Robotic Swarm Cooperation Using Phase Transitions

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Abstract: The advancements in the area of Multiple Robot Systems in the field of robotics shows clear advantages over single robot systems. Cooperation among members in multiple robot systems, specifically in swarm systems, can boost the potential of the technology towards use current applications. It is, however, a challenge to properly control multiple robot systems to act and work as a single unit in achieving a goal because of the complexity of such algorithm. Different techniques have been proposed to control swarm systems with the recent emergence of techniques based on physics concepts. This paper proposes the use of the physics concept of fluid phase transitions as a key technique in the control of swarm system towards swarm cooperation. As in previous studies, specific cooperative tasks require the swarm system to perform a series of swarm behavior, this paper shows its similarities to performing a series of phase transitions when performing cooperative tasks. This paper presents the integration of different concepts involving phase transition towards achieving swarm cooperation.

Key Words: Multiple Robot Systems (MRS); Swarm Robotics; Moving Particle Semi-Implicit (MPS) Method;

1. INTRODUCTION

The advancements in technology have proven to enhance the world's ability in solving problems. This is the same in the field of robotics, wherein the goal is to provide better efficiency, flexibility, and speed in automation. The continued advancements in Multiple Robot Systems (MRS) show its potential over single robot systems in areas such as task flexibility, time efficiency, and single-point failure resiliency (Darmanin and Bugeja, 2017). Moreover, MRS also presents an economic advantage as the cost of multiple simple robots may be cheaper than a single complex robot.

The challenge, however, is the control of the multiple members in MRS to perform cooperation. Cooperation in MRS looks to be one of its biggest advantages over single robot systems, as it is the key in performing complex tasks in the field of robotics. The term "cooperation" in MRS has been given different definitions, such as in degree of communication or member involvement. The underlying process that defines "cooperation" however, is the coordination of actions of the members within the system (Tuci et al., 2018).

In order to achieve cooperation in MRS, control laws must be set as to dictate the actions of each individual member. The control for MRS varies differently depending on factors such as team composition and available communication mechanisms. The heterogeneity in the composition of an MRS allows the exploitation of the diverse capabilities of individual members to achieve tasks more efficiently and effectively (Darmanin and Bugeja, 2017). However, this would, in turn, require more communication mechanisms available as task allocation will be crucial to the system's success (Parker, 2008).

Homogeneous robot teams, often referred to as swarms, consist of identical robots, both in software and hardware (Tuci et al., 2018). Swarm robotics takes its inspiration from the behavior of biological swarms such as in insects and birds (Parker, 2008). These social behaviors drive the goal of swarm robotics, which is to be robust, scalable, and flexible (Brambilla et al., 2013). A system is said to be robust when it is able to respond properly to the loss of a member in the system. The scalability of a system refers to its effectiveness in performing with varying group sizes. Flexibility in a system refers to the system's ability to perform different kinds of tasks in different environments properly (Brambilla et al., 2013).

Drawing inspiration from animal swarm behaviors such as aggregation, flight formation, and tracking, swarm robotic systems can also be seen as performing such behaviors when performing tasks (Bandala et al., 2014). Thus, cooperation in swarm robotic systems can be viewed as performing a series of swarm behaviors.

Different studies propose different control techniques in dealing with swarms. The work of Krieger et al. (2000) based the system's task distribution and information transfer to an ant colony. The work of Berman (2013), on the other hand looked into the role of ants in object transportation.

Aside from investigating animal swarms, approaches based on physics have also emerged as control techniques in swarm systems. Modeling the swarm members as a particle in a fluid simulation, Pac et al. (2007) controlled the swarm by varying flow parameters using Smoothed Particle Hydrodynamics (SPH) developed by Monaghan and Gingold in 1977. Also using the formulation in SPH, Pimenta et al. (2013) modeled the swarm as an incompressible fluid with external forces, despite SPH being initially developed for compressible fluids. Sheng et al. (2011) modified the SPH formulation to be able to use the density parameter in fluid flow to control the movement of the swarm.

The control of MRS has been the main challenge of the field. Studies have focused on either the motion control of the system or the ability to perform cooperative tasks. A single control concept that integrates both aspects would be able to expand the current applications of MRS and swarm robotics. The evidence brought about using fluid dynamics concepts to control swarms builds the motivation for swarm cooperation using phase transitions.

Aside from viewing the tasks as a series of biological swarm behaviors, it is also possible to see it as a series of phase transitions seen in fluids. This paper presents an idea of controlling swarm cooperation through fluid phase transitions. The following section discusses the theoretical framework behind this idea. This is then followed by a sample application in the form of cooperative object transportation discussing the procedure and concepts involved.

2. THEORETICAL FRAMEWORK

As mentioned, tasks for swarm robotic systems that require cooperation can be seen as swarm behaviors or a series of swarm behaviors. The collection of objects to a specific location is a swarm behavior called foraging. While cooperative object transportation can be seen as a series of behaviors that include flocking, aggregation, and formation control.

In physics, some substances undergo phase transitions due to external factors such as change in environment. Although different fluids react to different factors, phase transition is a known phenomenon for fluids. It is also a known fact that water can exist as three different phases of matter, namely: solid, liquid, and gas. Water changes from liquid to a solid, ice, when its temperature is low, while liquid to a gas, steam, when its temperatures is high. Similar to looking at tasks as a series of swarm behaviors, tasks can also be looked as a series of phase transitions in fluid particles. The relationship between fluid phases and swarm behaviors is shown in the following figure.

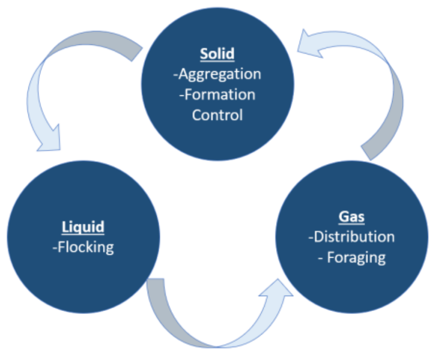

Fig. 1. Fluid Phases and Swarm Behavior

The idea of phase transition in swarm control was taken from the recommendation of Pimenta et al. (2013). Their work, however, focused on the mobile coordination of members in the system using the SPH formulation.

This work investigates the implementation of that idea using different theories and concepts in achieving a control technique for swarm cooperation using mobile robots.

3. APPLICATION: SWARM OBJECT TRANSPORTATION

Object transportation in MRS is classified by the method or technique used. Tuci et al. (2018) divided this into three classifications namely: pushing, grasping, and caging.

Pushing and caging approaches are defined as not having a permanent attachment to the object throughout the duration of the transport. Grasping, on the other hand, is defined as having a physical attachment to the object throughout the duration of the transport. This would then require the robot team to have a grasping mechanism. Several studies reviewed by Tuci et al. (2018) using the grasping approach opted to having the object pre-attached to focus on the actual transportation of the object.

This study proposes the use of the grasping approach wherein the object is to be placed on top of the robot team via manual attachment. The robot mission to test the proposed system along with its corresponding phase transitions is shown in fig. 2.

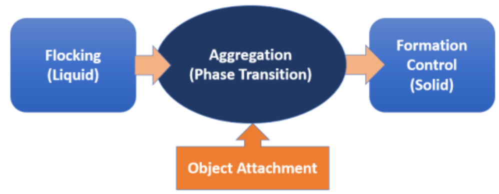

Fig. 2. Robot Mission

As the system assumes a liquid phase flocking towards the loading area, the Moving Particle Semi-Implicit method will be used as its control algorithm. The formation which the robot team is to hold during attachment and transport, assuming a solid phase, will be based on the supported area maximization concept.

The proposed system will be tested through computer simulations and using actual robots in a real testing environment. Varying obstacle positions and also object payload details will be done to test for the system's efficiency, flexibility, and robustness in performing cooperative object transportation.

3.1 Moving Particle Semi-Implicit Method

When the swarm is in its liquid phase, the Moving Particle Semi-Implicit (MPS) method is used. Similar to SPH, MPS is also a particle-based method. Both methods are classified as using the Lagrangian frame of reference as opposed to the more traditional Eulerian frame of reference. The main difference between the two is from the point of view by which fluid motion is described. In a Eulerian frame of reference describes motion from a fixed point in space, while a Lagrangian frame of reference is from within the fluid itself (Kelager, 2006).

The main difference between the MPS and SPH is that MPS was developed for incompressible fluid applications, while SPH was originally developed for compressible fluids.

Although recent developments have allowed SPH to be used for incompressible applications, some parameter assumptions make the computation more complicated. Application of SPH in swarm robotics in previous works slightly modified the original SPH formulation to have an incompressible flow behavior (Pimenta et al., 2013; Sheng et al., 2011). This makes MPS favored in this study as liquids are considered as incompressible fluids. The use of MPS in the control of swarm robotic systems has also been studied in a recent paper that is currently in publication (Chua et al., 2019).

MPS was originally developed by Koshizuka and Oka in 1996. Developments, modifications, and extended algorithms were made to improve and expand the applications MPS since then, as reviewed in the book by Koshizuka et al. (2018), but this study will use the original formulation.

The governing equations of the MPS are namely the Navier-stokes equation (Eq. 1) and the continuity equation (Eq. 2).

$$\frac{D\boldsymbol{u}}{Dt} = -\frac{1}{\rho}\nabla P + \nu\nabla^2\boldsymbol{u} + \boldsymbol{g} \qquad \text{(Eq. 1)}$$

$$\frac{D\rho}{Dt} = 0 \qquad \text{(Eq. 2)}$$

The left-hand side of Eq. 1 is the acceleration vector. The first term is called the pressure term which involves the density, ρ, and the gradient of pressure, P. The second term is the viscous term which involves kinematic viscosity, v, and the Laplacian of the velocity vector, $\boldsymbol{u}$. Lastly, the third term is the gravity vector, $\boldsymbol{g}$. The form used for Eq. 2 is the derived form with given incompressible and steady state conditions from the continuity equation.

The degree of influence a particle will have to neighboring particles is described by the weight function of MPS shown in Eq. 3.

$$w(r, r_e) = \begin{cases} \left(\frac{r_e}{r}\right) - 1; & (r < r_e) \\ 0; & (r \geq r_e) \end{cases} \qquad \text{(Eq. 3)}$$

Where:
r = Distance
r_e = Effective Radius

The weight function quantifies the amount of influence a particle has as the distance becomes smaller. While no influence for particles outside the effective radius. The proposed implementation of the MPS in swarm robotics systems is fully discussed in the recent paper (Chua et al., 2019).

3.2 Supported Area Maximization Concept

The supported area maximization concept is a novel approach that uses genetic algorithm to identify support coordinates for the robot teams. As the object is placed on top of the robot team, it is important to properly distribute the load among the robot members.

The study that presents this compares the supported area from an intuitive approach and results from the genetic algorithm is currently in the process of publication (Chua et al., 2020). The study varies the aspect ratio of the object and the weight of the object.

The concept is based on the idea that the maximum load of the robot translates to a force exerted toward the object. With the assumption that the object is flat, the force is equally distributed in a circular area. The ratio of the object weight and the maximum load capacity of a robot is then equal to the ratio of the object area and the robot's supported area shown in Eq. 4.

$$\frac{L}{W} = \frac{A_S}{A} \qquad \text{(Eq. 4)}$$

Where:
L = Load Capacity
W = Object Weight
A_s = Supported Area
A = Object Base Area

The maximization of the supported area would then mean that robots are properly distributed to be able to support and transport the object. This leads to the fitness function shown below.

$$max\ \frac{A_s}{A}$$

Computing for the radius of influence to be modeled in the genetic algorithm is shown in Eq. 5. Followed by a visualization of the concept shown in fig. 3.

$$r_s = \sqrt{\frac{LA}{\pi W}} \qquad \text{(Eq. 5)}$$

Where:
R_s = Radius of influence

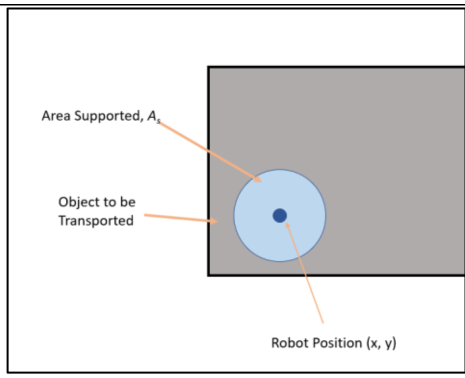

Fig. 3 Supported Area Concept

This concept was modeled using the optimization toolbox of Matlab (2019). The results showed that the coordinates for the positioning of robots using the genetic algorithm approach consistently gives a better supported area than the intuitive approach in both tests varying the base aspect ratio and varying object weight. The intuitive approach positions robots in the center of each quadrant of the rectangle. The graphed results for both tests are shown in Fig. 4. These results and further details on the study are discussed in the previously mentioned paper (Chua et al., 2020).

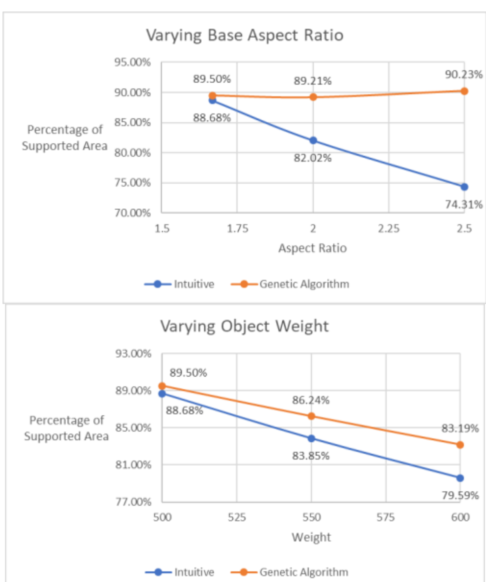

Fig. 4. Supported Area Concept Results

The application of this method will improve the positioning of the robot team when required to transport objects with more complex base geometries.

4. CONCLUSION AND RECOMMENDATIONS

This paper investigates the use of concepts of fluid phase transition in performing cooperative tasks for swarm robotic systems. Previous studies show that swarm systems perform a series of swarm behaviors to achieve a cooperative task. It is difficult, however, to use animal swarm behaviors as a model in swarm robotics control. The emergence of using physics concepts to model swarm simplifies this as computations and formulations are available to create a control algorithm. The similarities of fluid characteristics to swarm behaviors make it a favorable technique for control as it can enhance current methods.

The application presented in this paper, cooperative object transportation, shows an example of viewing a cooperative task as a series of phase transitions. This paper proposes the use of the MPS method and supported area maximization concept in a future study to perform cooperative object transportation using actual robots. An actual robot can also help test the effectivity of both methods with real world constraints.

Limited to cooperative object transportation, this paper was not able to discuss possible concepts for the control of the system when assuming a gas phase. This includes tasks such as foraging, exploration, and distribution. As the SPH is initially formulated for compressible flow problems, it may be used as a control

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