Journal of Mechatronics Engineering

Recent Advances in Swarm Mobile Robotics

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DOI: 10.21439/jme.v7i1.114

Received: April 21st, 2024. **Accepted:** November 26th, 2024

Abstract. This paper is a critical analysis of the recent advances in the field of swarm mobile robotics. The aim of this article is to analyze the latest developments and technologies applied in this field. The Science Direct and IEEEXplore databases were searched for articles published between 2014 and 2020. The selected articles, which refer to swarm robotics, were individually analyzed to identify their objectives, methodologies, and results. A statistical analysis of the keywords was performed to determine the most effective terms for searching these articles, which is further discussed in the paper. Although this analysis highlights the main areas of advancement, it also reveals challenges such as the non-standardization of simulation tools and the lack of public databases for certain types of applications. Nevertheless, the studies show significant potential for applications in real environments. Based on this analysis, several techniques, tools, and key findings from recent swarm robotics studies are presented.

Keywords: Swarm Robotics, Swarm Robots, Simulation Tools, Recent Advances.

1 Introduction

Robotics Swarm is a new method for coordinating multi-robot organizations. According to Marcolino et al. (2017), swarm formations are composed of the grouping of several relatively simple robots arranged in the same environment to mutually execute a common goal. The idea of using a system composed of multiple simpler components, instead of a very complex, costly, and cumbersome system, has sparked particular interest in robotics. This is how swarm robotics emerged (SECKIN; KARPUZ; ÖZEK, 2018). For Shenoy and Anupama (2018), the robotic swarm is an emerging research specialty that incorporates the major advantages of distributed computing, such as defect flexibility and scalability in the field of robotics. The parallelism provided in swarm behavior allows a large number of robots to accomplish a given task faster compared to a single robot due to parallel tasks being performed.m robotics systems encompass simpler, more decentralized, cooperative, self-organized robots that use local relationships among themselves to produce varied behaviors that are beyond the capabilities of individual robots.

Liu and Passino (2000) define robotic swarm as a collective intelligence that comes from a group of simple autonomous causers, where each is a subsystem that relates to its own environment that eventually is formed by other agents. Thereby, the solutions of desired tasks emerge from the interaction of the swarm between themselves and their interaction with the environment. However, the autonomous agent does not obey orders of a leader or some collective plan (LIU; PASSINO, 2000). Yie, Solihin and Kit (2017) and Maitra, Prasath and Padhi (2016) have similar concepts of behavior, wherein the best action in swarm robot is an aid activity between each other instead of individual work to accomplish a task. The swarm agents appears in the image by replacing humans by risking life jobs due to their concept of decentralization as a damaged unit does not affect the full performance of the system (MAITRA; PRASATH; PADHI, 2016).

Husni et al. (2017) and Seçkin, Karpuz and Özek (2018) introduce the concept of performing various tasks by swarms according to the application. These tasks can be classified as: aggregation, flocking, foraging, object clustering, navigation, path formation, collaborative manipulation and task allocation problems. The parallelism provided in swarm behavior allows a large number of robots to accomplish a given task faster compared to a single robot due to parallel tasks being performed.

Cuevas et al. (2013) mention that the main components of swarm intelligence are the self-organization and task division. Therefore, the each robot's individual response to the stimulus of the environment wherein they may act together to complete the task. The task separation avoids centralized supervision, thus the whole system adapts to internal and external changes (CUEVAS et al., 2013). A centralized model is useful and easy for implementations, such as (HIGUERA; DUDEK, 2013; JOSE; PRATIHAR, 2016). However, a decentralized approach makes the system robust, quick, simple and efficient, for exploration (LIU; LYONS, 2015), track trajectories (SABATTINI et al., 2015), communication (KUO; FITCH, 2014) and so on.

This approach appeared in the field of artificial intelligence, and also in biological studies about insects, ants and other populations that have a swarm behavior. Scholars from various fields studied the behavior of insects and animals, entomologists have studied them with the aim of modeling biological clusters and engineers employed the swarming behavior to solve problems with a high degree of complexity in the real world (CUEVAS et al., 2013).

Swarm robotics is a way to solve problems based on the collective behavior of animals and is focused on the relationship between the various robots, seeking to behaviors that reproduce the use of the human brain (AZNAR; PUJOL; RIZO, 2017). For Ben-Ari and Mondada (2018), swarm robotics is a robotic approach that attempts to manage group performance by repeating mechanisms inspired by the performance of animals. These mechanisms, often local and simple, allow the robots now grouped to achieve an overall goal that could not be achieved by only one robot.

Just as in nature, in swarm robotics there are partially simple control mechanisms that make distributed system's executable. That robots are based on the representation of insects, and emphasize particularities such as decentralized control, communication among members, local information and robustness. According to Aznar, Pujol and Rizo (2017), in general, robots behave like small insects, meaning they do not have many skills individually, but when combined into large groups, they provide surprising results. It has several purposes, including: rescuing people from natural disasters, replacing human workers in hazardous environments, and exploring unknown or dangerous environments, among others. The robotic swarm is also used to simulate minimum parameters of biological character, thus allowing the understanding of some biological phenomena, such as the collective behavior of bacterial systems.

Biomimicry is a general description for designing a process or system that mimics biology. Several systems of multiple mobile robots have been developed with the aim of imitating the real world with the prospect of performing functions such as collaboration and competition. In the natural world, animals that have the simple biological function, are able to attain high intelligence through the swarming (OTSUKA et al., 2015), (SALOMONS; KAPELLMANN-ZAFRA; GROSS, 2016).

The relevance to study multi-robot systems come from the unique advantages found concerning robots such as: parallelism, scalability, stability, economy and energy efficiency. There are other important features that make swarm robotics different from other multi robot systems such as: autonomy, homogeneity and cooperation. That system involves physical flexibility, overall system robustness, and greater reliability and efficiency using a group of autonomous robots to perform collective tasks (JEONG; LEE, 2016). The achieving collective performance of individual robots with detection, processing, and communication limitations still face a number of technical challenges, such as difficulties in establishing reliable communication and control among robots.

Due to the accelerated development of swarms robotic technology in which diverse applications are emerging, the timing is adequate to examine and study the safety of robotic robotic systems. Higgins, Tomlinson and Martin (2009) conduct a study to identify the major security adversities in the swarm robotic environment that are not found in other technologies in order to implement the technique in a reliable and detailed manner in terms of safety, even in adverse environments. Among the main security services are confidentiality, integrity, identification, authentication and finally availability. These activities, in military applications, monitoring, disaster relief, healthcare and commercial applications, allow the maintenance of the authenticity of information, preventing it from being altered by an unauthorized entity, or accidentally lost (HIGGINS; TOMLINSON; MARTIN, 2009).

Han et al. (2020) aimed to locate images captured using a UAV through resource extraction and classification techniques. The results indicated a processing time of less than 12 seconds, which could be significantly improved by using UAV swarms instead of a single UAV, especially for real-time data acquisition, due to their flexibility, efficiency, and reliability in performing tasks. Moreover, algorithms such as virtual pheromone and cardinality, which are discussed by Hoff et al. (2010), could be added to improve localization.

The Particle Swarm Optimization (PSO) algorithm shows simple operation, easy implementation, and high efficiency for function optimization (GAO, 2018). Sodhro et al. (2019) propose a Fuzzy-enabled quality of experience optimization platform during media communication in Internet of Vehicle (IoV) System. To improve communication between convergence and interoperability for the IoMT, the PSO-based algorithm could be implemented as an earlier stage of the monitoring forms for a satisfactory solution and thereby improve communication. Therefore, communication and spatial organization problems, such as those presented by Khanna et al. (2019), can be improved or solved through the optimization of particle swarms.

In Melo et al. (2019), navigation by the airboat used to measure water quality is a method for executing the Quaternion Ship Domains (QSD) model. This model is used to resolve decisions to avoid collisions (LIU; SHI; LI, 2018). The main advantage of using the QSD is that it can be applied not only in systems with navigation in extensive waters but also in situations where the waters are restricted.

The work by Santos et al. (2020) highlights the importance of diagnostic tests in assisting treatment decisions that will be administered to the patient. The authors discuss the concept of robotic swarms as a useful tool for transforming cardiac healthcare technologies through online monitoring, such as an algorithm based on a structural sensor network capable of predicting sensor failures (KRAUSE; HUSSEIN; BECKER, 2015) through the control of relevant information from the sensors in a multivariate statistical process.

Swarm Optimised Block Architecture Ensembles (SOBAE) is a method for deep CNN Convolutional Neural Networks (CNN) modeling with a central weighing repository to avoid unnecessary work, such as duplications that cause increased computational cost (Fielding; Lawrence; Zhang, 2019). CNN combined with SOBAE is an optimization tool for the location of the mobile robot proposed in (SILVA et al., 2020; DOURADO et al., 2019).

Several anomaly detections are effectively resolved using data mining techniques, such as the Artificial Neural Network (ANN). The applications for performing smoke detection in cloudy environments, as presented by Khan et al. (2019) and Muhammad et al. (2020), deal with noise inherent in the images, and the complexity increases as the dimensions of the data grow. A solution to this problem is the Self-Organizing Map (SOM), which reduces the information while preserving the topological relationships of the data elements in the 2D plane (SHAHREZA et al., 2011).

Robotics system acting with a swarm intelligence algorithm and Genetic Algorithm (GA) are more adaptive to solve problems which are multi-variable, nonlinear and non-convex (Wang et al., 2019). Therefore, the problems such as real-time face detection (Mehmood et al., 2019), data analysis in integration with the Industrial Internet of Things (IIoT) (HUSSAIN et al., 2020) and communication for industrial applications using IoT devices (SODHRO; PIRBHULAL; ALBUQUERQUE, 2019), digital signal monitoring system (XU et al., 2020), pattern recognition (SOUZA et al., 2019) are features for time optimization and data processing, in addition to reducing computational effort based on the swarm architecture.

This paper provides a critical analysis of recent advances in the field of swarm robotics, focusing on its tools, techniques, and applications. By reviewing articles published between 2014 and 2020, the paper highlights the methodologies, outcomes, and challenges faced in swarm robotics research. The goal is to offer an understanding of the current state of the field and provide essential insights for researchers interested in the future directions of swarm robotics. Additionally, a statistical analysis of keywords is conducted to identify the most effective search terms for locating relevant literature in this rapidly evolving area.

This paper is structured in 6 sections: Initially this introductory section followed by Section 2 which brings details concerning the database and research methods being applied, as well as the measure group developed during the systematic review proposed. Section 3 is dedicated to the principal theoretical concepts needed for the correct interpretation of this study. Section 4 analyzes the results from selected articles, and the most commonly used keywords. Section 5 is the discussion section, where we analyze the progress that has been made and we identify the challenges still to be overcome and the future perspectives in this area. And finally, in Section 6, the conclusion summarizes the results obtained in this study.

2 Methodology

The methodology adopted in this review is a systematic, six-step approach based on Valente et al. (2016): (1) development of research terms relevant to the ScienceDirect and IEEEXplore databases; (2) search; (3) removal of duplicate articles; (4) careful analysis and portfolio selection; (5) synthesis of keywords to optimize research terms in future studies; (6) evaluation of techniques used.

To realize the research in the databases were used this logical expression:

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(("swarm" OR "swarms")
AND ("robot" OR "robotic")
AND ("algorithm")
AND ("distributed"))
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Those logical expressions were adapted to the syntax for the Science Direct and IEEEXplore search engines, according to the rules described for each database and the search is filtered for articles published from 2014 to 2020. After identification and removal of the repeated articles, a total of fifty-eight papers were obtained; twenty-five from IEEEXplore and thirty-three from Science Direct.

In the analysis and classification phase, the items were individually verified and classified according to their main function: the task allocation algorithm, formation control, trajectory planning, tracking objects, exploration, mapping, swarm foraging, navigation, assembling or any algorithm applied to swarm robotics. After this analysis, only 25 papers from the 58 articles were identified as being suitable according to their function for this research into swarm robotics.

3 Swarm robotics

Swarm robotics is a multi-robot system approach, which consists of using a large number of simple and inexpensive robots. The cooperative actions of the swarm robots enable to perform difficult tasks (TOKAS; DAS, 2017) and for Nagavalli, Chakraborty and Sycara (2017) physical and computational limitations do not determine the accomplishment of the tasks, since the swarm of emergent behavior is the result of the acts of robots among them. An important feature is that the swarm robotics does not have individual leader, it means the behavior swarm is decentralized.

3.1 Swarm robotics based on nature

Swarm robotics is an approach which enfolds many robots with inspiration from the nature, such as bugs, ants, bees and other social insects which have swarm behavior (LANCASTER; GUSTAFSON, 2013). The behavior of swarms demonstrates remarkable abilities. Robots are, therefore, inspired by pheromones (RAVANKAR et al., 2016; NIIMI et al., 2017), path planning strategies (CHAARI et al., 2014; CHAARI et al., 2017), and methods for exploring the environment (RANGO et al., 2017; DIRAFZOON et al., 2014). They also draw from biological mechanisms (SUTANTYO; LEVI, 2015; GUZZI et al., 2014; MAITRA; PRASATH; PADHI, 2016) and other swarm behaviors to efficiently accomplish tasks.

The robots built by Kitamura, Nakamichi and Fukuda (2009) can be used in school practices to demonstrate the role of pheromones in ants. They can secrete pheromones where there is food, referred to as 'food pheromone', and the 'nest pheromone' for indicating the nest position. All this information is shown on the robot's display. Kitamura, Nakamichi and Fukuda (2009) highlight the importance of the pheromone in communication between ants for the knowledge the intelligence in swarms, once the use of pheromone is hard to implant in robots through chemical methods. Similarly, others autonomous robots based in nature that use concept of swarms, can be found in (SONG et al., 2020; MILLER; GANDHI, 2019; KLINGNER; AHMED; CORRELL, 2019; INACIO; MACHARET; CHAIMOWICZ, 2019).

3.1.1 Bacterial colony

A bacterial colony frequently has to deal with unfavorable environmental conditions, consequently, they developed sophisticated cooperative behavioral systems

(BEN-JACOB et al., 2016). They unite as a multicellular aggregate, facilitating molecular signal exchange for intercellular communication (BEN-JACOB et al., 2016). The bacterial community influence and change the environment besides defense themselves against dangerous actions (BLANCHARD; LU, 2015). Furthermore, according to Blanchard and Lu (2015), for reaching the aim, the activity of each organism is essential in a bacterial colony. Concepts related to bacteria implemented in robots are explained by Yang et al. (2015a), Montiel, Orozco-Rosas and Sepúlveda (2015),and Hossain and Ferdous (2015).

The main benefits of this kind of behavior are an increase in resistance, acceleration of colony growth, and ability to combat invading agents, among others. Xavier, Omar and Castro (2011) called bacterium as intelligent agent due to biochemical sensors that are used to sense the environment and presents a simple social interaction with great adaptability to changes in the environment. Thereby, the bacterial systems are a model to artificial intelligent systems due the simple behavior and adapt to changes (XAVIER; OMAR; CASTRO, 2011).

3.1.2 School of fish

The most striking feature in schools of fish is their synchrony. According to Scaradozzi et al. (2017), fishes have great efficiency abilities to move all its body developed throughout their evolution. Aureli, Fiorilli and Porfiri (2012) analyze the interaction between collective gregarious fish and a biomimetic vehicle, where the objective is to study how the behavior and attraction are developed with the presence of the distinctive characteristics of the robot. Since, the attraction is the result of several sensory cues, as smell, vision, sound and vibration (AURELI; FIORILLI; PORFIRI, 2012).

3.1.3 Colony of ants and swarm of bees

In colonies of ants, or swarms of bees, a substance called pheromone is used as a transmission medium (DORIGO et al., 2008). When a food source is found, a trail of pheromones is left to mark the site, this trail varies according to the distance, amount and quality of food. When an ant or a bee, is isolated and senses this pheromone it is induced to follow this path and, upon arriving at the place, it leaves an amount of its pheromone, increasing the presence of this substance at that point, i.e. indicating the trail of a food source for other individuals. The more individuals follow that trail the more reliable it becomes (DORIGO et al., 2008).

3.1.4 Flock of birds

For a bird to participate in a flock, it simply adjusts its movements to coordinate with the movements of its teammates, trying to stay close to its neighbors, but without any collisions. There isn't a leader in a flock of birds, any bird can fly in front, or behind the band (LIU; PASSINO, 2000). This collective behavior helps birds achieve advantages in certain aspects, including protection against predators, looking for food and "energy efficiency". Birds studies have been very applied in robots to research, such as for studying the behavior between chicks (GRIBOVSKIY et al., 2018), a project forward flapping wings (MOITRA et al., 2017; JAHANBIN et al., 2016), a metaheuristic algorithm based in nature, as the cuckoo species (STOJANOVIC et al., 2016).

3.2 Differential

3.2.1 Individual robots

The main differences and advantages over individual robots are explained below, according to Aznar, Pujol e Rizo (2017):

$Parallelism$: The population of a swarm of robots is typically large scale and may fulfill several goals simultaneously. This behavior can save time to complete the task, such as in open field mapping.

$Scalability$: The interactions performed by individuals in the swarm are done locally, therefore an individual can perform or give up on a task independently. A swarm is not limited to a fixed amount of individuals, and may lose or add individuals at any time without affecting the final goal of the group.

$Stability$: Similar to scalability, swarms are not significantly affected when some individuals have failures and disconnect from the group, thus a swarm can still work for its ultimate goal; however group performance of a small group of individuals may be degraded.

$Economy$: The individual robots are low cost, both in design, manufacturing and in maintenance, therefore the replacement of individuals is also lower costs. The entire swarm system is cheaper than designing a single complex robot to perform multiple tasks.

$Energy\,efficiency$: Each individual in a swarm is smaller and simpler than a single complex robot, which reduces energy costs and extends the swarm's overall lifespan. This makes the technology viable in environments without power sources or where wired electricity is not allowed.

3.2.2 Multi-robots systems

There are other research areas which have an emergent behavior of multiple robots as a source of study. These other areas can be confused with the study of swarm robotics, but there are some differences between them. A robotic structure of swarms is represented by autonomous robots that have the capacity of sensing and local communication, do not present centralized control or obtaining general information, are located in an environment possibly unknown and that perform a common action.

Based on the definition by Chamanbaz et al. (2017), one can easily differentiate robotic systems from swarms of other multi-robot strategies. It is common for multi-robot systems not to present any mode of decentralization in the computing, communication, and/or operation layers. Decentralized control allows the system to have scalability and flexibility as benefits (TAN; ZHENG, 2013). Below are its main features, according to Sorini and Falcone (2013):

$Autonomy$: Individuals of the swarm should be autonomous, able to feel and act in the environment.

$Quantity$: The number of boats in a swarm should be higher or at least the control rules should allow that.

$Homogeneity$: The robots must be homogeneous. There can be different types of boats in a swarm, but there should not be many groups.

$Cooperative$: Robots must be incapable or inefficient to meet the main task of the swarm individually, that is, they need to collaborate to achieve the success or to improve performance.

$Decentralized$: The robots have only local sensing and communication capabilities. This ensures that the coordination of the system is distributed, so that it can become a scalability of system properties.

For Cruz, Nedjah and Mourelle (2016), the advantages presented by multi-robot systems for an individual robot, are for tasks that require higher execution speed, high precision and flexibility to failures. A grouping of robots is performed if there are two or more tasks to be performed. This grouping happens according to its purposes and in case the set is heterogeneous. If it is homogeneous, this cluster occurs according to the distance between the robots and the places of accomplishment and execution of the tasks.

3.3 Tasks

Bayindir (2016) describes the following categories for tasks that can be executed by robots: (1) tasks for a single agent, (2) tasks that favor the use of several agents, (3) exclusively multi-agent tasks and (4) multi-agent tasks. The principle of robotic swarm focuses on the last three categories, and related works prove in many fields of application that using a large number of agents to solve a task in a subdivided way allows to make use of considerably less complex agents in the individual category.

Swarm robotics is applied to tasks such as: aggregation, grouping and classification of objects, navigation (MOREIRA et al., 2018), formation of paths, distribution and allocation of tasks, among others. When performing these missions, there must be a high interaction and relationship of the robots with each other (SEÇKIN; KARPUZ; ÖZEK, 2016). According to Zhou, Goldman and McLurkin (2017), homogeneous robots could execute actions through the swap tasks between themselves for accomplishing a goal, despite the costly process of rending and receiving data the swap task method reduces the physical efforts mainly in a large environment.

Varughese et al. (2018) present a method based on behavior natural swarm to find good quality food, the authors solve this task through the agents aMussels and the aFish, the robots randomly explore the underwater environment to find interesting food areas. The task allocation problem has a crucial effect on the swarm intelligence, Schwarzrock et al. (2018) developed a solution for allocating UAVs (Unmanned Aerial Vehicles) which are able to detect targets through sensors and receive tasks from a central entity. The method for allocating the UVAs, as described by Schwarzrock et al. (2018), is modeled on the Swarm-Generalized Assignment Problem (Swarm-GAP). This approach allows for satisfactory results due to the token-passing protocol in the communication among the swarm.

3.3.1 Aggregation

For Chamanbaz et al. (2017), the aggregation process causes individuals in the swarm to undergo a collective process of grouping and gathering. This type of behavior is quite common and of great importance in natural swarms as well as very useful for systems with multiple robots at certain stages of execution in the field.

In order to perform other tasks, such as collective movement, self-assembly and pattern formation, or to exchange information, the robots must initially gather together. Yan, Liang and Guan (2011) used an approach based on the control of two states (search and waiting) for each robot, such as the probabilistic finite state automata (PFSA).

The task of aggregation is essential for the swarms to perform complex tasks, such as group shifts, self-assembly and pattern formation, or to exchange information (KHALDI et al., 2018), (TIMMIS et al., 2016).

3.3.2 Pattern formation

According to Oh et al. (2017), the pattern formation methodology is defined, when the robots initially migrate to an established location, self-organize in a spatial pattern, and finally exhibit a specific graphical model. The formation of patterns in multi-robot systems also present problems such as the difficulty in maintaining the coordination of a set of robots to maintain a specific formation. This training, which must be maintained, can be a standard formation or adaptively formed through local interactions with the neighborhood and environment.

Pattern formation is the problem of creating an overall shape, changing the positions of the individual robots. Oikawa, Takimoto and Kambayashi (2015) implemented a control algorithm based on indirect communication of bugs by pheromones. He et al. (2018) classify some training control algorithms into three types: leader-based strategy, follower-based strategy, virtual structure-based approach, and a behavior-based approach. In the leader-follower strategy, some robots in the swarm receive general trajectory information and are appointed as leaders, while the robots that do not receive this information are designated as followers.

3.3.3 Target search

Bakhshipour, Ghadi and Namdari (2017) state that the use of swarm robotics for target search applications has increased significantly in recent years in circumstances where the search task is associated with a high level of danger or inaccessible workplaces. To this end, the most relevant applications are those in the form of autonomous army and for search and rescue in dangerous and inhospitable environments.

Swarm robotics can be very useful for search tasks, especially those in which the spatial arrangement of the source may be complex. Yang et al. (2015b) propose a decentralized control algorithm for a swarm of robots in order to perform tasks of target search, an algorithm that was motivated by the chemotaxis of bacteria. Cai, Chen and Min (2013) had already implemented an improved PSO (Particle Swarm Optimization) algorithm to accomplish the task of searching and removing objects.

3.3.4 Collective transport objects

According to Torabi (2015), the reintegration of individuals from the swarm to the group, is a collective transport behavior that can be combined with other behaviors such as exploration, pattern formation, self-assembly and task allocation for solving a complex task, for instance, a search and rescue operation in a dangerous situation such as after an earthquake. In collective transport, a group of robots needs to cooperate in order to transport an object which is heavy for a single robot to move.

Transport presents a problem for a single robot, but can be accomplished by swarm of robots, due to their cooperation to deal with the object carried. In addition, any parallelism to handle different objects by multiple robots at the same time can improve performance. Soleymani et al. (2015) demonstrated an autonomous building system in which independent terrestrial robots built a protective barrier by means of transport of pockets.

3.3.5 Objects track

Swarm robotics can be used to track moving objects in a complex and dynamic environment. The swarm collectively tracks the movement of objects and collects other information about the object in motion. Ma'sum et al. (2013) use Particle Swarm Optimization (PSO) algorithm in swarm quadcopter to track objects. The purpose is an implementation of a sensor camera able to detect the target based on the colors and other sensors to estimate the target velocity and position using Robot Operating System (ROS) as the main Software (MA'SUM et al., 2013).

3.3.6 Mapping

Swarm robotics could assist in collective mapping problems, where a set of robots explore and map a large region, such as underwater (WU et al., 2014), urban area (SPANOGIANOPOULOS; ZHANG; SPURGEON, 2017) and applying techniques through the fuzzy approach (KUMAR; KUMAR, 2012), a Particle Swarm Optimization (PSO) (SPANOGIANOPOULOS; ZHANG; SPURGEON, 2017) and so on. Collective mapping occurs with the addition of maps generated by each robot. Rango et al. (2015) used the operating procedure to search for landmines and to disarm them. While Howden (2013) used maps to find outbreaks of fire, using UAVs.

New approaches to locating and mapping mobile robots from computer vision (MARINHO et al., 2018) and omnidirectional maps (MARINHO et al., 2017) are proposed using characteristic extraction and classification methods as well as machine learning techniques.

3.3.7 Task allocation

Division of labor is not a task like the others, but it is a problem that can arise in a swarm of robots. Task allocation can be used in robots by centralized or decentralized methods and is generally considered as an optimization problem. (BRUTSCHY et al., 2014). In this problem is possible implementing several methods suited, such as a strategy based on occlusion surface whereby the robots push the object until the goal (CHEN et al., 2015) and agents methods with interdependent tasks (BRUTSCHY et al., 2014). Gazi et al. (2010) used an NFC (Network Formation Control) algorithm for the management of a swarm of robots, while Mendonça, Nedjah and Mourelle (2016) developed a decentralized algorithm for dynamic task allocation in a Elisa-III robots. Liang and Kang (2016) proposed an improved agreement protocol for the assignment of tasks in the Unmanned Underwater Vehicle (UUV) swarm system. In addition, the cluster of UAVs is explored by Wu et al. (2018) and Schwarzrock et al. (2018); each article proposes a different algorithm for task allocation.

3.3.8 Path planning

Path planning is an essential research area for robot automation and is also the basis for robot tasks (ZHOU et al., 2018a). It is proven that robots can collaborate with humans in various works in the handling of loads, cleaning tasks, inspection, autonomous research of submarine vehicles, etc (NIE; FENG, 2016).

A trajectory plan consists of each robot plotting a route from its point of origin to its point of destination, avoiding collision with fixed and another swarm of robots. Shi et al. (2013) used an improved Q-Learning algorithm for planning swarm routes while Zhou et al. (2018b) developed a tangent vector based artificial potential field (TVAPF) for the same issue, path planning, with dynamic strategies to achieve the goal.

4 Results

During the analysis of the selected articles related to swarm robotics a lot of keywords were used. In order to identify the most effective keywords to search for these articles a statistical analysis was applied to them (Figure 1). So, the later work with better results using the keywords chosen are examined in this session.

Mathias et al. (2016) proposed a decentralized algorithm for dynamic task allocation called LTDA^2 (local dynamic task allocation). The algorithm is executed regularly by the robots η in the cluster and executions occur simultaneously in each robot.

Based on the DTA (Dynamic Task Allocation) technique, the algorithm does not use an array to store the tasks allocated but stores locally assigned tasks to robots; thus the decision process is carried out individually by each robot swarm. It is important to note that the LTDA ^{2} algorithm provides the shortest convergence time, considering simulations in a swarm with less than 12 robots, thus proving to be a capable and efficient way for a certain task with swarms of robots.

Liu and Lyons (2015) expose a tool for remote interaction between humans and a swarm of robots. The way presented consists of a master robot, this one operated by a human, and by a group of robots that fulfill missions in remote environments. The operator can operate the swarm configuration of robots remotely, manipulating tasks designated as collision avoidance, robot dispersion and workspace limitation through the functions developed for the swarm. Regarding the control algorithm of the presented system, it is enough for the human operator to describe the parameters of the desired task without needing the individual position of the robot, and the robot would change at the same time its formation and position to adapt to the new disorganized environment.

Nedjah, Mendon and Mourelle (2015) proposed a distributed algorithm for task allocation called GDTA (Global Dynamic Task Allocation) and the Robot Elisa III was used for the simulation of the swarm. The suggested Dynamic Task Allocation algorithm defines, in a dynamic way, the task assignment configuration for the robot structured in three main stages: initialization, adjustment and execution. The algorithm is based on the GBPSO (Global Particle Swarm Optimization Best)

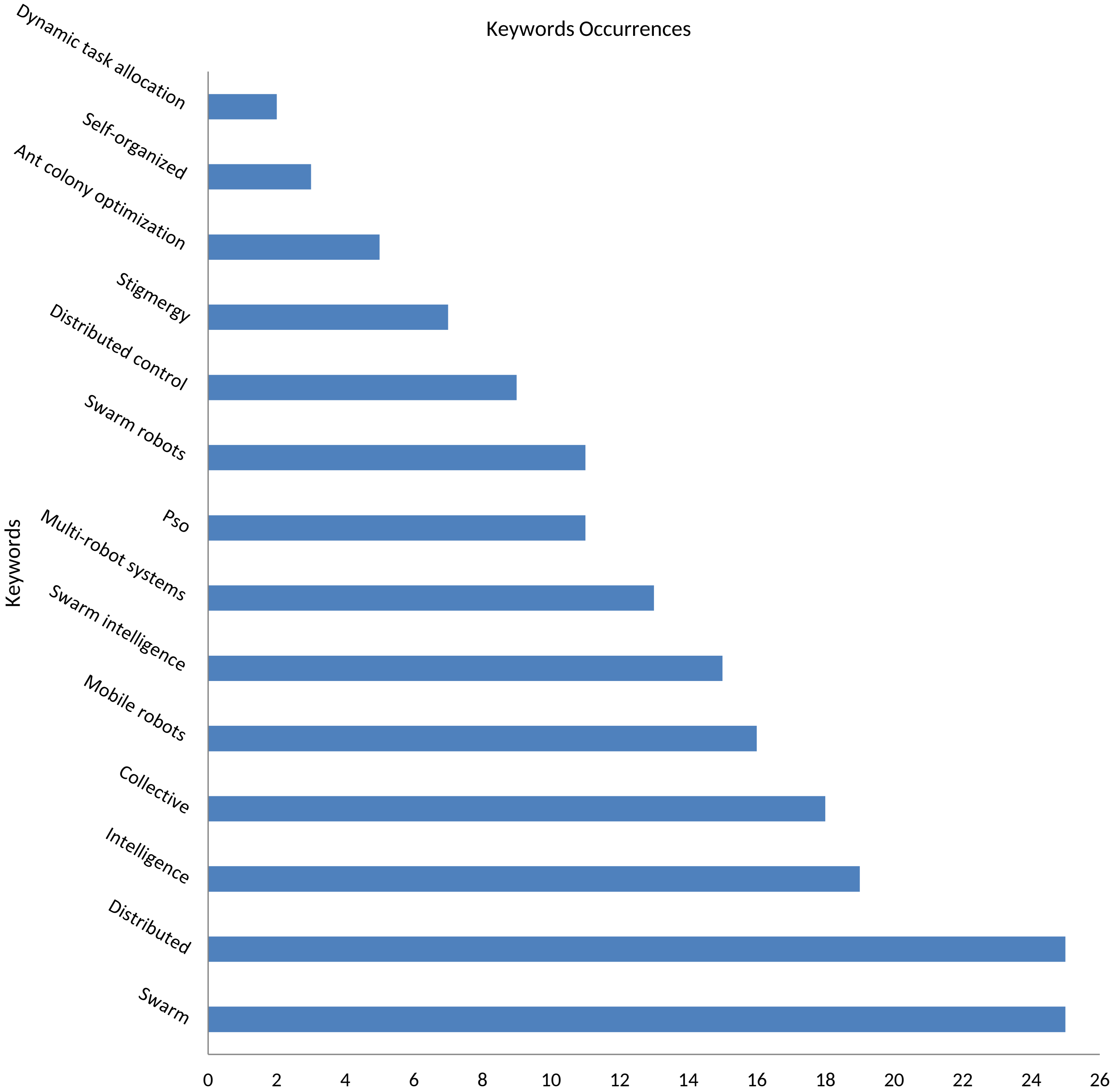

Figure 1: Keywords most used in selected works for techniques applied to swarm robotics.

algorithm optimization process with the goal of minimizing the global function destined a to DTA. After the execution of the algorithm, the convergence time is expected to increase, causing the increase of the number of robots in the swarm and the amount of tasks.

Oikawa, Takimoto and Kambayashi (2015) proposed an algorithm to control the formation of swarm robotics using mobile agents. The algorithm presented two types of agents: ant agents (AAs) and pheromone agents (PAs). Each AA has partial knowledge about the training they need to have. This knowledge consists of relative locations with neighboring robots that make up target formation. Since AAs precept an idle robot, it occupies the space of that robot and generates the PAs to attract other AAS to the location of the neighboring robots. Once the PAs are formed, the PAs clone and migrate to other robots to find target AAs. When AAs receive PAs, which have information to guide AAs, AAs move to the locations to which PAs point. Several tests were conducted in a simulator showing that this methodology contributes to the energy saving of robots since the migrations of agents are used instead of the physical movements of the robots. Efficacy is significant in the case of many robots.

Perreault, Wittie and Sheppard (2015) suggest a version of the dPSO (Distributed PSO), the C-dPSO. The algorithm aims to track moving targets, transmit solutions to the server during the search process and incorporate a communication component update equation of speed to keep a consistent connection with the server. The algorithm developed is based on the concept of decentralization for robotic swarms that preserves the swarm's communication with a central server, while seeking the solution with dynamic optimization. The calculation performed on each robot is a lightweight and convenient calculation for low cost and energy limited robots. The proposed communication arrangement proves to be useful in intelligent robotic cluster systems due to dynamic optimization.

Rango et al. (2015) propose a way for exploration in unknown environments and the detection of landmines. To accomplish this task, the algorithm is based on ACO (Ant Colony Optimization) and also uses the concept of pheromone and stigmergy to synchronize a set of robots and perform the task of exploration. In order to disarm the mines, two techniques were proposed: ATS-RR (ACO-based Team Strategy for Recruitment of Robots) based on ACO, and FTS-RR (Firefly Team Strategy for Recruitment of Robots) based on FFA (Firefly Algorithm). After numerous simulations, it was concluded that the FTS-RR presents better performance in the time to finalize the task and the number of accesses in the cell, essentially when the number of robots is low.

Soleymani et al. (2015) developed a system to construct a security barrier. The authors defined the autonomous construction activity as a robotic task in which one or more robots capture, transport and deposit material periodically to build a structure. Two control algorithms were also developed to simulate biological mechanisms, *estigmergy* and *templates*, where robots can compensate for the uncertainties of construction activities, regardless of a project or an explicit representation of the system to be built. The robot is guided, by a control algorithm, to produce the barrier without relying on external processing or a system that performs motion capture. Due to these mechanisms and properties inherent in the building blocks, it was possible for the swarm of robots to construct the barrier that separates a safe environment from a non-secure environment. The implementation of the algorithms used the ARGoS and the plataform MarXBot.

Roy, Maitra and Bhattacharya (2016) present the different characteristics of two well-known evolutionary methods: Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization Algorithm (BFOA) in the application of road development and obstacle bypass. It is observed that BFOA deals with the agent-to-agent arrangement as much as the shortest computing time, while the PSO generates an optimal trajectory that happens due to the existence of attraction, repulsion and formation gains. The results of the simulations show the effectiveness of the BFOA and the PSO in the obstacle path planning problem. After numerous tests, the study concludes that the PSO algorithm ensures the optimal path, while the BFOA algorithm is responsible for representing the shortest time and training.

Lima and Oliveira (2017) propose a new way of control for swarms of robots based on the memory model of two-dimensional cellular automata (CAAM) that controls a swarm of robots through the task of foraging in a known environment. Communication between robots in an indirect way through an organized process called *stigmergy*, leaves a trace produced by the deposit of pheromones in the environment throughout the movement. The interactions of the pheromone traits result in the ability to perform the task desired by the robot team. The simulations from the proposed model showed that the execution of the model allowed the production of visualization of behavior patterns analyzed in ant colonies and beyond the observation of pedestrian dynamics.

In Junior and Nedjah (2017), a class of distributed algorithms, called wave algorithms, is presented as a general technique to orderly coordinate the execution of subtasks that make up the collective navigation and to enable the execution of more complex behaviors. The proposed model is based on the execution of wave algorithms and on the passage of messages between the members of the swarm. The navigation is performed in three steps: (i) the recruitment and formation of groups of robots, (ii) the alignment of the robots and (iii) the movement of robots in a leading tracking scheme. The tests performed on the V-rep simulator show the group's ability to repair the corresponding position of the robots while maintaining the formation.

Hocraffer and Nam (2017) present the results of a meta-analysis of approaches with a focus on the human system interfaces in the coordination of UAV swarms, contributing with an overview of the advantages, challenges and shortcomings of the current UAV management interfaces. Tests were performed with different levels of automation, and it was found that it is more effective in larger swarms, that the human being only influences, and does not command, the swarm in the peer-to-peer mode, thus allowing the UAVs to behave in smart ways and achieve their goals with lower errors and minimal cognitive load for the operator. In contrast, by facing an active environment, humans can adapt to change faster than fully automated swarms.

Verlekar and Joshi (2017) simulated a method based on the behavior of ant chain formation and division of labor in bees, proposing a solution for the foraging task that can be performed by swarm robots in a shorter time and with lower power consumption. Swarm robots are designed to mimic ants and form chains, while foraging and task-sharing work is used to decrease energy expenditure. The chain-forming algorithm, which uses a global path and prevents the creation of bottleneck situations, was successfully implemented for two robots. For the location and navigation of the robots, the algorithm uses the OpenCV library with the Python language, coupled with magnetometer sensor readings.

Khaldi et al. (2017) present an innovative method of detecting exogenous faults for robot swarm monitoring. The method combines the flexibility of one of the frequently used techniques for size reduction called principal component analysis (PCA), increased sensitivity to the exponentially weighted moving average (EWMA) and cumulative sum (CUSUM) to sudden changes. The model is performed in a swarm of foot-bot robots, simulated performing a task of forming circles, through the viscoelastic control model. This study focuses on a better data-based fault identification technique and its application in the identification of failures in a swarm of foot-bot robots. The simulations were carried out in experimental trials based on ARGoS in a swarm of six robots.

Wei et al. (2017) propose an intelligent control algorithm based on CVT (Centroidal Voronoi Tessellation) for the planning of the self-assembly path of the mobile non-holonomic robotic modules labeled Sambots. This algorithm makes possible, by means of a collaborative planning method, to make swarm robots go from an initial virtual region to the virtual destination region. For the validation, simulations are performed in Matlab by executing the construction of the line, cross and H-shape configurations with Sambots robots by self-assembly.

Caccavale and Schwager (2017) present a decentralized control approach where a swarm of robots that does not have initial knowledge of an environment can define the graphical and discrete layout of the environment, consisting of multiple separate sub-regions. The range of robots such as communication, compass, GPS sensor and proximity are limited. There are numerous applications of the algorithm. Activities such as topological survey and reconnaissance of a variety of environments, such as rooms in a building, chambers in a network of caves and environments with trees, stones or other obstacles that limit the flexibility of robots. The study also confirms that all robots that use this algorithm, achieve a true graphical response in finite time.

Albani et al. (2017) report a road-map to take robotics to the field of weed control problems. Together with the concept presented, the results of orientations for the scenario of weed monitoring and mapping in an environment through a swarm of UAVs are presented. This road-map is implemented to recommend swarm robotics as a possible technology for monitoring and mapping applications and within the project Swarm Robotics for Agricultural Applications - SAGA. According to Albani et al. (2017), SAGA seeks to determine the use of a group of small UAVs for swarm monitoring of a field and mapping the presence of weeds.

He et al. (2018) concentrate on the UAV swarm arrangement-based train control. A new training control algorithm applicable to the UAV swarm is designed, in which the leaders are set in the swarm and can be motivated by the navigation feedback of their flockmates. The understanding protocol is employed by choosing position and velocity. No explicit leader exists in the new algorithm, meaning that all the swarm robots know nothing about choosing leaders, and because of these leaders are called implied leaders. The proposed algorithm can reduce communication consumption and make the swarm more adaptable and scalable.

Spanogianopoulos, Zhang and Spurgeon (2017) use nPSO (New Structure Particle Swarm Optimization) to obtain a rapid formation of UAV clusters in a congested urban environment and also solve the problem of finding ideal positions of UAVs. Since swarms of UAVs share the same workspace, it is necessary to have a means to quickly adopt a great free collision formation in the workspace. As the training task evolves, the algorithm reorganizes itself, accommodating new constraints, for a new, faster formation, ideal for airborne robots. The algorithm used in this application proposes to have a fast convergence showing that it does not require more than 1000 iterations for almost suitable training with groups of 18 and 25 UAVs and tests with 10, 20, 30 and 40 obstacles.

Zedadra et al. (2016) present a multi-agent foraging algorithm called Cooperative Switching Algorithm for Foraging (C-SAF) inspired by the classic ant system. This algorithm provides fast search, optimal return paths, and fast food scanning. On the problem of Multiagent Foraging, the authors develop a large-scale foraging system with hundreds and thousands of agents and qualitatively compare the proposed approach with similar and relevant work by reference comparison. The results show that the C-SAF algorithm spends less time to complete foraging and return larger amounts of feed. The algorithm is compared with the non-cooperative (NC-SAF), c-marking and non-cooperative (NC-c-marking) switching algorithms and implemented through a Multi-Agent Foraging framework.

For Liu et al. (2018), a swarm of heterogeneous robots next to the team assembly problem is presented. The authors investigate this problem of assembling an autonomous staff in a swarm of mobile robots to organize groups, each meeting specific needs as a movement planning problem. The paper by Liu et al. (2018) extends the original asynchronous robot model to a heterogeneous asynchronous robot model, assigning a color to each robot to characterize its type. The proposed algorithm depends on the chirality (robot has clockwise sense) between robots. When robots do not have chirality and are not yet aligned, there is no agreement with the leader of each arc. Thus, the proposed algorithm achieves efficiency only in robots with chirality.

Rosalie et al. (2018) propose a new mobility model for swarms of collaborative UAVs used to cover a certain area. To try to solve this problem, a mobility strategy is proposed that combines the assets of online and offline methods. The study of off-line routes is based on pre-computing the flight plan of the UAVs. The advantage of this method is the control and monitoring of UAV trajectories through the ground control station (GCS). However, the runtime trajectories of UAVs are calculated using the online method. Later, the author proposes the algorithm of optimization of the colony of caustic ants (CACOC) that establishes an approach of optimization of ant colony (ACO) with a dynamic chaotic system. The CACOC mobility model shows better results than the ACO UAV algorithm, as there is an increase in performance and a reduction in algorithm variation.

Zhou, Goldman and McLurkin (2017) created an algorithm for sorting robots in a Euclidean space inspired in an asymmetric tree topology with connected edges. The method uses operations at tree, such as add or remove edges for sorting and rectify the positions for better performance. These positions are limited between the lowest value and highest value attributed by the authors. Overall the tree represents the robots with its parents selected at a set of robots and allows the robot localization themselves on the path. The feature of this work is that to perform the task the graph does not depend on robots determinations and the implemented algorithm shows safety and efficiency in the process due the topological and geometric operations besides having flexibility for modifications.

In recent work, Tokas and Das(2017) propose a algorithm with an asynchronous timing model and color lights for synchronizing robots throughout a left boundary. The work uses randomly horizontal line obstacle in the environment and a graph whereby the robots at the beginning are connected and visible to other agents. The paper (TOKAS; DAS, 2017) is based on three simple and efficient work phrases from the CORDAL model (PRENCIPE, 2001) for achieving the goal. The first phrase is: $Look$, all robots perceive the neighbors' positions; it is necessary so that the visible neighbors have the same snapshot. When all robots are with blue color the second phrase namely $Computer$ starts one of them runs the assemble algorithm and based in the perceptions it compute the destination. In the $Move$ phrase, the robots advance toward the destination calculated in the previous phase.

Nagavalli, Chakraborty and Sycara (2017) developed an algorithm for finding the suitable sequence of behavior in order to perform complex task. The method uses the library which is the result of interaction the swarm robots in the environment and store the swarm behaviors on it to be implemented to navigate and to area coverage. The navigation simulation showed well move although the some unnecessary sequences. The application at area coverage demonstrated difficult to accomplish the tasks due the robots numbers on a simulation which was solved with different sequence combinations.

Bandyopadhyay, Chung and Hadaegh (2017) have implemented a distributed algorithm to control the shape of large-scale swarms. The work uses the swarm density and also the probabilistic method to apply the time Markov matrices for the required forms. The algorithm using multiple aerial robots under physical space is based on the Probabilistic Swarm Guidance (PSG) and the Inhomogeneous Markov Chain (IMC), these robots rate the swarm distribution at the local division, called by bins, and if it is a transient bin the robot search for another bin, but if it is not a transient the agent executes the Markov Matrix. The Markov matrix indicates the shape formation through of identity matrix as well as maximizes the swarm process.

An overview of the selected items is presented in Table 1, where the methods, tasks, simulators and robots used in each article are highlighted.

5 Discussion

During the analysis of the selected articles, a significant diversity in the tasks applied to swarm robotics was observed, highlighting the flexibility of this approach. However, there is no widely adopted standard simulator within the community, which results in variations in the results and makes comparisons between studies difficult. Some works use simulators such as ARGoS or V-REP, while others do not specify the simulator used, further complicating comparisons. Additionally, the choice of robot sets and the number of swarm elements also vary, affecting the replicability of experiments. The lack of a standardized public dataset limits objective evaluation and comparison of methods and algorithms.

Several of the techniques presented for task allocation showed potential applications. Mathias et al. (2016) showed that for swarms with more than 12 individuals the rate of convergence of the algorithm LTDA[2] becomes smaller compared to algorithms such as Card-dealer and Tree-recolor, and similar to the Extreme-Comm. Mathias et al. (2016) and Nedjah, Mendon and Mourelle (2015) used for simulated between 5 and 25 robots, for allocating 2 to 5 different tasks.

Nagavalli, Chakraborty and Sycara (2017) addressed the problem of finding the optimal sequences that robots should follow to complete a task using a simple library of swarm behaviors. To construct the library, Nagavalli, Chakraborty and Sycara (2017) use as a basis the mathematical definitions corresponding to the swarm behavior. The navigation application, using the multiplicative weight of 2 for the environment with 20 robots, resulted in a time to achieve the optimal sequence of 27.92 seconds. For area coverage, the simulation shows the best results as the multiplicative weight increases. Therefore, the algorithm developed by Nagavalli, Chakraborty and Sycara (2017) performs the task well. However, their simulations include unnecessary steps in the sequences.

Perreault, Wittie and Sheppard (2015) performed a comparison of the proposed algorithm, C-dPSO, with the dPSO. In addition, these authors also carried out an analysis of the algorithm using the decay of fitness values, for the fine tuning of the parameters.

In Liu and Lyons (2015), not only a task was presented, but a structure for interaction between humans and swarms in a remote environment. In this framework some basic tasks are implemented, such as: scattering and collision prevention, thus creating a stable control system to make the commands sent from the operator to the swarm of robots viable.

Rango et al. (2015) presented a set of tasks, where the most important in this work were the tasks of exploration (spatial distribution) and defuse landmines (spatial concentration). The simulations presented were developed by the authors and used the JAVA language. The three scenarios simulated were: fixed landmines and fixed robots, landmines spread evenly and fixed robots, landmines scattered randomly and robots evenly spread. The simulation used a grid 30 x 30 and two techniques were used to defuse the mines, ATS-RR (Ant based Team Strategy for Robots Recruitment) and FTS-RR (Firefly based Team Strategy for Robots Recruitment). As a result, Rango et al. (2015) concluded that the FTS-RR featured better performance against the time to complete the task and the number of accesses in the area, leading to a better distribution of robots and better times for the exploration of the environment and disarmament.

Roy, Maitra and Bhattacharya (2016) make use of the PSO and BFOA algorithms to minimize an error function, established after the evaluation of the attraction, repulsion and formation coefficients. 100 bacteria (BFOA) and 50 particles (PSO) are used for simulation in an environment with 28 obstacles, each algorithm running 30 times to acquire two parameters: length of generated path and the execution time. After

Table 1: Techniques used for performing tasks in swarm robotics.

Author	Method	Task	Simulator	Robot
Liu and Lyons (2015)	-	Teleoperated control system	3-DOF Robotic Manipulator	-
Tokas and Das (2017)	PSG-IMC	Asynchronous Timing model and light bulb	-	-
Nagavalli, Chakraborty and Sycara (2017)	Swarm behavior library	Best sequence	-	-
Zhou, Goldman and McLurkin (2017)	Algorithm distributed	-	-	-
Oikawa, Takimoto and Kambayashi (2015)	Mobile agents	Formation control	-	-
He et al. (2018)	Implicit leaders	Feedback formation	-	-
Soleymani et al. (2015)	-	Transport objects	ARGoS	MarXBot
Rango et al. (2015)	FTS-RR	Explotation and transport objects	Java-based	-
Mathias et al. (2016)	LDTA[2]	Task allocation	-	Elisa III
Nedjah, Mendon and Mourelle (2015)	GDTA	Task allocation	-	Elisa III
Perreault, Wittie and Sheppard (2015)	C-dPSO	Communication	-	-
Roy, Maitra and Bhattacharya (2016)	PSO and BFOA	Path planning	-	-
Lima and Oliveira (2017)	CAAM	Foraging	-	-
Junior and Nedjah (2017)	Wave algorithm	Navigation	V-REP	Kilobot
Hocraffer and Nam (2017)	-	Human-system	-	-
Verlekar and Joshi (2017)	Chain-forming	Foraging	-	-
Khaldi et al. (2017)	PCA, EWMA and CUSUM Monitoring	-	-	-
Wei et al. (2017)	Voronoi cell-based	Path planning	-	Sambot
Caccavale and Schwager (2017)	-	Mapping	-	-
Albani et al. (2017)	-	Mapping	-	-
Zedadra et al. (2016)	C-SAF	Foraging	-	-
Liu et al. (2018)	ASYNC	Assembling	-	-
Rosalie et al. (2018)	MAMM, MAMM2, CROMM, CACOC, CROMM	Area coverage	-	-
Bandyopadhyay, Chung and Hadaegh (2017)	PSG-IMC	Distribution control	-	-

the simulations, it was concluded that the PSO produces an optimal path and can avoid obstacles, whereas the BFOA generates the shortest time. Wei et al. (2017) deal with the problem of control and planning paths of self-assembly and angular control. The Voronoi cell-based coverage technique adopts the behavior-based control method and is compared to the "Reciprocal Velocity Obstacle"and "Permutation-Invariant Path Planning"algorithms for guidance control. Each behavior can mean collision avoidance, automatic rotation and linear forward/backward movement. The robot used to be the Sambot robot and the maximum number of iterations was 200.

Hocraffer and Nam (2017) review 27 articles on human-system interaction with UAV swarms, and conclude that more research on human factors is necessary in the management of UAV swarms and that the subject is still in a basic and very heterogeneous state. The most recent technological studies prove that there are no autonomous swarms that are fully operational, but it is still possible to realistically simulate them. The effect of different levels of automation on the performance of swarms, communication properties and the operator's cognitive workload was analyzed. Spanogianopoulos, Zhang and Spurgeon (2017) perform tests in an environment with fixed obstacles and a swarm of UAVs, to validate the use of the nPSO algorithm and to obtain a fast formation. In the simulations, the numbers of UAVs were varied as well as the number of obstacles, showing that the algorithm results in a fast convergence, using direct implementation, approaching an ideal solution.

He et al. (2018) test the protocol for control of leaders and followers in a swarm of 10 UAVs. A novel feedback formation control algorithm is used. The analysis of trajectory and velocity errors is examined following the dynamic relocations of leaders, confirming that there is an integration of the protocol with the controller, improving the adaptability and scalability of the system and each VANT can be designated as leader randomly receiving feedback from colleagues, a feature of great importance for military applications. To address the problem of area coverage by a swarm of UAVs in a military context, Rosalie et al. (2018) conducted simulations using chaotic dynamical systems. They modeled a set of 10 UAVs, each equipped with wireless communication, covering an area of $100m\ x\ 100m$, divided into $1m\ x\ 1m$ cells, with each robot moving at a speed of $1m/s$. To avoid collisions between UAVs, they do not have equal flight altitudes. The author tests the mobility models Random, MAMM, MAMM2 and CROMM, without the ACO algorithm and the CACOC and ACO UAV mobility techniques with the ACO algorithm. Without the ACO algorithm, the MAMM2 technique exceeds the first two in most metrics, but the CROMM technique outperforms MAMM2 in all but one of the metrics. Already with the ACO algorithm, the CACOC presents better coverage values.

One viable technology to monitor and map some applications is the use of UAV searches. For this, the Albani et al. (2017) implement the robotic swarm with a vision system and embedded navigation, performing simulations in a scenario with several points of observation, considering these points distributed uniform and patch, with 10, 50 and 100 UAVs. In the simulation, 200 evaluations were performed for each combination, showing that for uniform distribution, the collective monitoring strategy is 2 to 9 times slower, with better performance for low detection accuracy values. The patchy distribution, the strategy is also slower than the optimal strategy, but for high detection accuracy it has a better performance. To demonstrate the efficiency and scalability of the multi-robot mapping approach, Caccavale and Schwage (2017) perform simulations in an archipelago-like environment divided into islands and lakes are performed. Situations with 6 and 8 islands were evaluated, covering a number of robots from 5 to 100 and with a communication range of 5 and 7. From 60 to 100 robots in both simulation configurations, there is a significant linear increase in mean time by the mapping step, as well as the number of steps.

The investigation of a new model of control for swarms of robots dedicated to the task of foraging is investigated in (LIMA; OLIVEIRA, 2017). Separate experiments are performed to fit the constants involved in four states of the model: search, capture, storage and return. It was observed that the robot's skills of vision in the search, increase the efficiency of the team to complete the task, and also make adjustments in the parameters of dissemination of pheromone. The short-term memory resource of the robot increases the competence of the team, but if it is used too much, it raises the processing time considerably. Excessive number of robot causes wear on swarm performance. Zedadra et al. (2016) performed simulations using the Multi-Agent Forge framework on Netlog, with environments that are either obstacle-free or contain obstacles. From these settings, four scenarios were created: average time, returned food, path length, and scalability analysis. Each simulation was performed 50 times. As a result of the simulations, it has been shown that the mean time increases dramatically when the position of the food is far from the nest and can also change the length of the desired path. As challenges, it was intended to implement this approach using real robots in an open source framework. Verlekar and Joshi (2017) implement an algorithm inspired by the ant chain formation, with boats following a leader. A camera is used to identify and calculate the boat's centroid. The implementation of the technique is performed only in 2 robots, observing that the follower robot starts and finishes its trajectory before the leading robot, typical behavior of the chain following.

To control the execution of tasks of a swarm of robots, Junior and Nedjah (2017) propose the wave algorithm for navigation. Simulations of 36 kilobots with distance sensors are performed and randomly distributed through V-rep software. Some robots start the task by changing their color to the color associated with the initiator, and the rest of the robots change directions trying to follow the direction of the father robot. When all the robots are in the same direction, the task is finished. The evaluation of the algorithm shows that the recruitment time is 10 to 20 times less than the alignment time, with a significant increase of both times for the transition from 5 to 6, 13 to 14 and 21 to 22 of neighboring robots. Soleymani et al. (2015) developed a swarm for the construction of a structure that separates a safe zone from an unsecured zone. In their simulations a grid of 400 x 600 cm was used where the boundary is made of 20 marks that form a straight line of 350 cm, 5 reservoirs were also used. The distance between an area of the reservoir and the structure is about 330 cm. In this setting, 112 building blocks are deposited in the region. Simulation experiments were performed for scalability analysis for different group sizes ranging from 1 to 8 robots. For each group size, 200 simulation attempts were made. According to Soleymani et al. (2015), factors such as the quality of the built structure in terms of integrity deviation, maximum clearance and differences in uniformity remain more constant during construction with a single robot. On the other hand, the deposition rate increases rapidly. This increase in construction speed shows the advantage of the robot's parallelism in performing common tasks.

To validate the training control method presented by Oikawa, Takimoto and Kambayashi (2015), the simulations are performed in a simulator with a number of 20 to 50 robots with WiFi communication. Using 20 robots, it was concluded that all will be part of the training. On the other hand, with 50 robots, it was observed that 30 of them became redundant, but the time of convergence for 50 robots was much more efficient due to the consumption of less time in the initial stage. The approach also contributes to better energy savings. Similar to Zhou, Goldman and McLurkin (2017), the communication implemented is not direct and for better performance they avoid central control, Zhou, Goldman and McLurkin (2017) highlight the operations for keeps the communication in cost low with the simulation capacity of 150 robots, such as time and distance, this increases the robustness of the system, once the numbers of robots can be independent of the expenditures. The swarm control approach used by Bandyopadhyay, Chung and Hadaegh (2017) enables the performance of complex tasks due to the probabilistic method and Eulerian framework. As a result, the system demonstrates scalable communication between agents. To evaluate the cost reduction transitions based on the approaches used by Bandyopadhyay, Chung and Hadaegh (2017), the number of robot changes at the simulations, such as 10^4, 10^5 and 10^6, then the algorithm achieves great results since the PSG and IMC can perform 16 times less transitions than algorithms structured in Homogeneous Markov Chain (HMC).

Liu et al. (2018) simulate the team-assembly problem by simulating it in a plane within a circle and present several corollaries to prove that independent of the initial swarm configuration, robots can form teams where two robots do not occupy the same position. To show the sufficiency of the theorem, the asynchronous (ASYNC) algorithm proves that it can form up to 100 teams for any initial organization, for cases where we have the exact number of robots and for cases where there are additional robots. In Liu et al. (2018), a circular region is used, while Tokas and Das (2017) proposed a rectangular region, where the obstacles are randomly placed. All robots present an efficient and easy implementation for synchronizing time between each other through color lights. However, the model presented by Tokas and Das (2017) has drawbacks, such as communication occurring only once and limited robot visibility to detect obstacles. The limited vision can be addressed by using cameras and stereo vision methods, and a time-varying approach could be implemented in the algorithm to ensure that communication is checked at intervals throughout the assembly process.

In order to detect faults, Khaldi et al. (2017) perform simulations in a swarm taking into account the information available from its neighborhood. The ARGoS simulator for multi-robot systems are used to configure for a closed arena of 10×6 m^2 and 6 foot-bots. The authors use the virtual viscoelastic control (VVC) model for the robot circle formation to maintain swarm connectivity and coherence while moving. The simulation time step is set to 0.1 s, with five iterations, each experiment, for a total of 1500 time steps. Several types of defects are tested in the paper by Khaldi et al. (2017), such as drift faults, abrupt faults, and complete stop faults, among others. The results show that significant improvement in fault detection can be achieved using the EWMA graph, rather than principal component analysis (PCA), because EWMA is capable of detecting small and persistent faults, whereas PCA methods are better suited for detecting relatively large faults.

6 Conclusion

This article presented a critical review of past applications and studies, where techniques are used to analyze and solve robotic swarm problems. For each problem, the technique is described, the method is presented, the studies are grouped into categories and an analysis of the tools and metrics is provided. The survey included articles published from 2014 to 2020 in the Science Direct and IEEEXplore databases.

In general, the studies showed potential for applications in real environments, however, there are difficulties in terms of replication and comparison of the proposed methods. This is due to the nonexistence of standards, or popularization of a simulator, set of swarm of robots or databases for the study. This work suggests consolidated tools, which are used in recent studies of swarm robotics. Works such as Liu and Lyons (2015) and Soleymani et al. (2015) carry out not only simulations but also analyses with real robot teams. Furthermore, Rango et al. (2015) and Junior and Nedjah (2017) use simulators for navigation in order to explore different environments with obstacles.

In Rango et al. (2015), exploration in unfamiliar environments is carried out by a team of robots, which presents the concept of simultaneous navigation in the search area. To that end, algorithms that use metaheuristic approaches, such as ACO and FA, are executed for coordination tasks between robots. In addition, Junior and Nedjah (2017) demonstrate collective navigation based on subtasks performed by robots, using the wave swarm method to carry out complex tasks through simple task sequences. These studies can take robotic swarm to industrial applications at low cost and with advantages for the optimization of the process in time, navigation, location and communication.

Among the set of keywords used, the most important were "swarm robots", "distributed"and "swarm intelligence". With a spread configuration, the system is firm for imperfections and defects of individual robots and adaptable to add or remove robots as the proportion of tasks is changed. These words were the keywords most used by the authors studied in this review.

Most of the articles selected used PSO and ACO techniques, or implemented improvements of these two techniques. In addition, these two techniques, the use of artificial pheromones is worth highlighting, as this technique was often used for the implementation of the improvements of the previous techniques.

Considering critical verification and examination, investigation of procedures, keyword analysis and suggestions for future achievements in the development of swarm robotics, this review is particularly useful for researchers seeking to work on the development and / or enhancement of robotic swarm techniques.

Acknowledgment

The authors thank PPGET (*Programa de Pós-Graduação em Engenharia de Telecomunicações*) and PPGER from IFCE (*Instituto Federal de Educação, Ciência e Tecnologia do Ceará*), IFSP (*Instituto Federal de Educação, Ciência e Tecnologia de São Paulo*), FUNCAP (*Fundação Cearense de Apoio ao Desenvolviento Científico e Tecnológico*), CNPq (*Conselho Nacional de Desenvolvimento Científico e Tecnológico*) and UNIFOR (*Universidade de Fortaleza*) for academic support, CAPES (*Coordenação de Aperfeiçoamento de Pessoal de Nível Superior*) for financial support and the laboratory LEM (*Laboratório de Ensaios Mecânicos*) for providing laboratory infrastructure for the implementation of our activities.

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