

---

# Empirical Evaluation of Auction-Based Coordination of AUVs in a Realistic Simulated Mine Countermeasure Task

Sanem Sariel<sup>1\*</sup>, Tucker Balch<sup>2</sup>, and Jason Stack<sup>3</sup>

<sup>1</sup> Istanbul Technical University, Department of Computer Engineering, Istanbul, 34496, TURKEY [sariel@cs.itu.edu.tr](mailto:sariel@cs.itu.edu.tr)

<sup>2</sup> Georgia Institute of Technology, College of Computing Department, Atlanta, GA, 30332, USA [tucker.balch@cc.gatech.edu](mailto:tucker.balch@cc.gatech.edu)

<sup>3</sup> Naval Surface Warfare Center, Panama City, FL, 32407 USA  
[Jason.stack@navy.mil](mailto:Jason.stack@navy.mil)

**Summary.** In this work, we evaluate performance of our distributed cooperation framework, DEMiR-CF, for Naval Mine Countermeasure missions on the US NAVY’s ALWSE-MC simulator against different contingencies that may arise run time. Our cooperation framework integrates a distributed task allocation scheme, coordination mechanisms and precaution routines for multi-robot team execution. Its performance has been demonstrated in Multi-robot Multi-target exploration and Object Construction domains. Marine applications provide additional challenges such as noisy communication, position uncertainty and the likelihood of robot failures. There is a high probability that the initial assignments are subject to change during run time, in these kinds of environments. Our framework ensures robust execution and efficient completion of missions against several different types of failures. Preliminary results for MCM missions are promising in the sense of mission completion, and AUV paths are close to optimal in the presence of uncertainties.

## 1 Introduction

Undersea operations using AUVs (Autonomous Underwater Vehicle) provide a different and in some ways a more challenging problem than tasks for UAVs and UGVs. In particular, communication windows are restricted and bandwidth is limited. Coordination among agents is correspondingly more difficult. In traditional approaches, a central planner initially assigns subtasks for a set of AUVs to be performed in achieving the team goal. However, initial assignments of tasks may become inefficient during real time execution due to the

---

\* Sanem Sariel is also affiliated with Georgia Institute of Technology

real world issues (e.g. failures), and these allocations are subject to change if efficiency is a high concern. Therefore reallocations are needed and should be performed in a distributed fashion. To facilitate this flexibility, we offer a distributed auction based cooperation framework, **D**istributed and **E**fficient **M**ulti **R**obot-**C**ooperation **F**ramework (DEMiR-CF) [8], an online dynamic task allocation (reallocation) system to achieve a team goal while using resources effectively with integrated task scheduling and execution capabilities, that can also respond to and recover from real time contingencies such as communication failures, delays, range limitations and robot failures. DEMiR-CF has been implemented and tested extensively in the multi-robot multi-target exploration domain [7]. In this paper, we report performance of our framework against realistic difficulties in multi-AUV coordination for Naval Mine Countermeasure (MCM) mission on the US Navy’s Autonomous Littoral Warfare Systems Evaluator- Monte Carlo (ALWSE-MC) simulator [1].

## 2 Background and Related Work

DEMiR-CF is a distributed mechanism for real time task execution and designed to use advantages of auction based approaches and to integrate additional routines for solution quality. Other efficient works in auction based coordination research are: M+ [2], MURDOCH [5], TraderBots [3] and Lemarie’s allocation scheme [6]. According to the review given in [4], existing auction based systems are not fully capable of re-planning task distributions, re-decomposing tasks, re-scheduling commitments, and re-planning coordination during execution. Our approach aims at filling these gaps. We propose an integrated cooperation framework for multi-robot task execution, and here in this paper, we analyze performance of precaution routines and solution quality maintenance schemes for single-item auctions in a multi-AUV coordination context. Experiments are performed in a realistic simulation environment with real time constraints and events such as AUV failures, communication range limitations, failures and delays. Precaution routines embedded in the framework not only recover from failures but also maintain the high solution quality. With an efficient bid evaluation approach, the framework provides near optimal solutions [7]. Our experiments show that communication delays significantly impact the solution quality and should be analyzed in multi-robot systems especially working in harsh environments. As experiments and scenarios demonstrate, online task handling performance of the framework with task switching mechanism is promising.

Naval mine countermeasures (MCM) are actions taken to counter the effectiveness of underwater mines. MCM operations include finding and seizing mine stockpiles before they are deployed, sweeping desired operational areas, identifying mined areas to be avoided, and locating and neutralizing individual mines [10]. Our research is focused on the subset of MCM that involves locating and mapping all individual mines in an operational area. In general,

recognizing proud mines on the seafloor is not overly difficult; the difficulty arises with the abundance of non-mine objects on the seafloor that possess mine-like characteristics (*e.g.*, geologic outcroppings, coral, manmade debris, etc.). This ample supply of false alarms has necessitated the following strategy typically employed by the Navy: detect and classify the mine-like objects (MLOs) with high-coverage rate sensors (*e.g.*, sidelooking sonar), employ advanced signal processing techniques for maximal false alarm reduction, then revisit the remaining MLOs with identification-quality assets (*e.g.*, electro-optic sensors) to confirm them as mines or dismiss them as false alarms. It is this strategy which the research proposed herein attempts to implement in a distributed, near optimal fashion. Achieving this mission with an AUV team requires effective task allocation mechanisms and several precautions.

### 3 The DEMiR-CF Framework for Naval MCM Missions

DEMiR-CF is designed for complex missions including inter-related tasks (with precedence constraints) that require diverse agent capabilities and simultaneous execution. The framework combines *distributed task allocation and coalition formation schemes*, and *dynamic task selection scheme* as cooperation components, and *Plan B precaution routines* some of which are implemented by *dynamic task switching scheme*. These components are integrated into one framework to provide an overall system that finds near optimal solutions for real time task execution. The overall objective of the robot team ( $r_j \in R$ ,  $0 < j \leq ||R||$ ) equipped with our framework is to achieve a mission ( $M$ ) consisting of interrelated tasks  $T_i$  ( $0 < i \leq ||M||$ ), by incremental assignment of all  $T_i \in M$  to  $r_j \in R$  while optimizing the specified objective function. Details of DEMiR-CF are provided in [8], and an extended version of the overall framework and the implementation details given in this paper is provided as a technical report [9]. In this paper, we report experimental evaluations of our framework and details about application of the framework for a real mission execution. The reference mission in this research is to detect, classify, and identify underwater mines in a given operational area simulated in a PC-based software, ALWSE-MC [1], analysis package designed to simulate multiple autonomous vehicles performing missions in the littoral regions including mine reconnaissance, mapping, surveillance, and clearance. This mission employs two types of vehicles: unmanned underwater vehicles (UUVs) which are free swimming AUVs and possess large-footprint sensors (*e.g.*, side-scan sonar) for detection and classification (D/C) of mines and seafloor crawlers equipped with short-range, identification-quality sensors (*e.g.*, camera). The crawlers have the ability to stop at an object and take a picture with a camera.

Our general task representation is designed as being capable of representing complex tasks with inter-dependencies. In particular, in this case study, tasks do not have interdependencies. Two types of tasks are defined for vehicles: “visit waypoint” ( $w$ ) and “identify MLO” ( $t$ ). In the task representation,

required capabilities are represented for each type of task:  $reqcap_w$  contains side-scan sonar and  $reqcap_t$  contains cameras besides the standard capabilities of AUVs common in both types of vehicles. The coverage mission ( $M_C$ ) contains predefined number of waypoints ( $w_i \in M_C$ ,  $0 < i \leq ||M_C||$ ) to be visited by all UUVs ( $R_{UUV} \subset R$ ). One way of task representation is to directly assign tasks for each waypoint. However this representation has a drawback of high communication requirements for efficient completion of the mission. Instead, we represent waypoint tasks as interest points of regions/search areas ( $W_k = \cup w_i$ ,  $\forall w_i$  is unvisited, and  $W_k \subseteq M_C$ ). These regions (and corresponding centers) are determined by robots during runtime dynamically. The advantage of this representation is that the only information necessary to negotiate over tasks contains the interest point information, providing data compression. Regions determined by different UUVs may vary during runtime and sometimes overlap. However, the uncertainty related to the tasks is within an acceptable degree compared to the requirements of complete knowledge sharing. Before defining regions, relative distance values,  $reldist(r_j, w_i)$ , are determined for each unvisited waypoint  $w_i$  as in Eq. 1, where  $dist$  function returns the Euclidian distance between points.  $r_k$  locations are the latest updated locations of the robots. If there is no known active robot,  $reldist(r_j, w_i)$  value is taken as only the own distance.

$$reldist(r_j, w_i) = dist(r_j, w_i) - \min_{\forall k \neq j} (dist(r_k, w_i)), r_k \text{ is active} \quad (1)$$

Each robot defines its regions ( $W_{jk}$ ,  $1 \leq k \leq ||R_{UUV}||$ ) number of which equals to the number of UUVs believed to be running properly. After sorting  $reldist(r_j, w_i)$  values of unvisited waypoints, the regions are determined on the sorted list, containing approximately same number of waypoints. The first region is the region that the robot has the highest interest (but negotiations are needed to resolve conflicts if there is another UUV with a similar interest). The identification mission ( $M_I$ ) contains unknown number of tasks for MLO locations ( $t_i \in M_I$ ,  $0 < i \leq ||M_I||$ ) to be visited by crawlers. Therefore the tasks in  $M_I$  are generated online during runtime. For bid evaluations, we use heuristic functions proved to provide close to optimal results for multi-robot multi-target domain [7]. These cost functions, explained in the next section, provide time extended consideration of tasks for instantaneous assignment with a tractable and efficient way. A conceptual flowchart summarizing operations of UUVs and crawlers, and the general operations implemented by both types of AUVs is given in Fig. 1.

### 3.1 Exploration for Detection and Classification of MLO Locations

To begin the mission, the UUVs survey the operational area following waypoints determined *a priori*; however, corresponding regions containing waypoints may be reassigned by negotiations among UUVs autonomously. After determining regions, each UUV offers an auction for the highest interested region for itself and offers its selected interest point information as an auction. After negotiations on several auctions, each UUV is assigned to the closest

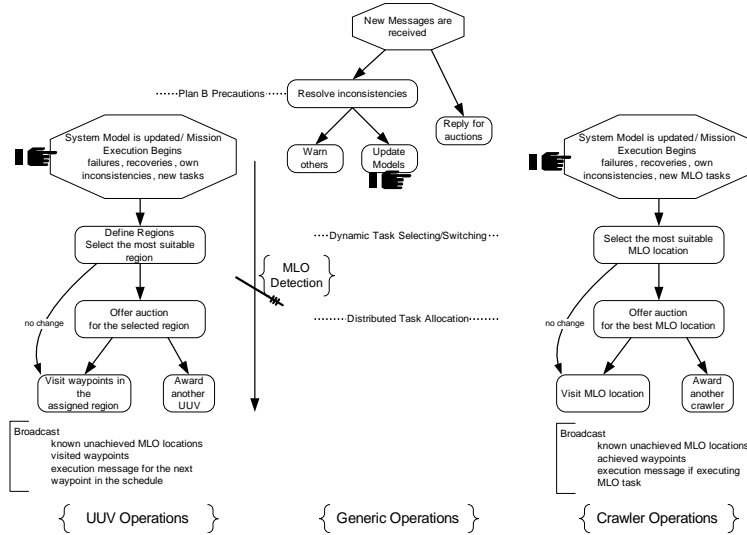


Fig. 1. Conceptual Flowchart related to the AUV Operations

region (interest point). If more than one robot is at the same distance to the interest point, the one with the minimum id is assigned. The other UUVs continue to offer auctions for the remaining regions. Allocations of the regions may also change during run time to maintain solution quality. Whenever UUVs detect UUV failures or recoveries from failures they change their region definitions accordingly and offer new auctions. After region assignments are implemented, each robot visits waypoints in the corresponding region ( $W_j$ ) by ordering them descendingly according to their cost values as in Eq. 2.

$$\begin{aligned}
 c(r_j, w_i) &= \alpha * dist(r_j, w_i) + (1 - \alpha) * [dist(w_{f1}, w_{f2}) \\
 &\quad - \max(dist(w_i, w_{f1}), dist(w_i, w_{f2}))] \\
 \{dist(w_{f1}, w_{f2}) &= \max(dist(w_k, w_l)), w_{i,k,l,f1,f2} \in W_j\}
 \end{aligned} \tag{2}$$

This heuristic function considers boundary targets,  $w_{f1}$  and  $w_{f2}$  in  $W_j$  which are the targets having the maximum distance value. The basic idea of this function is that these targets determine the diameter of the region ( $W_j$ ) and both of them should be visited. This heuristic method forwards robots to these farthest targets within their area to some degree. By introducing a constant ( $\alpha$ ), this degree can be adjusted and it is taken as  $2/3$ . This heuristic function produces close to optimal results for multi-robot multi-target domain [7]. If there are more than one pair of boundary targets, the pair of which has a member with the smallest distance to the UUV is selected.

As UUVs detect the MLOs on their way, they broadcast these estimated target positions to all AUVs (*i.e.*, tasks for crawlers are generated online).

Then MLO information can propagate (in bucket-brigade fashion) to all other AUVs in the group that can possibly be reached. Periodic broadcasting of important information (coming from either own sensors or external agents) is a way to handle communication range limitations.

### 3.2 Identification of MLOs

When crawlers are informed about MLO locations, they update their world knowledge and dynamically select the best MLO target to visit and offer auctions. Therefore they can switch among tasks when new tasks appear, if it is profitable. It is also possible that a crawler may inadvertently discover a mine without being informed of its position by a UUV. In this case, the crawler identifies the target, adds it to its task list as an achieved task, and broadcasts achievement information for maintaining system consistency. Crawlers determine their bid values by Eq. 3, where  $t_k$  is the closest unvisited MLO target to  $t_i$ . This cost function provides a greedy look ahead for visiting MLO targets rather than only considering the distances between target and the AUV. An additional penalty is applied to the cost, if there is another profitable alternative way of visiting tasks.

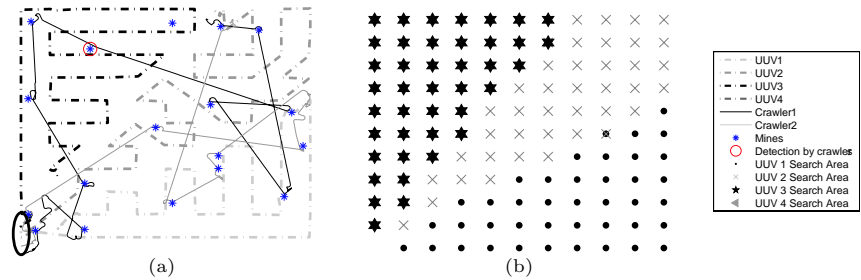
$$c(r_j, t_i) = \begin{cases} \text{dist}(r_j, t_i) + \text{dist}(t_i, t_k) - \text{dist}(r_j, t_k) , & \text{if } (\text{dist}(t_i, t_k) > \text{dist}(r_j, t_k)) \\ \text{dist}(r_j, t_i) & \text{otherwise} \end{cases} \quad (3)$$

In the identification task, when crawlers are within an area close to a MLO location, they begin keeping time while surveying the MLO location. Whenever the time limit is reached, they set the task status as achieved and broadcast this information. If there is detection during this time period, MLO location is considered as an actual mine and task achievement is directly applied, otherwise it is determined as a false alarm after deadline. In either case, the task is achieved.

## 4 Experimental Results

Performance of our framework and precaution routines is evaluated in ALWSE-MC. Three sample scenarios in the simulation are given to illustrate performance of our framework for Naval MCM missions. UUVs are equipped with sensors capable of detecting mines within 30 feet from skin of target. However they are not able to correctly identify them. Crawlers are equipped with cameras which can both detect and identify mines within 20 feet. None of the AUVs have certain search patterns. UUVs have internal navigation errors therefore their estimated location values are different from actual locations in most cases. Two AUVs can communicate each other whenever the receiver AUV is in the sender AUV's transmitter range, within its transmitter beam width, and sender AUV is within transmitter AUV's receiver beam width.

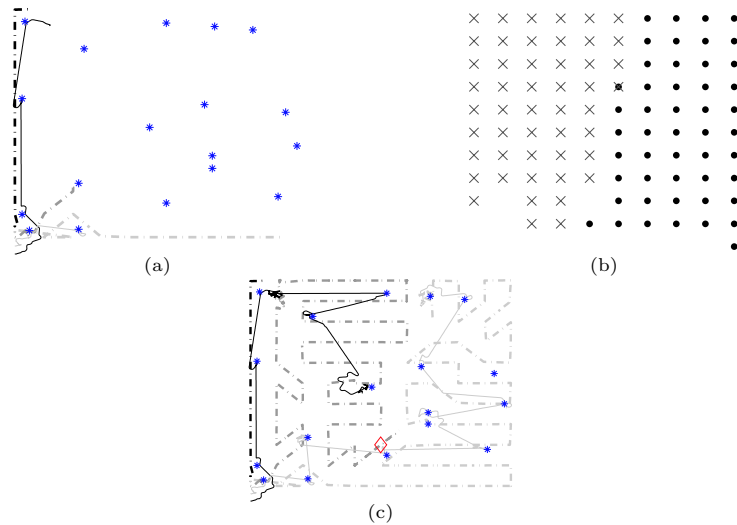
All UUVs and crawlers begin execution from a deployment area. There is no *a priori* information about mine locations. 121 waypoint locations (environment size: 200x200) are known but are not assigned initially. UUVs begin negotiations and divide the overall mission area into three (known number of UUVs) regions. Since they are within line of sight, they can communicate their location information. Therefore initially defined regions are nearly the same for all UUVs. Fig. 2 illustrates a successful mission scenario with three UUVs and two crawlers. Allocations of waypoints after negotiations can be seen in Fig. 2(b). Since there are no failures, waypoint assignments do not change during run time. However crawlers sometimes switch among tasks if they are not informed about tasks that are being executed. And sometimes parallel executions occur. Whenever they are in communication range, they can resolve the conflicts efficiently by means of the precaution routines. As in Fig. 2(a), crawlers can also detect mines without being informed. Routes of the crawlers may seem somewhat random. However it should be noted that tasks related to the MLO locations appear online during run time when they are discovered, and communication ranges are limited.



**Fig. 2.** Scenario 1. (a) UUVs cover the area by visiting waypoints. Crawlers visit MLO locations as they are informed. Deployment area is circled. (b) Each AUV is assigned to a region after auction based allocation of interest points.

In the second scenario, one of the UUVs fails on the same setting of scenario 1 (Fig. 3). Initial regions for all UUVs change after UUV3 fails (Fig.3 (b)). Other UUVs change region definitions and, after negotiations, they share the full area as indicated in the figure. Visited waypoints are not in their region coverage. Because of the uncertainties, some waypoints are left uncovered in schedules. However this uncertainty related problem is resolved by UUV2 and the mission is completed.

In the third scenario (Fig. 4), UUV3 fails and other UUVs detect the failure and they negotiate over the remaining unvisited waypoints and new schedules are determined as in Fig. 4(b). While these UUVs execute their tasks, another UUV (4) is released from the deployment area. Detecting a new UUV arrival, other UUVs change their region definitions accordingly (Fig. 4(d)) and offer auctions for these areas. UUV4 initially is not informed about the visited

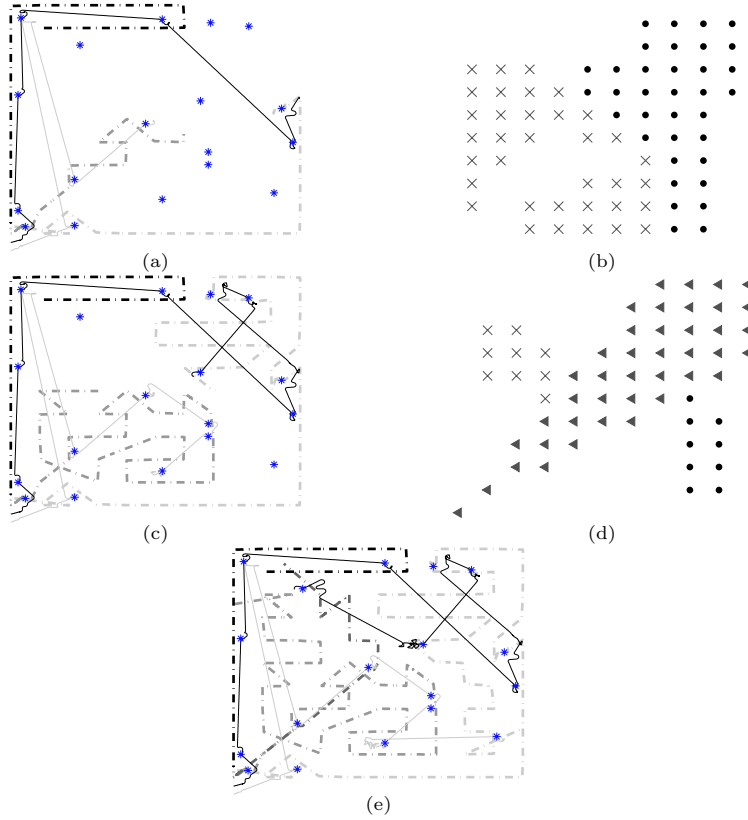


**Fig. 3.** Scenario 2. (a) Initially all UUVs begin execution. UUV3 fails, other UUVs take responsibility of all unvisited waypoints. (b) Region assignments are changed for UUV1-2 after detecting failure. Because of an uncertainty, one waypoint is left uncovered. (c) UUV2 completes its region coverage task, and adds the waypoint missing in (b) to its schedule after detecting that it is not visited.

waypoints and it defines its regions with this knowledge. After negotiations, the regions are assigned and schedules are formed. UUV4 redefines its regions by considering incoming information for visited waypoints.

On the same settings, experiments are conducted to evaluate message loss rate effects on mission completion success. Table 1 illustrates the results ( $\mu \mid \sigma$ ) averaged over 10 runs. When message loss rate is different from 0, as expected, performance is degraded but linearly. It should be noted that even for rate 0.75, the overall mission ( $M_C$  and  $M_I$ ) by final identification of mines is completed. Number of waypoint ( $w$ ) visits increase for high message loss rates. When message loss rate is 1 there is no communication among AUVs and they cannot correctly reason about region portions. Therefore each UUV searches the full area completely. Crawlers detect and identify 12.8% of mines by their local detection in a small area (MLO target information can not be communicated in this case). Since identification is not complete, overall mission is not completed. This table illustrates performance of our framework against message losses. As a final remark, auction generation and clearing in an environment with communication delays desires special attention. Especially auction deadlines should be determined by considering communication delays which may vary during run. Plan B precautions could resolve these kinds of problems. Precautions for delayed messages on out-of-date situations prevent the system from getting into stuck into further inconsistencies and deadlocks.





**Fig. 4.** Scenario 3. (a) UUV3 fails, other UUVs take responsibility of the waypoints initially assigned to UUV3. (b) Region assignments are changed for UUV1-2 after detecting failure. (c) Another UUV(4) is released from the deployment area. (d) Schedules are changed accordingly after negotiations. However UUV4 is not informed about visited waypoints and form regions by considering all waypoints. (e) After being informed about visited waypoints, UUV4 only visits unvisited waypoints in its schedule.

**Table 1.** Performance Results ( $\mu$  |  $\sigma$ ) for Different Message Loss Rates

Mssg Loss Rate	0	0.25	0.5	0.75	1
$M_C$ Comp. (%)	100.0   0.0	100.0   0.0	100.0   0.0	100.0   0.0	100.0   0.0
$M_I$ Comp. (%)	100.0   0.0	100.0   0.0	100.0   0.0	100.0   0.0	12.8   4.1
$M_C$ Comp. time	3349.4   60.5	3683.2   167.1	4909.0   430.1	5141.2   938.1	6304.2   139.0
$M_I$ Comp. time	2852.8   35.3	3227.6   205.3	4205.0   836.9	5021.2   692.7	N/A
(w) first visit	1380.1   6.1	1390.0   16.3	1922.0   92.8	2256.6   334.5	2936.0   104.5
(w) #of visits	1.0   0.0	1.0   0.0	1.01   0.01	1.09   0.04	3.0   0.0

## 5 Conclusions

In this work, we present performance of DEMiR-CF in the context of a Naval Mine Countermeasure mission in the realistic simulator, ALWSE-MC. DEMiR-CF is a distributed framework for multi-robot teams that integrates an auction based dynamic task allocation scheme and several precaution routines to handle failures and limitations of real world task execution, and maintains high solution quality with available resources. Precaution routines can respond to several failures some of which are illustrated in the scenarios shown in this paper. Evaluations also reveal high performance of DEMiR-CF on on-line task and situation handling. Since the framework is a single item auction method it can be used for the environments with limited, delayed or unreliable communication. In general, the framework is designed for more complex missions of interrelated tasks. Near future work consists of more complex missions with more limitations for AUVs and task execution. It should be noted that the selected application domain, objectives and limitations are similar to the Search and Rescue (SR) domain. Therefore we believe research in this work can also be useful for different kinds of domains such as SR.

## References

1. ALWSE: [http://www.ncsc.navy.mil/Capabilities\\_and\\_Facilities/Capabilities/Littoral\\_Warfare\\_Modeling\\_and\\_Simulation.htm](http://www.ncsc.navy.mil/Capabilities_and_Facilities/Capabilities/Littoral_Warfare_Modeling_and_Simulation.htm)
2. Botelho SC and Alami R (1999) M+: a scheme for multi-robot cooperation through negotiated task allocation and achievement. IEEE Intl. Conf. on Robotics and Automation
3. Dias MB, Zinck MB, Zlot RM, and Stentz A (2004) Robust Multirobot Coordination in Dynamic Environments. IEEE Intl. Conf. on Robotics and Automation
4. Dias MB, Zlot RM, Kalra N, and Stentz A (2005) Market-Based Multirobot Coordination: A Survey and Analysis, Robotics Institute. Carnegie Mellon University, Tech Report, CMU-RI-TR-05-13
5. Gerkey G and Matric MJ (2002) Sold!: Auction Methods for Multirobot Coordination. IEEE Trans. on Robotics and Automation, vol. 18 no.5, pp. 758-768
6. Lemarie T, Alami R, and Lacroix S (2004) A Distributed Task Allocation Scheme in Multi-UAV Context. IEEE Intl. Conf. on Robotics and Automation
7. Sariel S and Balch T (2006) Efficient Bids on Task Allocation for Multi-Robot Exploration Problem. The Nineteenth International FLAIRS Conference
8. Sariel S and Balch T (2006) A Distributed Multi-Robot Cooperation Framework for Real Time Task Achievement. The 8th International Symposium on Distributed Autonomous Robotic Systems (DARS)
9. Sariel S, Balch T, and Stack JR (2006) Distributed Multi-AUV Coordination in Naval Mine Countermeasure Missions. Georgia Institute of Technology, College of Computing, GVU, Tech Report GIT-GVU-06-04
10. Stack JR and Manning RC (2004) Increased autonomy and Cooperation in Multi-AUV Naval Mine Countermeasures. Proceedings of Undersea Defence Technology