# A Stochastic Approach to Generate Emergent Behaviors in Robotic Swarms

**Paulo Rezeck and Luiz Chaimowicz**

Laboratório de Visão Computacional e Robótica (VeRLab)
Programa de Pós-Graduação em Ciência da Computacão
Universidade Federal de Minas Gerais (UFMG)
Belo Horizonte, MG – Brazil

{rezeck,chaimo}@dcc.ufmg.br

***Abstract.*** *This work proposes a stochastic methodology utilizing Gibbs Random Fields (GRFs) to induce diverse emergent behaviors in robotic swarms, including flocking, segregation, cooperative object transportation, and pattern formation. Relying solely on local information and decentralized control mechanisms, our approach enables robust and scalable swarm behaviors. Through numerical simulations and real-world experiments with HeRo 2.0, a low-cost swarm robotic platform developed as part of this work, we demonstrate the benefits of the proposed methodology, including adaptability, robustness, and resilience. Overall, our stochastic approach holds promise for advancing swarm robotics by enabling the generation of versatile behaviors, contributing to the field's evolution and showing potential for new applications.*

***Keywords****: Robotics, Multi-agent system, Swarm robotics, Probabilistic robotics.*

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## 1. Introduction

Swarm robotics has emerged as a promising field at the intersection of robotics and multi-agent systems, aiming to revolutionize the way we approach collective tasks with autonomous systems. Traditionally, robotics has focused on individual agents performing specific tasks, but the advent of swarm robotics has paved the way for collaborative efforts among large groups of robots, mirroring the collective behaviors observed in nature. This shift in focus holds immense potential for various domains, including manufacturing, agriculture, disaster response, and environmental monitoring.

Despite rapid advancements in swarm robotics, a persistent challenge remains: the lack of flexible methodologies for accommodating diverse swarm behaviors. Traditional approaches often rely on task-specific solutions, limiting scalability and adaptability, hindering broader adoption in real-world applications, and innovation in the field. Driven by the need for versatile and scalable solutions, this work addresses these shortcomings by developing a unified and adaptable methodology. Motivated by the belief that such an approach is essential for realizing the full potential of swarm robotics in tackling complex real-world challenges, we aim to unlock new possibilities for swarm systems and accelerate their integration into various domains.

This work aims to achieve two main objectives in the field of swarm robotics. First, drawing inspiration from statistical mechanics and quantum mechanics concepts, we propose a novel methodology for synthesizing control strategies that induce diverse collective behaviors in robotic swarms, leveraging minimal sensing information. Specifically, we aim to extend Gibbs Random Fields (GRFs) to swarm robotics, designing decentralized control mechanisms to coordinate group behavior based on local information. Secondly, we seek to explore the flexibility of this methodology in addressing significant challenges within swarm robotics, as illustrated in Figure 1. These challenges encompass integrating flocking with segregation, enabling cooperative object transportation, and facilitating pattern formation behaviors. Through theoretical analysis, simulations, and real-world experiments, we demonstrate the effectiveness and versatility of our methodology in tackling these challenges.

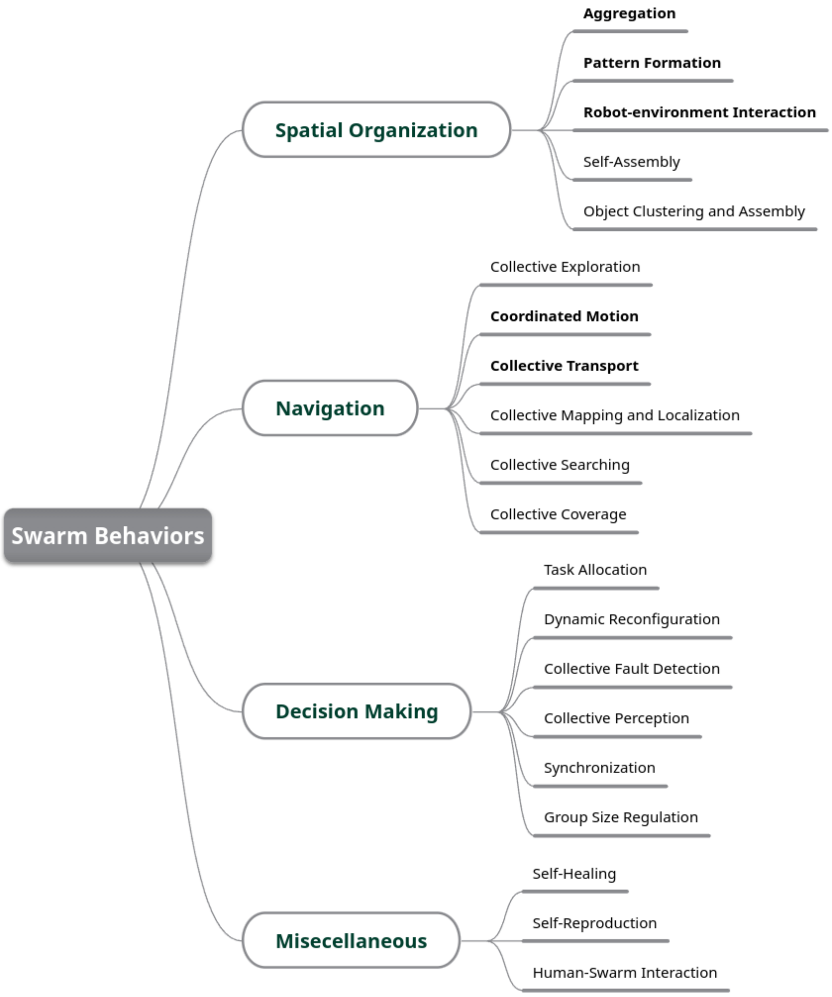



**Figura 1. Swarm robotics behaviors adapted from [Schranz et al. 2020]. The highlighted behaviors are tackled in this work.**

This work makes significant contributions to swarm robotics, leading to four publications in high-impact academic journals and conferences. Firstly, a novel stochastic and decentralized approach is introduced, leveraging dynamic Gibbs Random Fields (GRFs) to enable heterogeneous robot swarms to exhibit various behaviors through local interactions. This methodology facilitates the emergence of different behaviors. Specifically, methods for achieving simultaneous segregation and flocking behaviors [Rezeck et al. 2021b], cooperative object transportation [Rezeck et al. 2021a], and complex pattern formation [Rezeck and Chaimowicz 2022] are developed, showcasing the versatility and applicability of the proposed approach. Importantly, these contributions advance the state-of-the-art in swarm robotics, offering valuable insights that transcend traditional solutions. Additionally, advancements in the design and control of the HeRo swarm robotic platform are presented [Rezeck et al. 2023], enhancing its capabilities for real-world experiments to demonstrate the methodology's effectiveness. These contributions are crucial for advancing swarm robotics, offering new avenues for research and innovation in the field, while extending their impact to the broader landscape of computer science, particularly in distributed systems, optimization, and artificial intelligence.

## 2. Related Work

This work reviews the literature concerning the utilization of Markov and Gibbs Random Fields in the domain of swarm robotics, focusing on their potential applications and methodologies. Markov Random Fields (MRFs) and Gibbs Random Fields (GRFs) are mathematical models frequently employed in statistical mechanics and computer vision to describe interactions between individual components within systems. While extensively utilized in various fields, their application in swarm robotics remains relatively scarce, warranting further exploration and research in this area. An initial contribution in this field was presented by [Baras and Tan 2004], who demonstrated the efficacy of using MRFs to model and control swarm behavior. They proposed a method where a swarm of robots is modeled as a MRF on a graph, with robots and their sensing links forming vertices and edges, respectively. By employing Gibbs potentials to define interactions within the swarm, the authors facilitated global objective achievement, such as aggregation or dispersion, through simulated annealing based on the Gibbs sampler. This approach enabled efficient and scalable control of swarm movement, even for large robot swarms. Subsequent works by [Xi et al. 2006] and [Tan et al. 2010] further refined these concepts, introducing hybrid algorithms that combined gradient descent and Gibbs sampling to optimize multi-robot systems' behavior. These algorithms demonstrated convergence to minimal potential configurations, even in the presence of uncertainties in sensing, highlighting their robustness and effectiveness.

Recent advancements have extended the application of MRFs in swarm robotics to flocking behaviors. For instance, [Fernando 2021] proposed a flocking algorithm that utilized differential flat dynamics and MRFs to model robot interactions, facilitating online coordination and collision avoidance within the swarm. In parallel, our work, inspired by [Baras and Tan 2004], introduces novel methods that achieve segregation, flocking, cooperative object transportation, and pattern formation behaviors, all using our GRF approach. Our novel methodology brings several key advantages. Firstly, we incorporate robot kinematics, enabling continuous movement modeling within bounded environments, a significant departure from discrete lattice-based assumptions. Additionally, our method employs a novel potential function, the Coulomb-Buckingham Potential coupled with kinetic energy, offering encoding of low-level swarm behaviors. These advancements enable seamless aggregation, object interaction, and autonomous navigation without centralized coordination, showcasing the versatility and potential of our methodology as a general-purpose solution for swarm control.

## 3. Designing Swarm Behaviors

This section introduces Gibbs Random Fields (GRFs) to swarm robotics and outlines our methodology for designing swarm behaviors. Here, we use GRFs to model the spatial configuration of a swarm's behavior over time. By strategically combining specific potential functions, we engineer a potential energy within the swarm, translating its configuration into a single energy value. Through a conditional probability function, we sample velocities to globally minimize this energy value over time, leading the swarm toward desired behaviors. However, establishing a direct correlation between a potential energy function and a desired swarm behavior can be intricate, demanding intuition and creativity. Thus, we present an overview of our methodology depicted in Figure 2, along with sequential steps guiding its application. This approach offers decentralized control, in which robots make decisions based on local information without direct communication, enhancing system robustness and scalability. Additionally, its flexibility allows adaptation to changing environmental conditions or new goals, underscoring potential for diverse swarm behaviors.

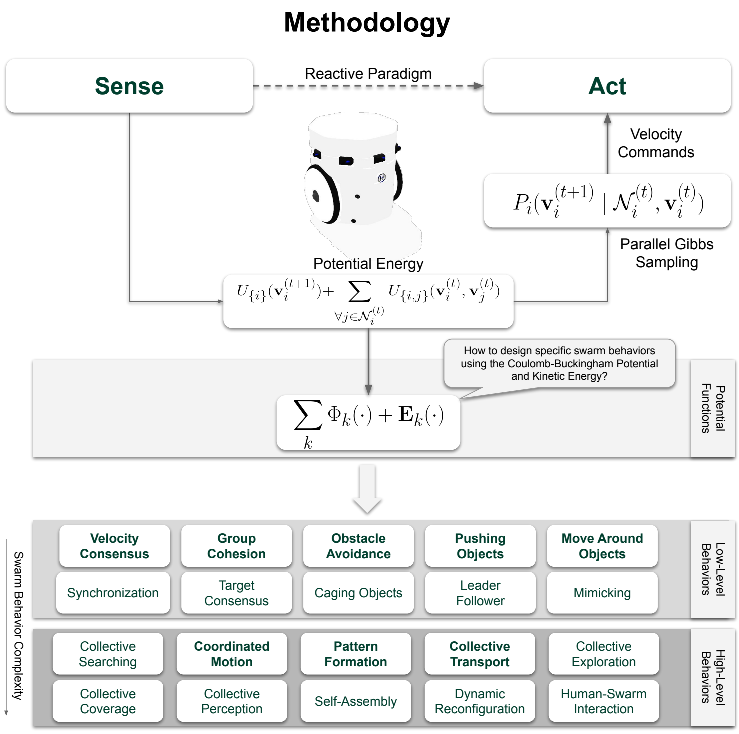



**Figura 2. Methodology for inducing diverse swarm behaviors through potential function combinations. Highlighted behaviors are tackled in this work.**

1. **Potential Functions as Primitives:** In our methodology, potential functions play a pivotal role as fundamental building blocks. The Coulomb-Buckingham potential, for instance, serves as a mathematical descriptor of electrostatic interactions among charged particles within the swarm. Depending on its configuration, this potential can induce attractive or repulsive forces, thereby enabling the emergence of intricate swarm behaviors. When combined with kinetic energy, which accounts for motion interactions, these potential functions influence the dynamics of swarm behavior, shaping its navigation patterns and group cohesion.

2. **Modeling Low-Level Swarm Behaviors:** In this step, we combine the primitive behaviors in various arrangements to capture diverse swarm behaviors, such as group formation, cohesive navigation, and robot-environment interaction. Achieving this requires a blend of intuition, creative exploration, and rigorous testing to design a potential energy function that effectively embodies the intended behaviors. These low-level behaviors essentially serve as the fundamental building blocks upon which higher-level swarm behaviors are constructed.
3. **Designing High-Level Swarm Behaviors:** Using the low-level swarm behaviors crafted in the previous step, we proceed to design high-level potential functions. These functions encapsulate more intricate swarm behaviors, such as collective transport, exploration, and searching. Especially for highly complex swarm behaviors, there might be a need to dynamically adapt potential functions based on the evolving swarm configuration to ensure optimal performance and adaptability.
4. **Executing Parallel Gibbs Sampling:** In this stage, we apply a parallel Gibbs sampling to model a probability function designed in this study. This function captures the likelihood of a particular swarm configuration based on the engineered potential energy. By appropriately designing the potential energy function, we can influence the stationary distributions of this probability. Consequently, sampling over this probability acts as a control mechanism, providing command velocities with maximum likelihood. Following these commands guides the swarm towards configurations that minimize the global potential energy while manifesting specific behaviors.
5. **Iterate and Experiment:** Apply an iterative approach to refine and optimize swarm behaviors. Through experimentation and analysis, we test and adjust potential energy functions to fine-tune the desired swarm behaviors for specific applications. This iterative process allows for continuous improvement and optimization of the swarm's performance and adaptability.

This methodology integrates mathematical formulations with computational algorithms to design swarm behaviors effectively. Subsequent sections detail its application in producing intricate behaviors like flocking, segregation, cooperative object transportation, and pattern formation. Additionally, the upcoming section outlines the design and implementation of a robotic platform for proof-of-concept experiments, which will be used to demonstrate the methodologies' versatility and efficacy in real-world scenarios.

## 4. HeRo 2.0: a Low-Cost Robot for Swarm Robotics Research

One of the contributions of this dissertation is the improvement of HeRo [Rezeck et al. 2017], an open-source and highly affordable robotic platform, used to validate our methodology's effectiveness in real-world experiments. HeRo 2.0 [Rezeck et al. 2023] emerges as one of the most accessible and capable robots available for swarm robotics research, integrating commercially available components and additive manufacturing techniques (Figure 3). Powered by an Espressif ESP8266 microcontroller, it ensures robust wireless communication and precise locomotion, complemented by a suite of sensors and differential-driven wheels. With features like Firmware Over-The-Air updates and seamless integration with the Robot Operating System (ROS), HeRo 2.0 enables extensive experimentation and encourages collaboration within the robotics community.

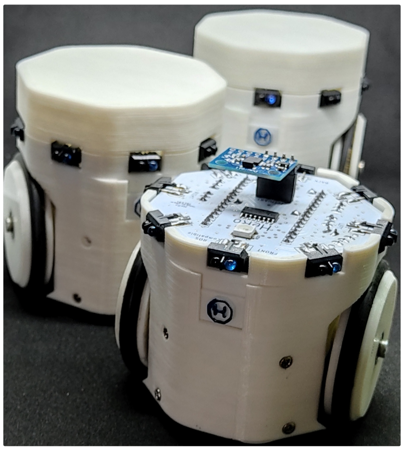


**Figura 3. Design of the open swarm robotic platform. The body of the robots was designed for and fabricated using additive manufacturing. Video link: https://verlab.github.io/hero_common/.**

In addition to its contributions to robotics, HeRo 2.0 holds promise as a valuable tool in computer science education and research. Its open-source nature and versatility make it an ideal platform for learning about swarm robotics and experimenting with decentralized behaviors. By providing hands-on experience with programming and experimentation, HeRo 2.0 can foster interest and skill development in robotics and computer science among students and researchers alike. Thus, it serves as a cornerstone in robotics research and education, paving the way for innovative advancements in the broader landscape of computer science.

## 5. Flocking-Segregative Behavior

Flocking-segregative behavior encompasses the simultaneous expression of flocking and segregation in robotic swarms. Flocking involves synchronized movement of robots, while segregation entails clustering based on shared characteristics while maintaining separation. Prior to this research, there was a gap in addressing both behaviors simultaneously from a random initial state, especially in scenarios with multiple distinct groups relying solely on local sensing. Figure 4 illustrates the flocking-segregative behavior.

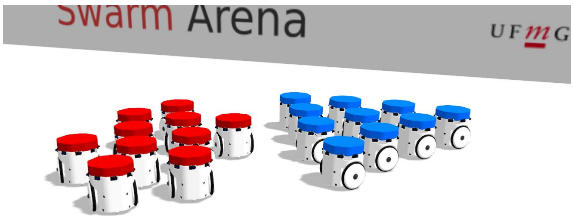
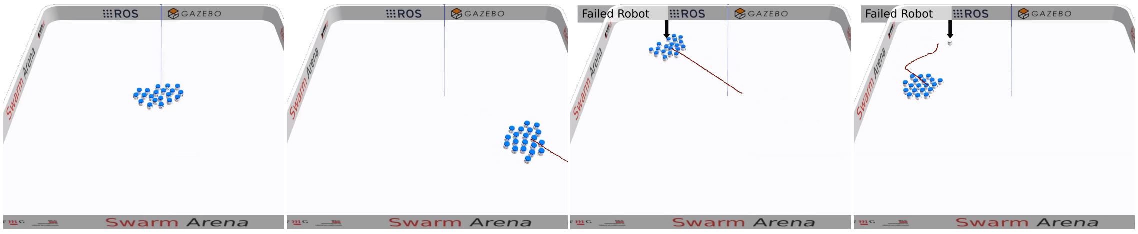


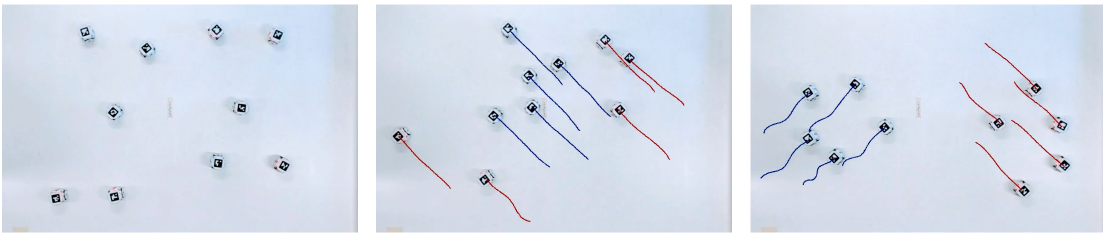

**Figura 4. Swarm demonstrates simultaneous segregation and flocking, forming distinct groups while maintaining cohesive navigation.**

The experiments aimed to validate the proposed method's efficacy in achieving flocking segregation. Simulated experiments involved varying configurations to analyze segregative behavior and comparing results with existing methods. Flocking behavior was evaluated by examining velocity consensus and cohesion in the presence of sensor noise. Physical simulations demonstrated the method's robustness in executing behaviors within complex environments or in scenarios with mechanical failures (Figure 5). Real-world experiments with HeRo robots served as a proof-of-concept, showcasing the swarm's ability to achieve segregation and flocking behaviors in constrained environments (Figure 6). Overall, these experiments underscore the significance of achieving flocking and segregation behaviors simultaneously in robotic swarms, opening possibilities for various applications like area coverage and transport.




**(a)** $t = 0$ **s.** **(b)** $t = 50$ **s.** **(c)** $t = 70$ **s.** **(d)** $t = 90$ **s.**

**Figura 5. Snapshots show method robustness amid robot failure at 70 seconds. Video link: https://youtu.be/Rq9ld4gHfo8.**



**(a)** $t = 0$ **s.** **(b)** $t = 30$ **s.** **(c)** $t = 130$ **s.**

**Figura 6. Snapshots of two robot groups exhibiting segregation and flocking. Video link: https://youtu.be/s1eLOmECcwc.**

## 6. Cooperative Transport Behavior

Robotic swarms, known for their emergent collective behaviors, are versatile and scalable, making them ideal for tasks like cooperative transportation. However, decentralized control methods face challenges such as aligning forces and adapting to varying object shapes. This work introduces a method enabling autonomous navigation and cooperative object transportation. Figure 7 illustrates this behavior, demonstrating robots performing cooperative transportation. Unlike prior approaches, this method emerges from local interactions without explicit communication. Robots estimate neighbors' positions and velocities, distinguish obstacles, and dynamically adapt parameters for navigation and transportation without predefined behaviors or learning methods.

To validate the cooperative object transportation method, simulated experiments were conducted using ROS middleware and Gazebo simulator, assessing scalability, adaptability, and robustness. Real-world experiments with physical robots further confirmed its effectiveness. Figure 8 showcases experiments with a swarm transporting an object through a complex environment, while Figure 9 displays experiments with real robots, demonstrating its versatility. A video on Youtube[1] provides additional insight. Overall,

[1]Cooperative transport link: https://youtu.be/hrkJKL3W3pQ.

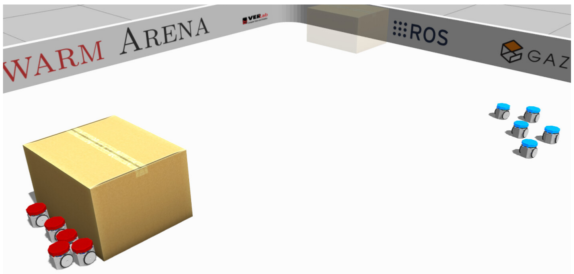
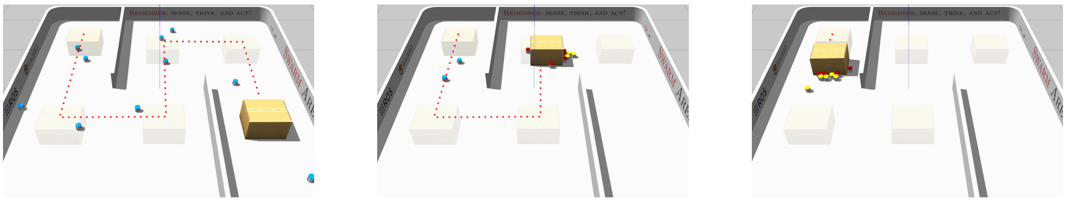


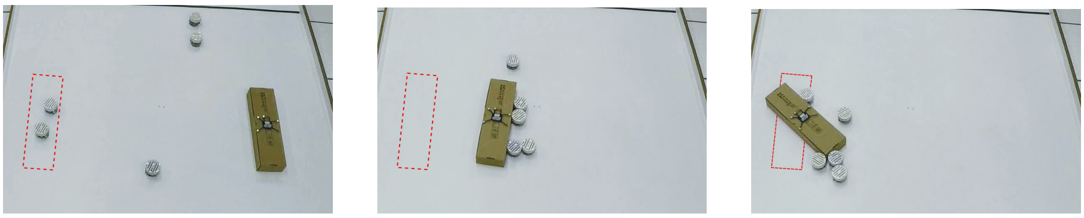

**Figura 7. Robots collaboratively transport a solid cardboard object toward a transparent goal. Red robots carry the object, while blue ones search.**

the method offers a decentralized solution for cooperative transportation tasks, providing scalability, robustness, and adaptability, thus contributing to the advancement of swarm robotics in real-world applications.



(a) $t = 0$ s. (b) $t = 485$ s. (c) $t = 919$ s.

**Figura 8. Simulated robots transporting an object toward target locations.**



(a) $t = 0$ s. (b) $t = 240$ s. (c) $t = 307$ s.

**Figura 9. Robots transporting an object toward a goal marked by a red rectangle.**

## 7. Pattern Formation Behavior

Pattern formation in swarm robotics entails coordinating robots to achieve specific shapes, inspired by phenomena observed in various scientific fields. Our approach enables a swarm of heterogeneous robots to form intricate patterns based solely on local interactions, drawing inspiration from particle interactions and molecular structures. Modeling the swarm as a dynamic Gibbs random field (GRF), our method enables diverse pattern formation without global information or predefined seeds. Figure 10 illustrates an example of a swarm forming a pattern resembling a molecular structure, showcasing emergent behaviors resulting from local interactions. Unlike existing approaches, our minimalist method demonstrates the feasibility of achieving complex pattern formation through emergent behaviors, enhancing scalability, adaptability, and enabling practical applications like modular robotics and temporary structure construction. This unique perspective, combining concepts from particle physics with swarm robotics, advances decentralized and distributed control methods for pattern formation in robotic systems.

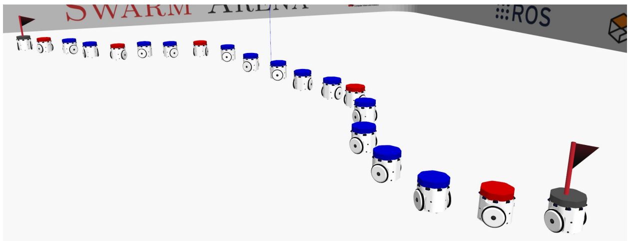
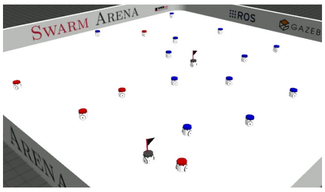
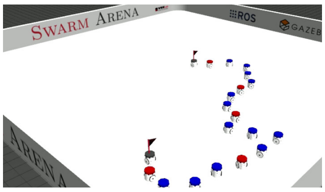



**Figura 10. Robots mimic carbon (red) and oxygen (blue) atoms, forming chain patterns for dynamic bridges. Red flags mark the chain's start and end.**

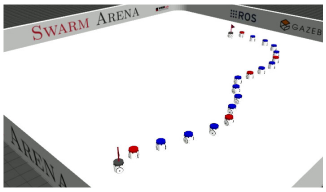
To further validate our approach, simulated experiments conducted in Gazebo showcase the swarm's dynamic convergence into structures resembling bridges (Figure 11). This simulation underscores the adaptability and responsiveness of our method in a controlled environment. Real-robot experiments further corroborate our method's efficacy, demonstrating the successful formation of chain-like structures with bridge-like topologies (Figure 12). The videos of each experiment are available online[2]. These experiments illustrate our method's potential in real-world scenarios and underscore its versatility and robustness across diverse environments.




**(a)** $t = 0$ **s.**

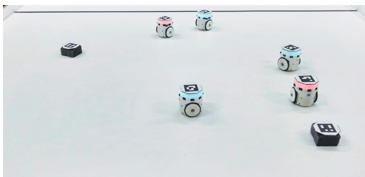



**(b)** $t = 115$ **s.**

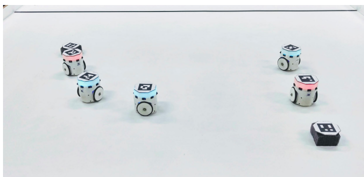



**(c)** $t = 135$ **s.**

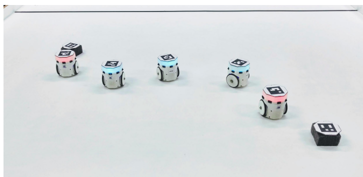
**Figura 11. 20 robots representing carbon (red) and oxygen (blue) atoms form bridge-like structures. Red-flagged robots mark the structure's ends.**



**(a)** $n = 0$ **s.**



**(b)** $n = 30$ **s.**



**(c)** $n = 50$ **s.**

**Figura 12. Snapshots of 5 real robots depict a dynamic bridge pattern with 2 carbon (red) and 3 oxygen (blue) atoms, bounded by black blocks.**

## 8. Conclusion and Future Work

This work presents a novel methodology extending Gibbs Random Fields (GRFs) to swarm robotics, aiming to model and control heterogeneous robot groups' behavior. Our approach offers decentralized control, guiding robots towards desired configurations within a GRF framework, enabling robust and scalable swarm coordination. We address intricate swarm challenges, including flocking-segregation dynamics, cooperative object transportation, and pattern formation, showcasing versatility and effectiveness. Simulated

[2] Pattern formation link: https://rezeck.github.io/chemistry-inspired-swarm.

and real-world experiments validate our methods, demonstrating adaptability, scalability, and resilience. The contributions of HeRo 2.0, our low-cost swarm robotic platform, are pivotal in real-world experimentation, validating practical viability. Our contribution extends beyond robotics, offering insights into decentralized and distributed control methods applicable across various computer science domains, particularly in distributed systems, optimization, and artificial intelligence.

Future work entails extending the methodology beyond sensing constraints for diverse swarm behaviors, including enhancing object transportation with sophisticated caging behavior and exploring cooperative coverage through dynamic spatial coverage methods. Additionally, integrating machine learning techniques for enhanced decision-making and pattern recognition will be explored. Addressing human-swarm interaction challenges and investigating convergence properties under dynamic conditions are crucial. Relaxing constraints could extend the methodology's applicability for achieving complex swarm behaviors, offering promising avenues for further research.

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