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Review of Collective Decision Making in Swarm Robotics

Rusul Ibrahim[a], Muhanad Alkilabi[b], Ali Retha Hasoon Khayeat[c], Elio Tuci[d]

[a] *College of Computer Science and Information Technology, University of Kerbala, Kerbala 5006, Iraq.Email:rusul.i@uokerbala.edu.iq*

[b] *Department of Medical Instruments Techniques Engineering, AlSafwa University College, Iraq . Email: muhanad.haider@alsafwa.edu.iq*

[c] *College of Computer Science and Information Technology, University of Kerbala, Kerbala 5006, Iraq.Email :ali.r@uokerbala.edu.iq*

[d] *Department of Computer Science, University of Namur, Namur 5000, Belgium.Email: elio.tuci@unamur.be*

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ABSTRACT

Swarm robotics is a distinctive type of multi-robotic system that relies on local communication among the swarm members to generate a desired global behaviour. This implies a lack of global information, requiring robots to sense and communicate using sensors and actuators located on their bodies. Consequently, the robots within the swarm must leverage collective intelligence to solve the problem at hand, as no individual robot can accomplish the task independently. This article provides an overview of swarm robotics in general, highlighting its characteristics that distinguish it from other multi-robotic systems and simultaneously serve as motivation to adopt a swarm robotics approach. A closer examination of collective decision making within swarm robotics and its design problem also provided, classifying design methods into manual design and automatic approaches. The most commonly used automatic approaches to design collective decision making in swarm robotics are explained, along with a mention of the benefits and drawbacks of such approaches. However, this review does not cover aspects such as the swarm collective behaviours – except collective decision making – and the swarm robotics tasks.

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1. Introduction

Swarm robotics is a distinctive kind of multi-robot system that is inspired by natural swarm systems, such as ants, honey bees, termites, and other types of social insects and animals [1]. In this approach, the task is delegated to a large number of robots that work in an autonomous and self-organised manner. Therefore, it does not depend on any centralised controller, meaning neither an external computer nor a leader robot. However, for decision making and coordination of activities, the swarm relies on interactions among individual robots and between the robots and their environment, leading to the emergence of the required collective behaviour.

∗Corresponding author Rusul Ibrahim

Email addresses: *rusul.i@uokerbala.edu.iq*

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A robot swarm can be *homogeneous*, involving robots with identical hardware and control software, or *heterogeneous* if its members have different hardware and/or control software. However, in both cases, the swarm is composed of redundant and relatively simple robots, allowing multiple robots to implement each single action. Therefore, when collective behaviour is accomplished, it cannot be the responsibility of any individual [2].

Each individual robot alone is unable to perform the task that a swarm is intended to accomplish. This implies that the swarm should leverage *swarm intelligence* traits inspired by social animals, and that is the focus of swarm robotics endeavours [3]. There are some main characteristics that may distinguish swarm robotics from other multi-robotics systems [4]:

- A swarm robotic system composed of autonomous robots physically located in the environment and capable of modifying it.
- A relatively high degree of redundancy within the swarm robotic system.
- Cooperation among swarm members is essential to solve tasks; no individual robot can handle the mission independently.
- Each individual robot possesses local sensing and communication capabilities, with no access to any global information.

These features are typically contributing factors to give the swarm desired properties of robustness, scalability, and flexibility.

In contrast to swarm robotics, other types of multi-robotics systems such as modular robotics systems, reconfigurable systems, cooperative, and competitive systems, may have access to global information through a centralised system. They are also not constrained to possess a high degree of redundancy, therefore they can be composed of two or three robots.

Swarm robotics is intended to develop applications such as monitoring, searching for survivors in disaster areas to facilitate rescue efforts, mine-clearing, elimination of debris and pollutants, exploration of dangerous climates, and healthcare assistance [2]. However, adopting the swarm robotics approach in real world applications remains one of the open issues in swarm robotics [5].

The biological inspiration mentioned earlier not only benefits swarm robotics but also provides a sensible explanation for social behaviours in biological swarms. In this case, robots are equipped with a software controller that enables them to emulate the observed collective behaviours in analysed insect societies or other biological systems. Therefore, swarm robotics can be considered a powerful tool to study such biological systems [6].

A swarm robotics system exhibits basic collective behaviours such as spatial organisation, navigation, and collective decision making. These behaviours can be integrated to address complex problems that the swarm is intended to solve [3]. Understanding and designing collective decision making are essential for developing swarm robots, where swarm robotics systems can achieve the required collective decision making through self-organisation inspired by natural systems [7].

This review is organised into five sections: Section 2 explains collective decision making within the swarm robotics. Section 3 illustrates the design problem faced when designing collective decision making and other collective behaviours within swarm robotics. Section 4 demonstrates the design approaches within swarm robotics literature and divides it into hand-coded approach and automatic approach. Finally, Section 5 is the review conclusion.

2. Collective Decision Making

Collective decision making is the mechanism that enables swarm robotics to make choices based on the influence of robots on each other, considering how robots affect each other when deciding between options. It is categorised into *task allocation* and *consensus achievement*. *Task allocation* aims to enhance swarm performance by allowing robots to group themselves according to the task they will work on. On the other hand, *consensus achievement* is relevant for missions that require the swarm to reach a common decision among different available options [3].

In swarm robotics, not only the individual robot should be autonomous, but the entire swarm must also be autonomous to make decisions independently. This necessitates the entire swarm's ability to make independent decisions, achievable through collective decision making. Therefore, collective decision making may be considered the key behaviour and the most significant capability of swarm robotics [8].

Consensus achievement can be *discrete* if the available choices are finite and countable, or it can be *continuous* if the available choices are infinite and measurable. In both cases, the swarm must deal with what is known in swarm robotics literature as the *best-of-n problem,* where *n* represents the number of available options. The objective is to reach a consensus on the best option among them concerning the task at hand. The swarm is considered to have solved the *best-of-n* once it makes a collective decision to choose one option among *n*. This collective decision is established either by a large majority, where a significant number of robots uphold the same option based on a threshold determined by the designer. In other applications, the swarm must reach a consensus where all robots share the same opinion to consider the establishment of collective decision [9].

When swarm robotics investigates a scenario with two options to make a collective decision and achieve consensus about the better one among them, the problem is referred to as best-of-2 (n = 2). Generally speaking, in swarm robotics literature, the best-of-2 scenario is the most examined [10].

Each option in the best-of-n problem is characterised by quality and cost, where quality is related to attributes concerning the swarm objective, and cost is associated with environmental bias. Both quality and cost may be represented by one or more factors of the target environment. In the best-of-n problem, swarm robotics aims to make a collective decision that maximises quality and minimises cost [11].

3. Design Problem

To design collective decision making or any other collective behaviour in swarm robotics, the designer is confronted with the challenge of identifying individual level behaviours with the goal of producing the desired collective behaviour [12].

The design problem arises from the self-organisation property of swarm robotics, derived from biological systems. In this context, each individual is responsible for its own behaviours, while the desired collective response must emerge from interactions between individual robots on one hand and between individual robots and the environment on the other hand. In this case, the designer must focus on the local level of the individual robot, referred to as the microscopic level, to generate the required collective response at the swarm level, referred to as the macroscopic level. However, this task is challenging due to the lack of a direct link between the two levels, the dynamic and nonlinear nature of the process. Additionally, there is no generic procedure to derive the simple interaction rules that lead to the complex global behaviour in demand [13].

Self-organisation, a predominant concept in swarm robotics, comprises four basic components: positive feedback, negative feedback, interactions between robots themselves and with the environment, and the balance of exploration and exploitation [8]. Positive feedback involves amplifying the effect of an event to guide the swarm to a stable state, and it is generated by the repetition of the individual decision making mechanism. Negative feedback, on the other hand, is the reversal of an effect and can be used to prevent the system from reaching an extreme state [14]. Therefore, maintaining the system in a stable and balanced state is the responsibility of the positive and negative feedback, along with restoring the system organisation after deviations caused by external influences. Consequently, the self-organisation property may emerge from the interactions of these two basic mechanisms of positive and negative feedback [15].

As mentioned earlier, perception and communication in swarm robotics are local and achieved through sensors and actuators situated on the robot body. Local communication can be explicit or implicit based on the mechanisms for exchanging information. Explicit communication occurs through direct information exchange between robots within a specified communication range. In contrast, implicit communication takes place through the environment, where robots sense and modify the environment, indirectly affecting other robots [16].

During exploration, robots assess the quality of the available options in the environment, while in the exploitation phase, a robot disseminates its current opinion about the best option with its neighbours. The dissemination time may vary based on the quality of the disseminated information, leading to the generation of a positive feedback loop [8]. Consequently, designing collective decision making in swarm robotics, or other collective behaviours, is a challenging task, as mentioned above. The design approaches used in literature will be further elaborated in the following sections.

4. Design Approaches

In general, there are two design methods in swarm robotics: manual design and automatic design. Manual design is the traditional method where an individual controller is designed, requiring an expert programmer to implement a suitable algorithm. This approach often relies on a simple finite state machine as an individual robot controller, which is considered challenging due to the micro-macro problem. Even skilled and experienced programmers need to undergo an iterative trial-and-error process to precisely adjust algorithm parameters until the desired collective behaviour emerges [17]. Consequently, the quality of the collective response generated using this approach depends entirely on the skill and cleverness of the designer [18]. Often, the desired collective response is intricately linked to the mechanisms driving individual behaviour, making it challenging for even a skilled designer to have insight into the development of individual behaviours within the system.

Alternatively, some approaches use mechanisms that automatically adapt the parameters of a manually designed algorithm at run time with respect to the environmental conditions [19]. However, these mechanisms offer solutions adaptive to specific problems scenarios.

Another way to design collective decision making in swarm robotics is the automatic approach, which includes multi-robot reinforcement learning, neuro and bioinspired automatic design, AutoMoDe, and evolutionary swarm robotics. Artificial evolution may be considered the most widespread automatic approach [20]. The automatic approach can reduce developer labour and its bias on the solution, helping overcome design problems in swarm robotics.

4.1 Hand-Coded Approach

The hand-coded approach underlying collective decision making adopts mechanisms to change the agents' opinions, including the Voter model, Majority rule, or variations of them. In the Voter model, an individual robot adopts the opinion of a randomly selected neighbour within the communication distance [21]. On the other hand, with the Majority rule, an individual robot changes its opinion to the opinion held by the majority of its group neighbours, counting its opinion with the group opinions [22], [23].

There are also some variations of those two mechanisms, such as Cross-Inhibition, inspired by the house-hunting process implemented by honeybees [24]. Another variation is the k-unanimity rule, where the robot receives the opinions of k randomly selected neighbours. If all the k robots favour the same option, it changes its opinion to the received opinion; otherwise, it maintains its previous opinion. When set k=1, the classical Voter model is obtained, making the k-unanimity rule a generalisation of the Voter model [21].

Another variation is introduced in [25] by combining Majority rule with Cross-Inhibition. This approach uses Majority rule to select neighbour opinions while updating the robot's opinion based on Cross-Inhibition. Other variations involve slightly different details of the Voter model or Majority rule, as seen in [26], [27], [28], [29]. However, in each case, the robot updates its opinion based on the influence of the group neighbours.

Despite the effective results achieved by the hand-coded approach in many collective decision making scenarios, some works address the limitations of such approaches, especially in handling dynamic environments. In dynamic environments, the swarm must adapt to changes in the quality of options over time. The challenges arise due to a strong dependence on the designer's intuition in composing collective behaviour into individual behaviours and determining the communication rules to be followed by individual robots [30].

4.2 Automatic Approach

Despite the fact that there are numerous ways to design collective decision making in swarm robotics automatically (as mentioned in Section 4), we will discuss in this section the most well-known methods: evolutionary robotics and AutoMoDe.

Evolutionary swarm robotics provides an effective solution to the design problem that arises in the emergence of global collective behaviour in swarm robotics. It does not require the decomposition of global behaviour to determine individual behaviours. Therefore, its evaluation is dependent on group performance, where the fitness function is computed based on the emergence of the desired collective swarm behaviour [15]. In this approach, a neural network serves as an individual controller, reading the robot's sensors as input and returning an output used to command the robot's actuators and, consequently, the individual robot's opinion. The parameters and sometimes the structure of the neural network are optimised using an evolutionary algorithm [31]. Despite use of an artificial neural network as an individual controller with weights generated by artificial evolution, finite state machines have sometimes been employed as an individual controller instead of neural networks [13].

Evolutionary swarm robotics faces several challenges, one of which is the extensive computational process that requires a considerable amount of time and resources for the evolution of the best genotype. This process must be repeated for each specific scenario, making it impractical for real robots. Consequently, simulations are often used, introducing the issue of the reality gap, where the successful genotype in the simulator may not perform well when transferred to real robots, leading to overfitting [32]. Another challenge is that the solution driven by artificial evolution is considered a black box because it is difficult to analyse mathematically [33]. As a result, designers may face difficulties in maintaining and improving the evolved solution [12].

A recent alternative design approach based on Evolutionary Robotics (ER) has been introduced [34]. In this approach, the decision-making unit generating the agent's opinion is an artificial neural network synthesised using evolutionary computation techniques [35]. An essential feature of the ER approach is the automation of the design process, significantly reducing the influence of designer assumptions. Recent research [36] indicates that the ER approach outperformed the hand-coded approach in terms of the robustness, adaptability, and scalability of the collective response of the group.

Automatic modular design (AutoMoDe) is another approach to automatic design, automatically generating probabilistic finite state machines. AutoMoDe explores the search space using an optimisation algorithm, where the search space consists of all possible finite state machines generated using modules. Modules represent the states of finite state machines, represented by behaviours, and transitions between these states based on predefined conditions. For a given task, AutoMoDe automatically searches for the modules that represent the best collection within the search space to solve the problem. The reality gap problem is addressed using a bias-variance trade off, where pre-existing modules are used to inject bias. AutoMoDe-Vanilla serves as a proof of concept and is implemented using e-puck real robots [37].

Table 1 - The design methods used in some research.

Reference	Design Method	Details
[21]	Hand-Coded/ k-Unanimity Rule	The robot changes its opinion to the opinions of k randomly selected neighbours. If all the k robots favour the same option.
[22], [23], [38], [29], [26]	Hand-Coded/ Voter Model	The robot adopts the opinion of a randomly selected neighbour.
[25]	Hand-Coded / Majority rule & Cross Inhibition	Using Majority rule to select neighbour opinions while updating the robot's opinion based on Cross-Inhibition.
[34], [36], [39], [40], [41]	Automatic Approach / Evolutionary Robotics	A neural network synthesised using evolutionary optimisation technique, used as an individual controller.
[37], [42]	Automatic Approach / Automatic Modular Design (AutoMoDe)	Generating probabilistic finite state machines using an optimisation algorithm.
[43], [27]	Hand-Coded / Majority rule	The robot changes its opinion to the opinion held by the majority of its group neighbours

5. Conclusion

The review provides a comprehensive overview of the swarm robotics field, covering its characteristics, design problems, challenges, and collective behaviours, with a particular emphasis on collective decision making. It also discusses the various approaches to design collective decision making in swarm robotics, offering insights into the advantages and disadvantages of each approach.

From the state of the art, the limitations of the hand-coded approach can be observed, particularly in terms of adaptability and scalability. The increasing trend toward automatic methods in designing collective decision making in swarm robotics highlights the need for general solutions that can be applied to various problems. The current research focuses on *best-of-n* problems, particularly in the context of only two options, suggests a gap in addressing scenarios where *n* is greater than two.

A significant challenge is the absence of a general method or approach that can be implemented to design collective decision making in swarm robotics. Adopting the automatic approach may reduce the effect of this challenge, but it needs further improvements to be more adaptive to many problem scenarios. Moreover, validating the design model on physical robots may give a deeper understanding about how the local interactions influence the swarm collective behaviour.

In conclusion, the automatic approach, such as evolutionary robotics, holds promise for designing collective decision making in swarm robotics, despite its computational complexity. This is attributed to the adaptability and scalability of solutions generated using this design method. In the future, we intend to take advantage of evolutionary robotics to design collective decision making in swarm robotics for addressing various types of tasks. Additionally, we aim to test the ability of such solutions to tackle *best-of-n* problems where n is greater than two and to adapt to dynamic environments where the quality of options changes over time.

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