

Taking Swarms to the Field: A Framework for Underwater Mission Planning

Sherif Tolba, Reda Ammar, and Sanguthevar Rajasekaran

School of Engineering
University of Connecticut
Storrs, CT 06269-4155

Emails: {sherif.tolba, reda, rajasek}@enr.uconn.edu

Abstract—Large scale missions in unpredictable and unstable underwater environments are beyond the capabilities of a single intelligent and complex robot. Relying on one robot is far from optimal as loss of the unit means failure of the whole mission. On the contrary, robotic swarms depend on large numbers of simple, cheap, and error-prone robots that exhibit global desirable features like fault-tolerance, scalability, and robustness. The study of underwater robotic swarms from the overall mission-planning perspective has been very limited. Planning specific parts of a mission has mostly been the focus of previous research. We propose a general framework for designing and planning underwater swarm missions. We break a typical mission down into its primary constituents and study the requirements for each sub-mission separately. Initially, the swarm self-organizes to form a shape that maximizes residual energy and minimizes water resistance during transport towards the target. This is followed by path planning and shape maintenance, in which the swarm strives to maintain its collective shape and move in cohesion on a collectively-selected path. Next, another self-organization phase takes place to optimize mission-core accomplishment at the target. Remaining phases, in the back trip, are the counterparts of the first two. Related work in each phase is presented and discussed and future work is also highlighted.

I. INTRODUCTION

Early works in Swarm Robotics date back to the late 1980's, even before the term was coined. First works are attributed to T. Fukuda and S. Nakagawa in their 1987 work "A Dynamically Reconfigurable Robotic System (Concept of a system and optimal configurations)" [1], and to G. Beni and J. Wang in their work "Swarm Intelligence in Cellular Robotic Systems" in 1989 [2] and Beni in [3]. Beni is known to be the originator of the term *swarm intelligence* [4], which then extended to become an entire field of research and is the umbrella field for *swarm robotics*. The concept of a Cellular robotic system (CEBOT) was introduced by Fukuda and Nakagawa, where a large number of autonomous robots called *cells* constituted the CEBOT. The system was first called Dynamically Reconfigurable Robotic System (DRRS) and was referred to later as the CEBOT. Despite depending on the idea of self-reconfiguration and using a hierarchy of reconfigurable robotic structures: cells, cellular modules, cellular robots, groups, communities, and finally the named cellular robotic system, the system as defined by Fukuda et al. was not a pure swarm as known in the modern literature. Beni et al. on the other hand presented very soon after that, in 1989, a concept similar in name, the Cellular Robotic System (CRS), but more adequate to the current understanding of swarm robotics. The concept still diverged to some extent from swarms found in

nature in the sense that robots were confined to specific cells and did not occupy continuous space. T. Ueyama and Fukuda [5] later, in 1993, proposed a self-organization mechanism of cellular robots and used bio-inspired *genetic information* passing between cells. In that work, the use of random walk and utilization of simple rules in the self-organization process made CEBOT converge more towards similar behaviors in natural swarms.

The theory of swarm intelligence was further developed by E. Bonabeau, M. Dorigo, and G. Theraulaz [6], where biological swarms found in insect colonies, bees, wasps, etc. were studied and models were built to describe their behaviors as well as optimization techniques were inspired from their unique distributed problem solving capabilities.

A. Underwater Swarms

Being rich in natural swarms, most significantly embodied in fish schools, oceans have been undoubtedly one of the main target environments for swarm robotics applications. Although a big body of research has focused on the development and use of Autonomous Underwater Vehicles (AUVs) and Unmanned Underwater Vehicles (UUVs), the limitations of such single unit systems have led researchers to search for alternatives like swarms to accomplish the tasks at hand much more efficiently. As is the case with ground robotic swarms, underwater swarms possess the qualities of robustness, scalability, and fault-tolerance. In order to be useful, underwater swarms must abide by the limited resources individual agents have and the time constraints of the mission while achieving the targeted goals. Literature is full of publications on individual mission parts like self-organization, path planning, task allocation, etc. However, to the best of our knowledge, there has been no complete planning for a typical mission with the goals of conserving resources, maximizing swarm lifetime, and overall mission utility while respecting time constraints.

In this paper, we propose a framework for underwater swarm mission-planning, which can also be generalized to ground and aerial swarms. A typical mission is analyzed and broken down into its basic building blocks: *swarm release, initial self-organization and shape formation, path planning and shape maintenance, target identification and task partitioning/allocation*, and the *back trip*. Each of these blocks is discussed in details and relevant research is presented. Seamless integration of the parts to reconstruct the original mission is also considered. Finally, we suggest a suitable measure for the overall mission performance that focuses on time constraints, cost, and profit of the mission.

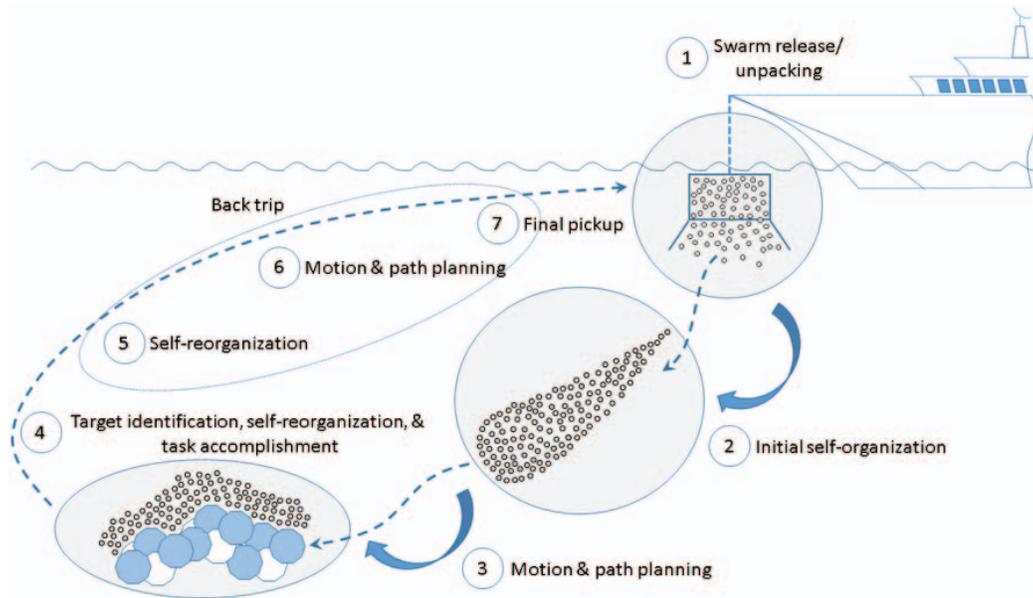


Fig. 1: Typical phases of a generic underwater mission

B. Practical Considerations

The nature of underwater environment and its intrinsic constraints make it unique when compared to ground or air. As far as communication is concerned, several limitations manifest: limited bandwidth, multipath propagation, time-varying channels, and spatial variation just to name a few. Bandwidth and transmission range are greatly affected by the signal-to-noise ratio (SNR). The latter is, in turn, determined by transmission loss and noise level. Transmission loss takes two forms: energy spread with distance and sound absorption with both distance and the frequency range. This imposes a limitation on the usable bandwidth. Additionally, transmission loss changes spatially based on the presence of shadow zones. Noise on the other hand can be ambient or man-made (e.g. ship movements). Another factor affecting acoustic communication is multipath propagation, which is based on water depth (shallow or deep water), frequency, and transmission range. Channel temporal variations that result from multipath propagation also cause problems like inter symbol interference (ISI) [7]. In order to have successful and efficient communication, all these factors must be taken into consideration when selecting the acoustic communication system and during mission planning. The effect of these factors is especially obvious when a single or small number of underwater vehicles are used and even in sparsely deployed underwater sensor networks (UWSNs). In robotic swarms, they are expected to have a weaker effect as swarms are meant to consist of large numbers of agents that are usually dense. Some works and real implementations exist in the literature that use other forms of communication like light signals [8] or RF communication [9].

Motion of vehicles is another important consideration. Real implementations have limited number of degrees of freedom (usually 6). Path planning should be designed with motion constraints, due to mechanical construction and water current movements, being carefully considered.

The following sections are organized as follows: In section II, building blocks of the mission planning framework are presented. Section III will discuss each block and related research in details. Next, the consolidation of these blocks into one cohesive mission is discussed in section IV. Mission utility and performance measures are then presented in section

V. Section VI contains a brief discussion and caveats. Section VII presents conclusion and future work.

II. MISSION PLANING FRAMEWORK

A typical underwater swarm mission can be thought of as a sequence of indispensable steps wherein, if a step is removed the mission becomes either impossible or very expensive. Because of the nature of robotic swarms, consisting of large numbers of simple robots, there must be a mechanism to properly release the agents from a central location into the water. This initial release must guarantee that agents will be able to form an initial cohesion so that they don't lose their local connectivity, disperse apart, and possibly divide into disjoint groups. For this reason, an initial *swarm release or unpacking* phase must exist, where agents are released from a dense-packing state into the target environment and activated. In this paper, environment refers to aquatic environments such as oceans, seas, lakes, and rivers. Once the swarm is injected into the environment and agents are activated, an initial self-organization phase should follow. In that phase, agents employ control algorithms distributively to achieve the previously mentioned cohesion. At the same time, they maintain repulsion forces that prevent the swarm members from colliding with each other. In this same phase, agents need to decide, still in a distributed manner, the global shape that eases transport while maintaining a balance in global energy consumption. We call this phase: *initial self-organization*. The next phase is *path planning*, where the swarm will collectively move along a path that achieves certain local constraints and is formed by applying distributed, simple rules. The goal in this phase is to maintain shape, move collectively towards a common target, and minimize energy consumption and forward-trip time. When the target is found (more details are presented in Section III-4 below), the fourth phase, *self-organization and task accomplishment*, starts. In this important phase, the swarm reorganizes itself in a pattern that matches the target and optimizes data collection. This is application-specific, however, we present two target coverage examples in this paper. The fifth and sixth phases are, again, *self-organization and path planning*. They are counterparts of phases two and three,

respectively, but with different constraints and rules as the return trip has a different nature from the forward trip. Finally, if the swarm successfully returns to the base, the last phase would be *swarm pickup and recovery*. Figs.1 and 2 show the above discussed phases and some related concepts and considerations. In the following section, we discuss the details of each of these phases and study the relevant literature.

III. FRAMEWORK SPECIFICATION

The four major processes that mission planning framework relies on are: self-organization, shape-formation, path planning, and task-allocation/partitioning. A large body of literature exists for each of these processes, however, a unified framework where mission planning based on their proper consolidation does not yet exist to the best of our knowledge. The following subsections detail each of the seven mission phases using these processes.

1) *Swarm release/unpacking*: This phase is application specific and depends on the environment. For example, in ground swarms, agents will start from an initial stationary position based on initial placement; this can be random or according to a specific pattern based on the choice of the designer and the requirements of the design. It should, however, be noted that the correct definition of “swarm” entails that large numbers of agents be used, which makes initial organization of agents according to a specific pattern difficult if not impossible. Another consideration is that the impact of initial configuration on the swarm’s performance should be minimal. This can be achieved if local rules are carefully chosen so that agents can quickly transition from the initial disorganized state into the self-organized, efficient-functionality state. In the case of underwater swarms, the swarm can be either injected into the water on an agent-by-agent basis, giving them the chance to self-organize as they are deployed, or they can be released simultaneously and then allowed to self-organize. The first approach is very slow, especially for large swarms. For this reason, and for a general mission, it is more appropriate to select the second approach of releasing agents simultaneously. A suitable assumption is that agents are initially densely-packed in a container, e.g. cage, and are liberated into the water almost at the same time by opening the container. Phase I in Fig.1 shows an example release mechanism.

2) *Initial self-organization and shape-formation*: Self-organization is a global, collective, emergent behavior that results from the local interactions between neighboring agents by applying simple, distributed rules [6]. This phenomenon can be noticed in biological systems like ant and bee colonies, animal herds, bird flocks, and fish schools. The purpose of the initial self-organization is to maintain a balance between cohesive and repulsive forces among agents. The goal is to achieve a suitable separation to prevent collision while still saving agents from dispersing away from the swarm and being lost. Additionally, it is used to form a shape that facilitates transport and preserves energy. Although the term “self-organizing” was introduced long ago in late 1940’s by cybernetician W. R. Ashby [10], the earliest known flocking model based on self-organization was introduced by C. Reynolds in 1986 [11] [12] [13]. Several models for attraction-repulsion have been proposed in the literature. For example, [13] and [14] used the Morse potential flocking model given by Eq.1 to model this behavior.

$$v_F^i(t + \delta t) = \left[G_S^i * \exp\left(\frac{-r_c(t)}{20}\right) - G_A^i * \exp\left(\frac{-r_c(t)}{20}\right) \right], \quad (1)$$

where v_F^i is the change in the flocking potential of agent i for a δt time increment, G_S^i and G_A^i are separation and aggregation gains for agent i , respectively, and $r_c(t)$ is the distance of the closest neighbor in a set of n neighbors (usually limited; e.g. 4-7) at time t . G_S^i and G_A^i are selected based on the desired degree of separation. For example, Oyekan et al. [13] used 1 and 0.99, respectively.

In [15], Hildenbrandt et al. modeled behaviors of starlings in terms of social forces. They defined *social force* as the sum of separation, attraction (cohesion), and alignment forces following Reynolds’ original model [12]. Eq’s.2, 3, 4, and 5 show these three forces and their combination to form the social force affecting agent i .

$$\mathbf{f}_{s_i} = -\frac{w_s}{|N_i(t)|} \sum_{j \in N_i(t)} g(d_{ij}) \mathbf{d}_{ij} \quad (2)$$

$$\mathbf{f}_{c_i} = C_i(t) \frac{w_c}{|N_i^*(t)|} \sum_{j \in N_i^*(t)} X_{ij} \mathbf{d}_{ij} \quad (3)$$

$$\mathbf{f}_{a_i} = w_a \left(\sum_{j \in N_i^*(t)} \mathbf{e}_{x_j} - \mathbf{e}_{x_i} \right) / \left\| \sum_{j \in N_i^*(t)} \mathbf{e}_{x_j} - \mathbf{e}_{x_i} \right\| \quad (4)$$

$$\mathbf{F}_{Social_i} = \mathbf{f}_{s_i} + \mathbf{f}_{c_i} + \mathbf{f}_{a_i}, \quad (5)$$

where \mathbf{f}_{s_i} , \mathbf{f}_{c_i} , \mathbf{f}_{a_i} are the separation, cohesion, and alignment forces w.r.t. agent i , respectively, in Newtons (N). w_s is the weighting factor for separation ($1/N$), $N_i(t)$ neighborhood of agent i at time t , \mathbf{d}_{ij} unit vector in the direction of j (from i), $g(d_{ij})$ is the halved Gaussian (see [15] for details). $C_i(t)$ is the degree of centrality of agent i in the group (length of the average vector of the direction towards its neighbors N_G), w_c is a weighting factor for cohesion, $N_i^*(t)$ are agents located in the topological neighborhood (reduced neighborhood) of agent i , and X_{ij} is an indicator of whether d_{ij} is inside a radius r_h of a *hard* sphere within which agents are attracted to each other. w_a is a fixed weighting factor for alignment and \mathbf{e}_{x_i} , \mathbf{e}_{x_j} are the forward directions for agents i and j , respectively.

Shape formation was extensively studied for the 2D case, but not as much for 3D shapes. For example, Yeom [16] developed a multi-agent based approach for constructing 3D shapes inspired by biological morphogenesis. Cell processes like differential cell-adhesion, gene-regulation, and inter-cell communication were used as a basis for building the model. A genetic encoding scheme for multi-agent robots was also presented. The agents used behavioral and constructional policies to make local decisions and a genetic algorithm-based evolutionary process was used, where fitness of the agents was continuously evaluated using suitable fitness functions. Diffuser and sensor model was used for inter-agent communication and each agent decided its next behavior based on neighbor position information. The target of the approach was dynamically reconfigurable bio-inspired systems, but it



Fig. 2: Concepts used in each phase and some related considerations

can be adapted to the case of shape formation in robotic swarms. This may be suitable for underwater as well as aerial swarms. Examples of other swarm robotic 3D shape formation approaches include [17], [18]. Many other works covering formation control exist in the literature like [19]–[23]. However, most of these works study the process in 2D. While this can work well for ground robots, not all of them can be easily extended to the 3D case.

3) *Path Planning*: Path planning has been studied in different contexts for ground, aerial, and underwater single and teams of robots. Here, we focus only on underwater path planning. Obstacle avoidance is also usually studied as part of this process as it is pertinent to motion in complex environments. Ref. [24] proposed five evolutionary algorithms (EAs) for underwater path planning and obstacle avoidance. This included a genetic algorithm (GA), a mimetic algorithm (MA), particle swarm optimization (PSO) and ant colony optimization (ACO) algorithms, and a shuffled frog leaping algorithm (SFLA). Path planning was formulated as a nonlinear optimal control problem (NOCP) and each of these algorithms was used to solve the problem with the goal of minimizing a time-energy cost function. The solution of the NOCP leads to a two-point boundary value problem (TPBVP). Simple and complex environments containing obstacles and energy sources were considered and results were compared to the conjugate gradient penalty method (CGP) to show the efficiency of the proposed algorithms. It was assumed, however, that the environment and map are known a priori, which may not always be the case. Cochran et al. [25] explored the use of extremum-seeking in planning the paths of underwater vehicles in 3D. Their approach has the advantage that the path is computed based on local information (sensed gradient of the chemical or other substance/phenomenon) without location awareness, which is especially useful in underwater environments because of the absence or extreme difficulty of position tracking and identification. Their approach was a generalization of the application of the same technique in 2D. They also considered different vehicles and actuation types as well as static and moving targets. In a different context, evolutionary robotics was utilized by Sperati et al. in [26] to form shortest paths between a source and a target area as a dynamic chain for a swarm of robots. Individual robots used red and blue LEDs to communicate indirectly, where the form of communication evolved during the chain formation process. The limitation of the approach is that it required a continuous back and forth transport of robots between the source and target areas. For some applications, this is acceptable, but for underwater missions, this may not be the best approach as targeted areas could be deep and energy and time constraints are a main

concern. The approach targeted exploration and navigation in unknown environments, but presence of obstacles was not studied.

Taking into consideration the effect of external fields, a two-step algorithm based on level-sets was proposed by Lolla et al. [27]. The goal was to find the time-optimal path between start and final positions for underwater vehicles moving in time-varying flow fields. In the first step, a forward wave-front is evolved from the start to the end location and its evolution is tracked until it reaches the destination. In step two, the path of the vehicle is tracked by solving particle tracking equation backwards in time from destination to source to determine the path that takes the minimum time; this is the time-optimal path. They showed that the optimal path is governed by Eq.6, which when integrated backwards in time starting from the final position $\mathbf{x} = \mathbf{x}_f$, will result a particle trajectory corresponding to the optimal path.

$$\frac{d\mathbf{x}}{dt} = -\mathbf{V}(\mathbf{x}, t) - F \frac{\nabla\phi(\mathbf{x}, t)}{|\nabla\phi(\mathbf{x}, t)|} \quad (6)$$

$$\phi(\mathbf{x}) = \begin{cases} d(\mathbf{x}), & \text{if } \mathbf{x} \text{ is outside the front} \\ -d(\mathbf{x}), & \text{if } \mathbf{x} \text{ is inside the front} \end{cases} \quad (7)$$

$$d(\mathbf{x}) = \min_{\mathbf{x}_i} |\mathbf{x} - \mathbf{x}_i|, \text{ for all } \mathbf{x}_i \in \text{front} \quad (8)$$

$$\frac{\partial\phi(\mathbf{x}, t)}{\partial t} + F|\nabla\phi(\mathbf{x}, t)| + \mathbf{V}(\mathbf{x}, t) \cdot \nabla\phi(\mathbf{x}, t) = 0, \quad (9)$$

where $\mathbf{x} \in \mathbb{R}^n$ is a position vector in space, \mathbf{x}_s and \mathbf{x}_f are the start and final positions, respectively as shown in Fig.3, $\mathbf{V}(\mathbf{x}, t)$ is a time-dependent external velocity field, F is the vehicle's nominal speed, $\phi(\mathbf{x})$ (or $\phi(\mathbf{x}, t)$) is the *signed distance function*; an arbitrarily-selected time-varying scalar field for which the level sets are found, and $d(\mathbf{x})$ is the shortest distance from a point \mathbf{x} in space to the front (see Ref. [27] for more details). $\phi(\mathbf{x}, t)$ is evolved in the first step of the algorithm using the initial value partial differential equation 9.

4) *Target Identification and Task Accomplishment*: This stage can be further broken into three sub-stages: 1) Target search and identification, 2) At-target self organization and target coverage, and 3) Task partitioning and allocation. Target search and identification is application dependent and is sometimes considered part of the path planning stage when target is known as has been shown for some of the techniques in the previous subsection. For generality, the case of unknown target location should be considered. This case is

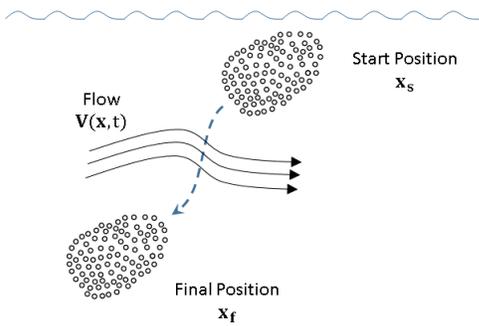


Fig. 3: Swarm navigation in the presence of time-varying flows - figure follows Fig. 1 in [27]

very common in search and rescue, and discovery operations. For example, Couceiro et al. [28] surveyed multi-robot search inspired by swarm intelligence, where five cooperative search algorithms were compared computationally and benchmarked through simulations and real experiments. They showed that evolutionary algorithms usually give better results than non-evolutionary ones. Robotic Darwinian Particle Swarm Optimization (RDPSO) algorithm [29] [30] was also found to outperform the others in terms of convergence speed and handling of multiple dynamic sources, giving evidence that socio-biological inspired algorithms are suitable for search problems that can be formulated as optimization problems. At-target self organization and target coverage are also application-specific. Ref. [31], for example studied the multi-agent boundary coverage problem, where robots search a bounded 2D environment for a set of targets and encircle them. The advantage of the approach is its ability to adapt to changes in the environment such as number of targets, and that search and encircling patterns need not to be defined a priori. The drawback is that every point in the environment has to be inspected.

Two hybrid swarm-fuzzy target-search strategies have been proposed by Venayagamoorthy et al. in [32]. The first approach, *fuzzified swarm of robots*, used a fuzzy term in the canonical particle swarm optimization (PSO), to replace part of PSO dynamics. The second method, *swarm-fuzzy controllers*, used a swarm of robots running fuzzy controllers. The two strategies were compared to the greedy search approach and shown to surpass it in terms of convergence percentage, time, and number of iterations. The approaches were studied only in two-dimensions. Keeter et al. [33] proposed four random walk lévy flight based algorithms for cooperative search in aquatic environments. This included *independent*, *bounded-region*, *biased angle*, and *biased jump length* sparse target searches. Simulations and experiments showed that these randomized algorithms outperform systematic raster sweep.

When the targets have been identified as a result of the search process or direct transport from source to destination (in case of known target locations), the next step is to self-organize in order to adequately cover the target with load balancing and/or division of labor taken into consideration. Target coverage by swarms of robots has been studied by many teams. For example, Rutishauser et al. [34] proposed an algorithm for collaborative coverage by a team of miniature robots based on communication for environments with unknown extensions. Coverage time was shown to decrease linearly with the increase in the number of robots. The algorithm was validated

through quantitative analysis, experiments with real miniature robots, and a discrete event simulation (DES) where quantitative and qualitative results matched. In the worst case, it was shown to degrade to the case of independent, random coverage when communication and positional information were affected by noise. Staňková et al. [35] devised a Stackelberg-games based approach (StaCo) for the multi-robot Voronoi coverage problem. The proposed scheme consisted of a heterogeneous team of leader and follower robots, where leaders had more advanced perceptive abilities than followers. The former group selects locations that aid the latter to achieve faster and more efficient convergence when their local objectives are optimized; this takes place without communication. Theoretical analysis and study of different cases showed that StaCo outperforms the classical Lloyd's algorithm and is similar to it in the worst case. It is worth mentioning that this approach was applied in 2D and its application to complex 3D environments still needs to be investigated.

The third and most important part of this phase is task partitioning or division of labor and task allocation. Labella et al. [36] implemented and analyzed an ant-foraging inspired algorithm for labor division that used simple, local adaptive rules to guide the behavior of individual robots. The approach emphasized the importance of the effect of local learning on the overall behavior and emerging labor division in the group. Agents did not have to communicate and only depended on local adaptivity. The algorithm was employed in an object retrieval task and the analysis showed that communication between agents is not necessary for efficient task accomplishment. Object retrieval efficiency of the group was measured using an efficiency index as in Eq.10:

$$v = \frac{\text{performance}}{\sum_{\text{robots}} \text{duty time}}, \quad (10)$$

where *performance* was defined as the number of retrieved objects and *duty time* is the time spent by each robot searching or retrieving (the time it was on duty). Ref. [37] further extended task partitioning among robots by considering communication. The similarity of the problem of deciding whether or not to partition a task with the multi-armed bandit problem was exploited. Proposed solutions to the latter in the field of reinforcement learning were shown to be applicable in the case of task partitioning in robotic swarms. The authors used three algorithms from the multi-armed bandit problem's literature along with a previously designed ad-hoc algorithm to test the task partitioning behavior of robots in simulation. These algorithms used local cost estimates to guide individual decisions. They were compared to four reference algorithms that did not use estimate values to make decisions. The tests were done for the social (with communication) and non-social (without communication) cases. Results showed that communication can be helpful in making faster local decisions, however, it can cause lower awareness of environment variations.

Ducatelle et al. [38] studied the problem of task allocation in robotic swarms. Multiple concurrent tasks were considered and two algorithms were proposed and compared in terms of scalability and robustness. The first was light-signaling based while the second used gossip-based information exchange. Tasks were announced by certain robots and all others assigned themselves to tasks using the proposed algorithms. Gossiping algorithm was shown to perform better for small numbers of robots and for highly cluttered environments, while the

two algorithms performed nearly the same for simple environments. A social-welfare inspired task-allocation approach for multi-robot systems was also presented by Kim et al. in [39]. The proposed algorithm was distributed and intended for uncertain dynamic environments. *Resource inequality* (see Eq.11) was defined based on Atkinson's inequality index [40], and Atkinson's welfare function was adapted to derive *resource welfare* (Eq.12). Tasks were allocated to individual robots based on the maximization of task completion ratio while minimizing resource (energy) usage. It is worth mentioning that the approach utilized inter-robot communication and, in some cases, tight-coordination. The superiority of the algorithm to a market-based approach was verified through simulations.

$$I_R = 1 - \left[\frac{1}{n} \sum_{i \in R} \left(\frac{Re_i}{\overline{Re}} \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}} \quad (11)$$

$$W_R = \overline{Re}(1 - I_R) = \left(\frac{1}{n} \sum_{i \in R} Re_i^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}}, \quad (12)$$

where n is the number of robots, Re_i is the resource (energy) residual for robot i , \overline{Re} is the average resource residual of the team of robots, ε strength of penalty for the inequality ($\varepsilon \in [0, \infty)$, penalty increases as ε increases), and R the team of robots.

IV. MISSION RECONSTRUCTION

Individual mission phases need to be combined in a seamless way in order for the mission to be accomplished efficiently. Decisions on the appropriate times to start phase transitions and how to perform them are critical to the success and performance of the mission. For example, starting a shape change phase when close to the target in preparation for a load-balanced target-coverage can have a big effect on the overall mission time. This area of the planning process needs further investigation and a generalized approach that can be applied to a generic mission needs to be explored.

V. MISSION PROFIT AND PERFORMANCE MEASURES

To evaluate the overall performance of the mission, an appropriate measure is required. Because the resources available to each agent are limited, a mission profit function that takes into consideration the costs imposed on these resources needs to be formulated. We begin by assuming that a swarm of fixed size of N robots densely packed at the source are released into the water, nearly simultaneously, at time t_i . We define overall mission time T_m as the time between t_i and the time t_f at which all surviving agents are successfully recovered. Percentage of mission completion as well as recovered agents are represented as fractions R_c and R_v , respectively. The shorter the mission time and the larger the percentages of mission completion and recovered agents, the better the performance. In a time critical mission, which we assume is the case, a time constraint T_r has to be respected. The ratio between the T_r and mission time T_m defines the degree of time compliance R_t . Mission profit or gain G_m can be represented as in Eq.13. An optimization problem with the goal of maximizing mission profit can be formulated. We leave this as a future work.

$$G_m = R_t R_v (\alpha R_c G_d + (1 - \alpha) L_d), \quad R_v, R_c \in [0, 1] \quad (13)$$

$$\alpha = \begin{cases} 0, & \text{if target not found} \\ 1, & \text{if target found} \end{cases} \quad (14)$$

$$G_d = \begin{cases} V_m - C_m, & V_m > C_m \\ 1, & V_m = C_m \end{cases} \quad (15)$$

$$L_d = \frac{1}{V_m + C_m}, \quad (16)$$

where $T_m = T_{ft} + T_{bt} + T_{ct}$, T_{ft} and T_{bt} are forward and back trip times, respectively, T_{ct} is *core task* time, $R_t = T_r/T_m$ is the degree of time compliance, G_d is the dollar gain, V_m is mission monetary value/profit, C_m is mission monetary cost, and L_d is the dollar loss.

VI. DISCUSSION

The basic building blocks of a typical generic underwater swarm mission have been presented in the previous sections. Each of these phases is a field of research studied by different disciplines like swarm intelligence and robotics, cellular automata, autonomous robots, morphogenesis, sociology, socio-biology, behavioral ecology, neurocomputing, etc. We would like to emphasize that covered literature in this work is by no means comprehensive and is only intended as a guide to a consolidated mission planning process. The reader is encouraged to refer to the cited works in each area to get more specific insights about other related works.

VII. CONCLUSION AND FUTURE WORK

In this paper, we presented a general framework for planning underwater robotic swarm missions. First the limitations of existing single unit AUVs and benefits of the alternative robotic swarms were highlighted. Practical considerations specific to underwater environments were pointed out. Main phases involved in a typical mission, which constitute the building blocks of the framework, were discussed and relevant literature was also presented. These phases are: swarm release, initial self-organization and shape formation, path planning and transport, target search and identification, task partitioning and allocation, and the back trip to the source. The importance of a seamless reconstruction of the mission was also emphasized. Finally, a profit function was proposed as a performance measure that focuses on time constraint compliance and incurred cost/profit. As a future work, we plan to study optimal shapes for resource preservation during transport. Another direction is seamless transition between different phases and online processing of collected data at the target. Load balancing, optimal target sampling, and time-constraint adherence are also worth investigation.

ACKNOWLEDGMENT

The authors would like to thank professor Bing Wang for her constructive comments on this paper.

REFERENCES

- [1] T. Fukuda and S. Nakagawa, "A dynamically reconfigurable robotic system (concept of a system and optimal configurations)," in *Proc. SPIE*, vol. 0856, 1987, pp. 588–595.
- [2] G. Beni and J. Wang, "Swarm intelligence in cellular robotic systems," in *Proceedings., NATO Advanced Workshop on Robots and Biological Systems, Tuscany, Italy*, June 1989, pp. 26–30.
- [3] G. Beni, "The concept of cellular robotic system," in *Intelligent Control, 1988. Proceedings., IEEE International Symposium on*, Aug 1988, pp. 57–62.
- [4] G. Beni, "From swarm intelligence to swarm robotics," in *Swarm Robotics*, ser. Lecture Notes in Computer Science, E. Åžahin and W. Spears, Eds. Springer Berlin Heidelberg, 2005, vol. 3342, pp. 1–9.
- [5] T. Ueyama and T. Fukuda, "Self-organization of cellular robots using random walk with simple rules," in *Robotics and Automation, 1993. Proceedings., 1993 IEEE International Conference on*, May 1993, pp. 595–600 vol.3.
- [6] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*. New York, NY, USA: Oxford University Press, Inc., 1999.
- [7] R. S. Istepanian and M. Stojanovic, Eds., *Underwater Acoustic Digital Signal Processing and Communication Systems*. Norwell, MA, USA: Kluwer Academic Publishers, 2002.
- [8] D. Sutantyó, P. Levi, C. Moslinger, and M. Read, "Collective-adaptive lévy flight for underwater multi-robot exploration," in *Mechatronics and Automation (ICMA), 2013 IEEE International Conference on*, Aug 2013, pp. 456–462.
- [9] S. Sendra, J. Lamparero, J. Lloret, and M. Ardid, "Study of the optimum frequency at 2.4GHz ISM band for underwater wireless ad hoc communications," in *Ad-hoc, Mobile, and Wireless Networks*, ser. Lecture Notes in Computer Science, X.-Y. Li, S. Papavassiliou, and S. Ruehrup, Eds. Springer Berlin Heidelberg, 2012, vol. 7363, pp. 260–273.
- [10] W. Ashby, "Principles of the self-organizing dynamic system," *Journal of General Psychology*, vol. 37, no. 2, pp. 125–128, 1947.
- [11] C. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," in *Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques*, ser. SIGGRAPH '87. New York, NY, USA: ACM, 1987, pp. 25–34. [Online]. Available: <http://doi.acm.org/10.1145/37401.37406>
- [12] C. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," *SIGGRAPH Comput. Graph.*, vol. 21, no. 4, pp. 25–34, Aug. 1987. [Online]. Available: <http://doi.acm.org/10.1145/37402.37406>
- [13] J. Oyekan, D. Gu, and H. Hu, "A model for using self-organized agents to visually map environmental profiles," *Ecological Complexity*, vol. 19, no. 0, pp. 68 – 79, 2014.
- [14] J. A. Smith and A. M. Martin, "Comparison of Hard-Core and Soft-Core Potentials for Modelling Flocking in Free Space," *ArXiv e-prints*, May 2009.
- [15] H. Hildenbrandt, C. Carere, and C. Hemelrijk, "Self-organized aerial displays of thousands of starlings: a model," *Behavioral Ecology*, vol. 21, no. 6, pp. 1349–1359, 2010.
- [16] K. Yeom, "Morphological approach for autonomous and adaptive system: The construction of three-dimensional artificial model based on self-reconfigurable modular agents," *Neurocomputing*, vol. 148, no. 0, pp. 100 – 111, 2015.
- [17] Y. Meng, H. Guo, and Y. Jin, "A morphogenetic approach to flexible and robust shape formation for swarm robotic systems," *Robotics and Autonomous Systems*, vol. 61, no. 1, pp. 25 – 38, 2013. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0921889012001637>
- [18] C. Pinciroli, M. Birattari, E. Tuci, and M. Dorigo, "Evolving a collective consciousness for a swarm of pico-satellites," *IRIDIA, CoDE, Université Libre de Bruxelles, Belgium, Tech. Rep.*, 2008.
- [19] L. Barnes, M. Fields, and K. Valavanis, "Swarm formation control utilizing elliptical surfaces and limiting functions," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 39, no. 6, pp. 1434–1445, Dec 2009.
- [20] X. Yan, J. Chen, and D. Sun, "Multilevel-based topology design and shape control of robot swarms," *Automatica*, vol. 48, no. 12, pp. 3122 – 3127, 2012.
- [21] D. Jeong and K. Lee, "Dispersion and Line Formation in Artificial Swarm Intelligence," *ArXiv e-prints*, Jun. 2014.
- [22] S. Kalantar and U. R. Zimmer, "Control of open contour formations of autonomous underwater vehicles," *Advanced Robotic Systems, International Journal of*, pp. 309–316, Dec 2005.
- [23] S. W. Ekanayake and P. N. Pathirana, "Formations of robotic swarm: An artificial force based approach," *Advanced Robotic Systems, International Journal of*, vol. 7, no. 3, pp. 173–190, Mar 2010.
- [24] M. P. Aghababa, "3D path planning for underwater vehicles using five evolutionary optimization algorithms avoiding static and energetic obstacles," *Applied Ocean Research*, vol. 38, no. 0, pp. 48 – 62, 2012.
- [25] J. Cochran, A. Siranosian, N. Ghods, and M. Krstic, "3-D source seeking for underactuated vehicles without position measurement," *Robotics, IEEE Transactions on*, vol. 25, no. 1, pp. 117–129, Feb 2009.
- [26] V. Sperati, V. Trianni, and S. Nolfi, "Self-organised path formation in a swarm of robots," *Swarm Intelligence*, vol. 5, no. 2, pp. 97–119, 2011. [Online]. Available: <http://dx.doi.org/10.1007/s11721-011-0055-y>
- [27] T. Lolla, M. Ueckermann, K. Yigit, J. Haley, P.J., and P. Lermusiaux, "Path planning in time dependent flow fields using level set methods," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, May 2012, pp. 166–173.
- [28] M. S. Couceiro, P. A. Vargos, R. P. Rocha, and N. M. Ferreira, "Benchmark of swarm robotics distributed techniques in a search task," *Robotics and Autonomous Systems*, vol. 62, no. 2, pp. 200 – 213, 2014.
- [29] M. Couceiro, R. Rocha, and N. Ferreira, "A novel multi-robot exploration approach based on particle swarm optimization algorithms," in *Safety, Security, and Rescue Robotics (SSRR), 2011 IEEE International Symposium on*, Nov 2011, pp. 327–332.
- [30] M. Couceiro, R. Rocha, and N. Ferreira, "Ensuring ad hoc connectivity in distributed search with robotic darwinian particle swarms," in *Safety, Security, and Rescue Robotics (SSRR), 2011 IEEE International Symposium on*, Nov 2011, pp. 284–289.
- [31] J. Sebestyenova and P. Kordel, "Self-organizing robotic system for area coverage and surround of contamination found," in *Computational Cybernetics (ICCC), 2013 IEEE 9th International Conference on*, July 2013, pp. 309–314.
- [32] G. K. Venayagamoorthy, L. L. Grant, and S. Doctor, "Collective robotic search using hybrid techniques: Fuzzy logic and swarm intelligence inspired by nature," *Engineering Applications of Artificial Intelligence*, vol. 22, no. 3, pp. 431 – 441, 2009.
- [33] M. Keeter, D. Moore, R. Muller, E. Nieters, J. Flenner, S. Martonosi, A. Bertozzi, A. Percus, and R. Levy, "Cooperative search with autonomous vehicles in a 3D aquatic testbed," in *American Control Conference (ACC), 2012*, June 2012, pp. 3154–3160.
- [34] S. Rutishauser, N. Correll, and A. Martinoli, "Collaborative coverage using a swarm of networked miniature robots," *Robotics and Autonomous Systems*, vol. 57, no. 5, pp. 517 – 525, 2009.
- [35] K. Staňková, B. Ranjbar-Sahraei, G. Weiss, and K. Tuyls, "Staco: Stackelberg-based coverage approach in robotic swarms," in *ADAPTIVE 2013, Proceedings*, 2013, pp. 71–76.
- [36] T. H. Labella, M. Dorigo, and J.-L. Deneubourg, "Division of labor in a group of robots inspired by ants' foraging behavior," *ACM Trans. Auton. Adapt. Syst.*, vol. 1, no. 1, pp. 4–25, Sep. 2006.
- [37] G. Pini, M. Gagliolo, A. Brutschy, M. Dorigo, and M. Birattari, "Task partitioning in a robot swarm: a study on the effect of communication," *Swarm Intelligence*, vol. 7, no. 2-3, pp. 173–199, 2013.
- [38] F. Ducatelle, A. Förster, G. A. DiCaro, and L. M. Gambardella, "Task allocation in robotic swarms: new methods and comparisons," *Istituto Dalle Molle di Studi sull'Intelligenza Artificiale (IDSIA), Lugano, Switzerland., Tech. Rep.*, 2009.
- [39] M.-H. Kim, S.-P. Kim, and S. Lee, "Social-welfare based task allocation for multi-robot systems with resource constraints," *Computers & Industrial Engineering*, vol. 63, no. 4, pp. 994 – 1002, 2012.
- [40] A. B. Atkinson, "On the measurement of inequality," *Journal of Economic Theory*, vol. 2, no. 3, pp. 244 – 263, 1970.