bn + R.F. transceiver	3 cm^2	- Coverage control. - Vehicle routing - Exploration - Swarm robotics	- Low cost - Has a differential drive microrobot designed to work on the testbed table - There needs to be more effort in the maintenance of automatic sensor calibration - Recharging autonomously - Detect the positioning via a webcam - Wireless - Open-source	The low-power R.F. transceiver equipped with Wi-Fi led to a lower data rate, which is limited to 2 Mbit/s	- I.R. sensors (distance and bearing) - Accelerometer and gyroscope (velocity and position) - Battery voltage sensor - Light	Unknown	Low	[79,80]	20152016
Roberto	- 32 KB RAM - 256 KB flash	- 16 MHz ARM cortex 32-bit	Bluetooth + Smart ANT+	1.6 cm^2	- Area coverage urban search and rescue - Surveillance - Micro-assembly - Wireless sensor networks (WSNs) - Medicine - Swarm robotics	- Ability to perform complex tasks - Simplified design - Easy maintenance - Different topologies of the network can be used - Following a particular path through a camera in real time - Open-source	The low-power I.R. used is simple in implementation but causes the slow transfer of data and specific range	- Light - Range - Gyro - Camera - Accelerometer - Compass - Distance - Bearing	Known	Low	[81,82]	20162017
TurtleBot3 burger	2/4/8 GB	32-bit ARM cortex	Wi-Fi	138 mm $\times$ 178 mm $\times$ 192 mm	- Area coverage - Motion planning - SLAM (Simultaneous Localisation and Mapping) - Navigation - Manipulation - Search and rescue - Swarm robotics	- Small - Low-cost - Reliable - Programmable - Most popular - Strong sensor - Open-source - Two-wheel differential-drive uncrewed ground vehicle (UGV)	- Measuring speed with the robot gets worse when the distance of the robot increases (use GPS to solve this problem) - The capabilities of sensors are limited in navigation (the on-board stereo camera is used to improve quality)	- LiDAR sensor. - Sensors for navigation (3-axis gyroscope, accelerometer, and magnetometer) - Touch sensor - Distance sensor - Ultrasonics sensor - Humidity and temperature sensor - Colour sensor - Magnetic sensor - Illumination sensor	Unknown	Low	[66,83,84]	201720212022

Table 2. *Cont.*

Hardware	Memory	Processer	Communication	Size	Applications	Strength	Limitation	Sensor	Application Environment	Cost	Ref.	Year
E-puck 2	RAM: 192 KB 1024 KB flash memory	32-bit STM32F407 @ 168 MHz (210 DMIPS), DSP and FPU, DMA	- USB Full-speed, Bluetooth 2.0, - WiFi	7.5 cm^2	- Area coverage - Mapping - Exploration - Signal processing - Automatic control - Distributed intelligent systems. - Position estimation and path finding of a mobile robot - Swarm robotics	- It is a popular choice for swarm robotics due to its size and commercial availability - Powerful controller - Flexibility - Open-source	- To avoid damage, epuck2 robot must be handled with precaution because it is fragile - Decrease in battery charge and high temperature affect its performance	- 8 infrared sensors (up to 2 m) - 3D accelerometer - 3D gyro - 3D magnetometer - VGA colour camera (160 × 120) - 4 red LEDs and 4 RGB LEDs - 4 microphones	Unknown	Low	[85,88]	20182021
Colias IV	256K	32-bit ARM Cortex M4 Atmel 8-bit	Bluetooth	4 cm^2	- Area coverage - Neural networks - Image processing - Visual tasks - Swarm robotics	- Strong ARM processor - Microrobot can realise bio-inspired visual detecting models such as LGMD1 and - Other related neural models on board in real time - Enormous capabilities regarding connectivity - Open-source	- In behaviours of aggregation in swarm robots, it is difficult to coordinate between robots and achieve communication without global synchronisation (it can be solved using R.F. or optical approaches).	- Distance - Bump, - Light - Range - Bearing - Tiny camera - 2 digital microphones	Unknown	Low	[89]	2018
WsBot	4 MB flash memory	32-bits 160 MHz Espressif ESP8266	Wi-Fi	3 cm^2	- Designed mainly for, but not restricted to, the testing - In smart factories (The WsBot executes the forklift actions) - In small-scale real warehouse experimentations	- Tiny differential Robot and ROS-based - Because of these features, is used in many research studies - The robot is compact - Low cost - Quick to assemble - Low complexity - Easy to program	The small size and not containing any sensors by using low-power computing units lead to not having high computing power	No built-in sensor	Known		[90,91]	2019

Table 2. *Cont.*

Hardware	Memory	Processer	Communication	Size	Applications	Strength	Limitation	Sensor	Application Environment	Cost	Ref.	Year
HeRo 2.0:	Tensilica LX106 32-bit @ 80/160 MH 4 MB	Espressif ESP8266 (32-bit 160 MHz) microcontroller	- Wi-Fi 802.11 Bgn - Bluetooth	6.7 cm^2	- Mapping - Decentralised coverage - Flocking behaviour and transportation tasks performed with a group of HeRo robots validate the robot's capacities for real-world swarm applications and educational use	- Scalable - Sensing and networking capabilities - Sensor accuracy - Easy to assemble using off-the-shelf components - Deeply integrated with the most-used robotic framework available today: ROS (Robot Operating System) - The automated platform is entirely open - Composed of a 3D-printed body - Open-source - Superior to other commercial models	Difficulty with the following: - Reproduction/assembly: It needs manual modification or finishing through assembly, requiring time and effort. This procedure is essential for the Robot's transmission mechanisms, affecting wheel motion and encoder readings if left unattended. - Robot calibration: The performance of the robot is affected by its low-cost components. This leads to the user calibrating the I.R. sensors and motors occasionally. - Wireless recharge: Manual recharge for robots by plugging in a cable rather than wireless because of the high wireless cost compared with a cheap robot. – Mechanical wear: Using low-cost components affects the durability. This leads to the replacement of some of the material after some time.	- Distance - Light - Encoder - IMU	Known	High	[92]	2022

6. Applications for Swarm Robotics to Perform Area Coverage Tasks

There is a comprehensive application of swarm robots due to the increased reliability in adopting new technology in research and analysis over large open spaces and terrains to achieve area coverage. Swarm robots are increasingly used in various fields, such as the military, archaeology, and oil sectors. Today, geologists can visually represent the earth's surface using three-dimensional imaging, using swarm robots. The result is the reduced cost of operations because it can take several hours to map a large area, which initially requires several days or weeks. In the military sector, the swarm application is used in intelligence collection. The military deploys a swarm of UAVs in various parts of the world to conduct reconnaissance simultaneously. Such capability provides the military with updated data and information that enhances readiness and the ability to respond to threats [94]. In the oil sector, swarm robots estimate the level and depth of oil spillage. Initially, it would take two-to-three weeks for oil companies to assess the scope of damage when oil spilt in the open seas. Today, oil companies are deploying swarm drones to assess damage from oil spills and suitable effective methods to be used to control the damage. Overall, there is continuous development and research in swarm robots that seek to enhance the integration and application of robots to enhance the quality of life [95].

There are many applications of swarm robotics for area coverage:

According to [96], the low-cost robots were applied for sustainable broad-acre agriculture to increase production and decrease the environmental impact. These robots were controlled and run by a centralised laptop. The project focuses on using robotics to deal with resistant weeds, a critical problem for Australian farmers. The used robots have low-cost cameras and positioning sensors to achieve a large-scale area coverage task while avoiding other robots and obstacles. Experimental results were obtained from one real Robot and 12 simulated robots cooperating and having a 3G mobile data connection for 2 h on a 55-hectare field in Emerald, Australia. Through implementation, the real robot "sprayed" 6 hectares, missing 2.6% and overlapping 9.7% within its assigned field partition, and successfully avoided three obstacles.

Ref. [34] claims that five robots with an XBee module presented the problem of seeking electromagnetic sources by area coverage by implementing many modified PSO algorithms on mobile robots according to the physical constraints presented by both robots and the environment. The area covered is 5×5 m^2, and applying the Vicon tracking system gives the information of the robot's precise position with the support of an indoor GPS system used to recognise markers on the robots. The type of robots used with an XBee module in experiments improved from the Parallax Shield-Bot, which Arduino controls. These robots search for the target source, a module of XBee hanging above a floor at a height of 20 cm in the middle of the area to avoid the probability of collision with the robot. Also, the avoidance strategies for static and dynamic obstacles occurred in PSO in this experiment.

In the investigation of [97], many swarm robotics were used to achieve area coverage in a known environment by applying a new proposed cooperative strategy for spraying in a large field while using the local information of robots. Spraying is distributing Plant Protection Products (PPPs) on the crop at various stages in the cultivation process. To cover an area divided by the proposed strategy into regions, there must be a guarantee that each area will be visited only once by the robot. In the simulation experiment, 50-to-250 tracks exist in the field; the distance between the two ways is 20 cm, and the track length is 20 m. The dimensions of the robot used are 50 cm, and all robots have the same velocity of 0.5 (m/s).

Ref. [80] examined that many swarm robots formulated a letter of R by using GRITSBot robots executed on Robotarium (remote access to multi-robot testbed). Robots were used for an R-shaped area coverage of the testbed, using thirteen GRITSBot robots distributed in this shape.

According to [98], ten real robot-type e-pucks were used to create a collective map of the environment. The map quality is based on the individual behaviour of the swarm during the exploration. The mapping approach was used for the environment by a random walk. At first, each robot maps the background and then merges its map with another robot's map into a single global one. Many types of random walks were used, and their map quality was compared to that of swarm robots. The results from one of the types of random walk methods, the ballistic motion, are better for mapping in a closed environment called an arena (walls of 0.94 m in length surround the area of 2.30 m^2). The arena's atmosphere comprises five obstacles of rectangular 0.02 m^2 or no barriers.

Ref. [99] claims that the system of swarm robots was implemented for painting on the Robotarium (remotely accessible for swarm robotics testbed). The experiments illustrated that painting resources influence the resulting image. Swarm robots used nine pieces of experimental paint equipment. The proposed painting system demonstrated the motion trails of 12 robots over the canvas with an overhead projector. A human user can affect the painting output by determining the desired colour densities on a canvas area for different colour tones: cyan, blue, pink, orange, and yellow. Swarm robots work simultaneously and are distributed in a place to cover a 2.4×2 m^2 canvas and complete six functions for the density of colours for 300 s. In the end, the integration of the colours presents a result close to the density specification of the user.

According to [100], cleaning an industrial environment by using a multi-robotic dirt-cleaning algorithm requires a team of many iRobots. The experiment was performed for two iRobots on cardboard boxes as an environment. The iRobot encompasses a Hokuyo laser scanner to scan the environment and change the laser data into a two-dimensional map and a sensor of a piezoelectric that creates electrical pulses when it hits the dirt and gives a reading of dirt measurement. At first, the environment is divided into square cells, using the Grid Divide Algorithm and randomly deployed play sand as 10 g for each cycle. Then, the A* Path Planning Algorithm is used to locate the optimal cleaning path for each iRobot. These algorithms permit the robots to clean professionally, using rising vacuum motor power in an area with high dirt. The obstacles were static in this work. The results demonstrate that cleaning is enhanced by a swarm of robots rather than a single one in regard to the time consumed and battery usage.

The problem of non-convex area coverage by distributing many mobile robots in the area with obstacles was addressed. Each robot was supported by an omnidirectional range of sensors of a standard radius. The swarm robots are required to move to particular locations [101]. As a result, better algorithms for robot distribution were derived for the problem of area coverage and homing. Six mobile robots, AmigoBot, and a visibility-based approach with the aggregate objective function were used. The exact position and orientation were given to robots in the beginning. Due to the non-convexity of the entire region of 8.7 m^2, it is impossible to cover it. Consequently, the swarm reached a local maximum where the allocated region was 5.4 m^2, approximately 62.14% of the total area in 40 s.

The management system of swarm robots in hospitals has been proposed to decrease the risk to doctors and medical staff, especially during the COVID-19 pandemic. Swarm robots are assigned many tasks to manage biomedical waste and floor cleaning simultaneously. Initially, the transmitter sends a signal to the bots to transfer to the area of interest via an indoor positioning system. The robots cover an area for cleaning, and the bots have an automatic disinfecting box to perform disinfection operations and aggregate the bio-waste. Each bot has a system of cleaning attached to it to achieve the task of cleaning [102].

First, we present the handling of area coverage problems to find targets by swarm robots. When the robot finds the target, it must connect to the base station via wireless communication through intermediate transfer robots. Real swarm crawler robots and the Lévy flight strategy were exploited to find the target in large environments. The experiments were performed in the building's corridor at Setsunan University. Besides this corridor, there are several classrooms. Therefore, the walls surround the experiment's environment (the rooms' doors were kept closed in the investigation). The target is an infrared-emitting ball, and the base station is a laptop [103]. The results refer to this approach being significant in the indoor environment to detect the marks with a 100% success rate.

Table 3 provides a thorough synopsis of swarm robotics' many uses, down to the necessary algorithms, facets of coordination, centralization of the system, obstacles to be considered, hardware platforms, simulation environments, strengths, limits, and environmental settings. A multi-robot planner with poor coordination and no centralization, employing tiny, inexpensive cooperative robots, is the application's focus within the framework of sustainable broad-acre farming. In spite of the system's scalability and resilience, it cannot fix issues when robots fail because the environment is unpredictable [96]. Particle Swarm Optimization variations, when applied to small robots built from Parallax Shield-Bot hardware, show great coordination without centralization, making them ideal for source-seeking applications. While the method has limits due to physical constraints given by robots and the environment in a defined setting, its merits lie in the quick and affordable calculations and the fact that it escapes local optimal solutions.

Swarm robots rely on a network of interconnected robots to complete activities like spraying vast fields without the need for a single leader or controller. The method relies on local data for decision-making and has shown effective in the actual world with little computing demands [97]. Using GRITSBot robots in a familiar setting, R-shaped aggregation tasks use a cooperative technique with moderate coordination and centralization. Despite some restrictions on its use, the system has gained praise for its affordability, security, adaptability, collision avoidance, and fault tolerance [80]. Whether in a familiar or unfamiliar setting, e-puck hardware may implement a random walk algorithm with strong centralization and coordination for mapping and exploration tasks. When it comes to open surroundings or real robot tests, the system falls short, but it does a great job at mapping closed regions [98].

Using a Voronoi algorithm and a robotic system with strong centralization and coordination, a group of mobile robots works in a familiar area to distribute tasks such as painting. Although user-driven painting is unique, it has limits due to painting resource constraints that impact the final artwork [99]. Using iRobot gear in an unfamiliar setting and cleaning industrial areas through multi-robotic algorithms demonstrate poor coordination and centralization. As opposed to a single robot, the system is more efficient in cleaning, but it cannot handle obstacles that change position without rerouting [100]. Applying a visibility-based strategy with strong coordination and minimal centralization, executed on AmigoBot hardware in a known environment, solves non-convex area coverage challenges. While the algorithm performs well when trained on local information, it has difficulty when applied to large regions [101].

Table 3. The specifications of each application.

Application	Algorithm	Application Domain	Coordination between Robots	Centralised System	Obstacle	Hardware	Simulation Platform/Controller	Strength	Limitation	Environment	Ref.	Year
Area coverage by swarm robots for sustainable broad-acre agriculture	The multi-robot planner	Task allocation and coordination	Weak	Y	Static	Small, low-cost cooperative robots (*Gator T.E.* (vehicle)	/	- Robustness - Scalability - Minimising the overlapping of areas - Increasing broad-acre agricultural productivity by low-cost robots	Does not adaptive to the problem if one robot failure	Unknown	[96]	2015
Area coverage for source seeking	- Particle Swarm Optimisation with Inertia Weight - Particle Swarm Optimisation with Constriction Factor - Standard Particle Swarm Optimisation (SPSO)	Exploration	Strong	Y	Static and dynamic	Small robots modified from the Parallax Shield-Bot	Arduino	- The best and most convenient diversity of PSO is inertia weight PSO - Fast and inexpensive computations - Escape from local optimal solutions	- Physical constraints presented by both robots and the environment	Known	[34]	2015
Area coverage for spraying a large field	Cooperative strategy by swarm robot	Task allocation and coordination	Strong	N	No obstacle	Many robots on a team	/	- Depends on their local information to produce a decision - Real robots can be applied successfully - Few computational needs	- All robots are working and participating at once - The distance between locations of two consecutive checkpoints must not exceed more than the discovery range of robots	Known	[97]	2016
Area coverage of the testbed in an R-shape	Cooperative strategy by swarm robot	Aggregation	Moderate	Y	No obstacle	GRITSBot robots	Robotarium	- Low-cost - Safe - Flexible - Collision-avoidant - Fault-tolerant	Not applicable to some situations	Known	[80]	2016
Area coverage to perform a collective map of the environment	Random walk algorithm (Brownian motion and Levy walk	Exploration And Mapping	Strong	Y	Static	e-puck	Arena	- Better for mapping in closed environments	- Not applicable in open environments - Not applicable in many actual robot experiments	Unknown	[98]	2019
Area coverage for drawing a painting	A robotic painting system + Voronoi method	Task allocation	Strong	Y	No obstacle	Team of mobile robots	Robotarium	- The novelty of this method is represented by an external factor through the user (artist) affects the robot's motion to paint specific colours - The end integration of the colours presents a result close to the user's density specification	- Painting resources are limited, and this influences the resulting painting	known	[99]	2019

Table 3. *Cont.*

Application	Algorithm	Application Domain	Coordination between Robots	Centralised System	Obstacle	Hardware	Simulation Platform/Controller	Strength	Limitation	Environment	Ref.	Year
Cleaning industrial environment	Multi-robotic dirt-cleaning algorithm+ Grid Divide Algorithm + A* Path-Planning Algorithm	Task allocation	Weak	Y	Static	iRobot	/	- Cleaning is enhanced by a swarm of robots rather than a single one, in both time-consuming and battery usage	-Does not handle the case of dynamic obstacles and replanning for path	Un known	[100]	2020
Solving the non-convex area coverage problem	Visibility-based approach	Exploration	Strong	N	Static and dynamic	AmigoBot	/	- Determines the optimal direction motion for each robot, which influences efficiently solving the homing problem - Requires only local knowledge	- Does not work well for vast areas	Known	[101]	2021
The management system of swarm robots in hospitals to decrease the risk to the doctors and medical staff, especially during the period of the COVID-19 pandemic	Management system by swarm robots	Exploration and task allocation	Weak	Y	Static and dynamic	Mobile bot		- Decreases the risk to the doctors and medical staff, especially during the period of the COVID-19 pandemic	- To perform extra functions, one must attach more equipment, such as an arm-like structure for medicine delivery	Unknown	[102]	2021
Area coverage problems to find targets	Lévy flight strategy	Exploration and task allocation	Moderate	Y	Static and dynamic	Swarm crawler robots	Arduino	- Detecting the targets with a 100% success rate is significant indoors	Not exact/accurate results for the position of targets	Unknown	[103]	2022

Using mobile bot hardware, the application explores weak coordination and centralization in static and dynamic environments, with a focus on swarm robot management systems in hospitals during the COVID-19 pandemic. Though it may necessitate more hardware for enhanced capabilities, the system effectively reduces dangers to medical personnel. Last but not least, swarm crawler robots operating in an unfamiliar setting face challenges with area coverage while trying to locate objects using a Lévy flying approach that combines modest centralization and coordination. When it comes to indoor target detection, the algorithm really shines, but when it comes to pinpoint accuracy for target positions, it really struggles [103].

7. Discussion

The variety of algorithmic approaches used in swarm robots for area coverage is highlighted in the publications that were surveyed, demonstrating how adaptable these systems are. The varied tactics are illustrated by three well-known methods: Ant Colony Optimization (ACO), Honey Bee Optimization (MBO), and Particle Swarm Optimization (PSO). The versatility of swarm robotics in tackling multiple problem areas is exemplified by this variation, which also displays the inventiveness of researchers.

The articles that were surveyed differ significantly in their approach to exploration, task allocation, or hybrid systems that combine the two. Some research emphasizes methods for allocating and coordinating tasks, while others centre on the discovery of previously uncharted settings. A good example of the complex decision-making required for algorithm selection is the fact that the choice is frequently conditional on whether the area coverage problem has static or dynamic obstacles.

The reliability of data sources is highly related to how well swarm robots perform in area coverage tasks. For robots to understand and move around in their environments, sensing technologies like GPS, infrared cameras, and light detection and ranging (LiDAR) are crucial. It turns out that the swarm's adaptability and coverage of a specific area are heavily impacted by the sensing technology that is chosen.

The papers that were analysed cover a wide range of practical fields, such as healthcare, exploration, mapping, and agriculture, among others. Because every application model has its own specific needs and difficulties, it is clear that we need tailored algorithms and coordination strategies. The effectiveness and versatility of swarm robotics systems can be greatly improved by adapting them to different industries and environments.

The development of swarm robotics for the coverage of large areas can be shown by looking at the research that was surveyed over time. More efficient algorithms, better hardware integration, and more useful applications are all the results of recent developments. The maturation and greater popularity of swarm robots over the years have made it a generally accepted solution for complicated area coverage challenges.

There have been some successes, but there are still some obstacles in the field of swarm robots. Recurring limitations brought up by the papers under consideration include scalability, adaptability to new situations, and the creation of strong coordination mechanisms. In order to direct future research toward resolving these constraints, it is critical to acknowledge these obstacles.

The publications that were surveyed highlight the significance of hardware in swarm robots. Improved capabilities are displayed by robots like GRITSBot, TurtleBot3, and e-puck 2 that have complex control systems, high-tech sensors, and strong networking capabilities. When the swarm's gear is well-integrated, it increases their efficiency and lets them cover more area.

By highlighting open topics in the field, the survey points the way toward potential future research and development directions. Possible future research avenues include adaptive algorithms, swarm robotics integration with new technology, and dynamic obstacle avoidance. Swarm robotics applications can be improved, and the industry can advance if these knowledge gaps are filled.

Final observations on algorithmic diversity, methodological considerations, sensing technology influence, application-specific challenges, evolution over time, persistent obstacles, hardware's role, and possible future research directions are presented in the detailed discussion. All of these findings add up to a full picture of where swarm robots for area coverage stand right now.

8. Conclusions

There is increasing usage of swarm robots in various fields and occupations. The evolution of technology in the twenty-first century has played a significant role in enabling the large-scale application of swarm robots, especially for solving area coverage problems. The algorithms used in this survey, either metaheuristic or classical, refer to using a swarm of robots in specific areas to achieve certain goals. The technology used in swarm robots relies on the development of numerous naturally inspired algorithms, like Particle Swarm Optimisation (PSO), Honey Bee Optimization (MBO), and Ant Colony Optimisation (ACO), which are the most used and suitable for robotics in this domain, and many metaheuristic swarm intelligence algorithms. These algorithms and methods are utilised according to the type of problem and the requirements of the environment, which are either known or unknown and may contain obstacles, which constitute the most complex problem, or be free of obstructions. Individual coverage is an emerging trend in recent surveys, as each bot interacts with the rest of the swarm team to achieve the goal by covering the area. Relatively better algorithms than the previous ones were used. However, there still needs to be more coverage of the concerned area. From this survey, we conclude that modern algorithms are less dependent on calculations than the previous algorithms containing elaborate mathematical models. Such algorithms are combined with a wide variety of hardware, like sensors, cameras, communication, and controlling devices, to enhance the functionality of swarm robots. Combining algorithms and hardware expands the range of applications and usage of swarm robots in numerous areas, like defence, medicine, geology, and business.

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