International Journal of Engineering Research and Technology.
ISSN 0974-3154 Volume 11, Number 5 (2018), pp. 715-724

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Simulation-based Effectiveness Analysis of Mission Planning for Autonomous Unmanned Surface Vehicles (USVs)

Jung Ho Kim
Department of Software Engineering, Korea Aerospace University, Seoul, Korea.

Jung Hoon Kim
The 6th R&D Institute, Agency for Defense Development, Korea.

Yong Jun You
The 6th R&D Institute, Agency for Defense Development, Korea.

Sung Do Chi*
Department of Software Engineering, Korea Aerospace University, Seoul, Korea.
*(*Corresponding Author)*

Abstract

Recently, the environmental perception and autonomous planning of unmanned surface vehicle (USV) gradually become one of the kernel technology problems. To solve the problem of optimal mission planning for USV, this paper presents a simulation-based approach on the basis of the autonomous agent architecture. Our approach is differentiated with others in that it supports (i) the simulation-based framework for analyzing the effectiveness of USV mission planning, (ii) highly autonomous multi-agent architecture that can identify objects, estimate self-states of USV, perceive the situation, decide the mission goal if necessary, plan/re-plan to achieve the goal, and allocate the resources, etc. (iii) the measure of effectiveness (MOE) model specially designed for USV mission plan. Simulation test performed on the mine search example has been successfully applied to illustrate the feasibility of our technique.

Keywords: Unmanned System, Autonomous Unmanned Surface Vehicle (USV) Modelling & Simulation Framework Multi-Agent Architecture

I. INTRODUCTION

It has long being recognized that the employment of unmanned surface vehicle (USV) could provide significant advantages in civil and military applications. There are many different types of missions in complex environment. Military applications include battle damage assessment, delivery of weapons, target following, target destroying and reconnaissance, just to name a few. Civil applications include search, rescue, pipeline monitoring, terrain scanning, mine hunting and so on **Error! Reference source not found.**. The key performance attributes for USV include operation in varying sea state conditions that may have significant effect on platform device characteristics as well as the planning strategy [2]. For this reason, the perception and autonomous mission planning of USV gradually become one of the kernel technology problems [3]. As a result, the autonomous USV systems are expected to have an ability to execute missions according to the objectives that require a very long patrol time in dangerous marine environments. The agent-based simulation is a technique to generate the possible behavior in such complex environments [3]. An agent is known as an entity that perceives and acts in its environment [4]. It is further characterized as a capability of interacting with other agents and having a set of internal goals to guide their behavior in an attempt to satisfy their goals given their resources, abilities, and perceptions [5].

Currently there exist several researches on the agent-based modeling and simulation about USV systems. Li et.al. [6] have been proposed the systematic planning method for the surveillance and reconnaissance mission by using the Hierarchical Task Network (HTN). The technique has been partially utilized for designing the task planning agent proposed in this paper. The DeCoAgent(Deliberative Coherence Agent) announced by Okan [7] has been gracefully upgraded the conventional BDI(Belief-Desire-Intention) agent model by attaching the adaptive decision making module resulting in allowing the characteristics of autonomy, proactivity, adaptation, and social abilities. Even though it showed a high level of autonomy, it still has limitations since it cannot deal with the reactive tasks. To overcome such limitations, we have proposed the middle-out agent model by coherently combining the deliberative (top-down) and reactive (bottom-up) AI.

To cope with complex objectives in complex environment, an autonomous systems requires integration of symbolic and numeric data, i.e., reasoning and computation. A pure AI approach is too qualitative to handle the quantitative information. On the other hand, control researchers have a fairly narrow view-point so that they mainly focus on refinement rather than robustness of a system and they usually consider only the normal operational aspects of a system, however, autonomous systems have to deal with abnormal behavior of a system as well. Thus, it is crucial to have a strong formalism that allows coherent integration of symbolic and numeric information in a valid representation process to deal with a complex dynamic world **Error! Reference source not found.**, [9], **Error! Reference source not found.** It is the reason why we propose the autonomous multi-agent architecture based on the Hierarchical Encapsulation and Abstraction Principle (HEAP) architecture **Error! Reference source not found.**.

The paper first reviews backgrounds and previous works on USV agent modelling for dealing with given missions. It then proposes a simulation-based framework for analyzing effectiveness of mission planning. The multi-agent architecture for autonomous USV mission operation is followed. Finally, it shows the case study applied to mine search simulation to demonstrate the feasibility of proposed technique.

II.OVERALL METHODOLOGY BY SIMULATION BASED MISSION PLANNING ANALYSIS FOR AUTONOMOUS USV

Overall concept of proposed methodology is described in Fig 1. It is consisted of the central model repository with six phases. The central model repository coherently contains and manages various models, knowledges and information such as mission scenarios, structure models, behavioral models, rule-based knowledges and measure of effectiveness (MOE) / measure of performance (MOP) reports, etc. The method starts from Phase0 in which the mission scenario to be tested is selected from the scenario base within the model repository. Next step, Phase I is to create the structure model that is automatically selected from the structure base according to the mission scenario previously selected. Based on the structure, behavioral atomic models are automatically retrieved from the model base.(Phase II) By combining the structural model with behavioral models, the simulation model is created in Phase III. The simulation for mission effectiveness is performed on the basis of the predefined scenario in Phase IV. Finally the MOE/MOP analysis report of a simulation result is generated in Phase V.

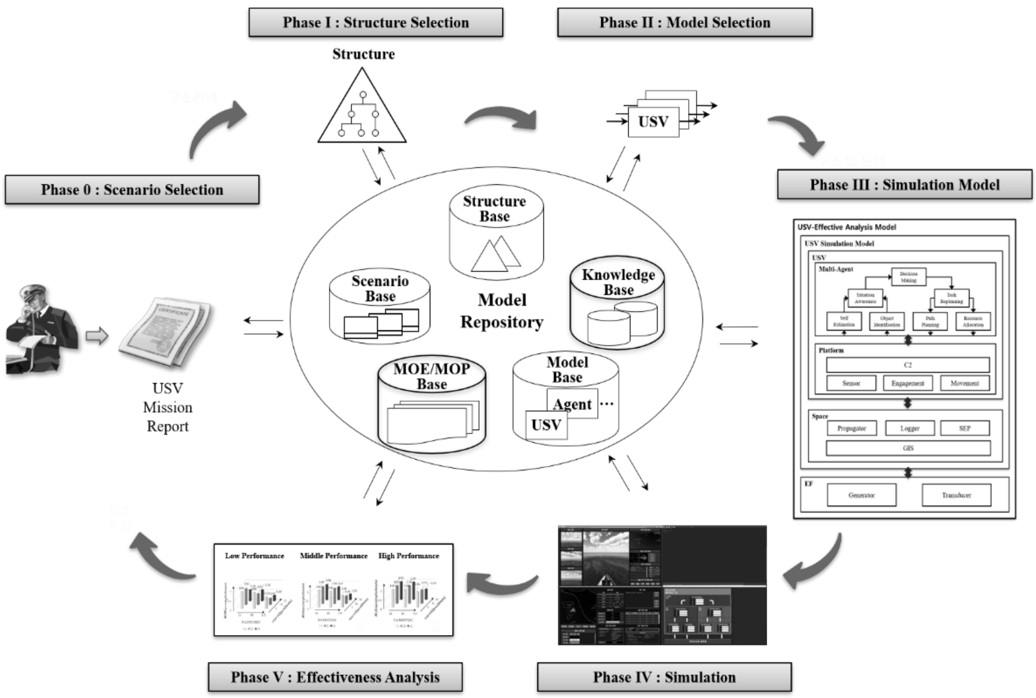


Fig 1 simulation-base analysis methodology

Fig 2 briefly denotes a concept of simulation model. The left upper part of the figure shows the marine environment with a USV and mission area. The right hand side of the figure represents a corresponding model respectively. The USV is consisted with two parts; Agent and Platform. The Agent system is again divided into seven unit agents. It takes charge of a brain of USV, i.e., perception, decision-making, planning and action. Platform is a kind of body of USV. It is divided into Command & Control (C2), Sensor, Engagement, Movement. The C2 bridges the upward sensory signals and downward command signals between the agent and platform. The Sensor model takes charge of Camera, Side scan sonar, IR sensor, etc. The Engagement model deals with the guns, mines, canons, etc. and the Movement model is constructed on the basis of the USV dynamics. Once the USV model is constructed, next step is to build s space model in which the Propagator, Logger, Spatial Encounter Prediction (SEP) and GIS are required to generate a mission dynamics of the USV. Detailed descriptions of the Space model are in **Error! Reference source not found.**, [**Error! Reference source not found.**. Finally, we also need a special model for injecting scenario-based events as well as for collecting and analyzing the simulation results. It is so called the Experimental Frame (EF) model that consisted with Generator and Transducer, respectively. Detailed descriptions are available in [12],[13].

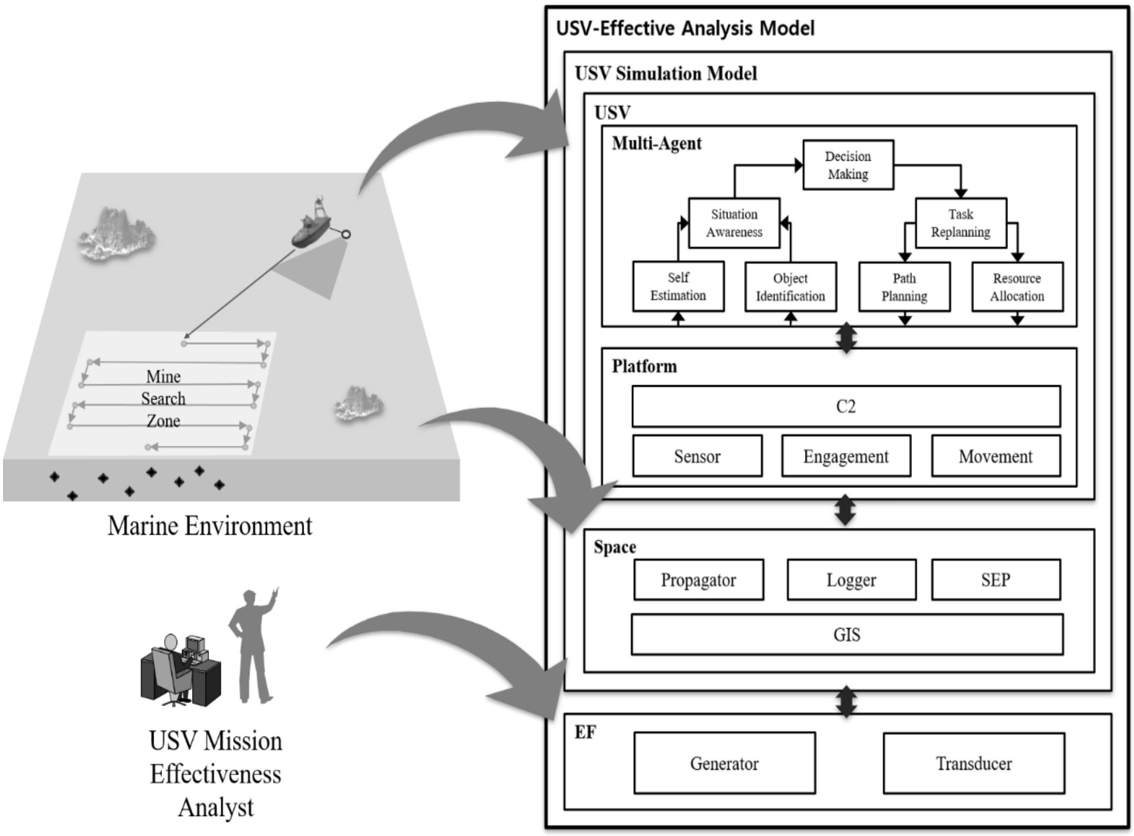


Fig 2 USV evaluation modelling concept for mission planning effectiveness

III. AUTONOMOUS AGENT MODELLING FOR USV

As we mentioned earlier, the core part of USV for dealing with the complex mission is an agent system. To do this, we have employ the Norman's seven stage of human behavior model [14]. To realize such model, we also adopt the HEAP agent architecture proposed by Zeigler **Error! Reference source not found.**. As a result, we have proposed an autonomous multi-agent architecture for the USV mission operation as shown in Fig 3. Major role and function of each agent is as follows;

- Object Identification Agent: It takes all sensory information to classify and identify the objects. By utilizing the macro-functions for the signal processor, pattern classifier and fuzzifier, it extracts the symbolic data for upper agent from the numeric data from sensors of USV platform.
- Self-estimation Agent: It checks self-state of USV such as speed, direction, fuel state, etc. by analyzing the data from sensors of platform.
- Situation Awareness Agent: By comparing the object and itself information from Object Identification Agent and Self-Estimation Agent, it decides the current situation. For example, when the directions of both sides are exactly opposite, then it should aware the dangerous situation since the collision is expected.
- Decision Making Agent: It first checks weather the goal or sub-goal is reached. However if the unexpected situation happens, then it can change the goal. Decision tree representation is adopted.
- Task Planning Agent: It performs task level planning on the task network representation by using the conventional searching algorithm. That means it generates the sequence of tasks that can move the current state to goal state.
- Path Planning Agent: It takes charge of detail path planning based on conventional searching algorithms.
- Resource Allocation Agent: It deals with the detailed schedule of given task. Available resources with starting time, ending time and duration are specified.

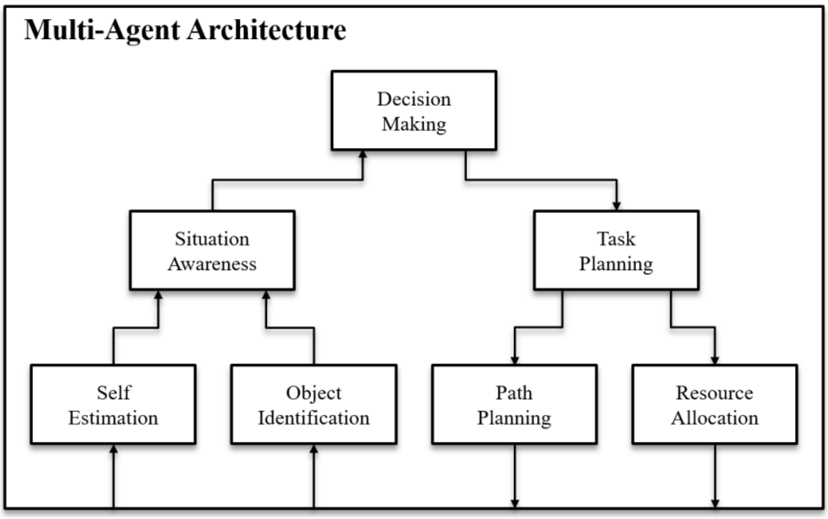


Fig 3 autonomous multi-agent architecture for USV

Each agent in the multi-agent architecture is again divided into four components; Knowledge Base(KB), Fact Base(FB), Inference Engine(IE) and Macro-Functions(MF) as shown in Fig 4. IE is located in center since it receives input data(fact) and finding goal fact by firing the knowledges in KB and retrieving and updating the fact from/to FB**Error! Reference source not found.**. If the fact data need to be abstracted or classified or transform etc., then the proper macro functions may be executed. In this way, the symbolic based inference (top-down AI) and numeric based algorithmic computation (bottom-up AI) maybe suitablly combined. Note that the top-down AI is specialized for the logical reasoning to solve the perception, decision, and planning problems. However the bottom-up AI mainly deals with the identification, classification, and control problems.

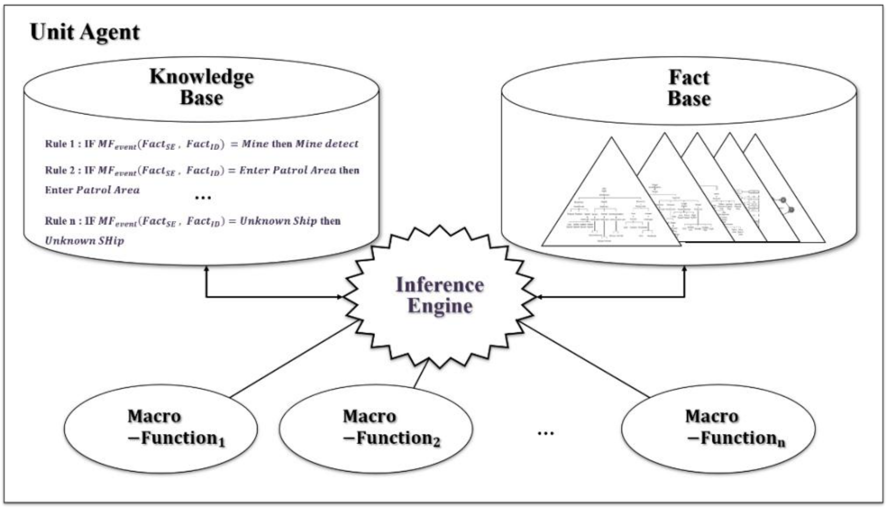


Fig 4 unit agent diagram for USV

IV. CASE STUDY OF EFFECTIVENESS ANALYSIS OF MINE SEARCH MISSION

In order to clearly demonstrate the feasibility of proposed approach, we have performed several simulation experimentations on example marine environment how the mine search mission of the USV works effectively according to the speed, search width, sonar performance, etc. Overall concept is described in Fig 5. In order to establish the criterion for evaluating the effectiveness in a quantitative manner, we have referred the previous works **Error! Reference source not found.**, [9], **Error! Reference source not found.** to define the measure of effectiveness (MOE); MOE_{time} and $MOE_{accomplishment}$. The MOE_{time} stands for an effective area coverage rate and the $MOE_{accomplishment}$ stands for a clearance rate. Each MOE is defined as follows:

$$MOE_{time} = V_{actual} / V_{max} = (S_{mission} / T_{acual}) / (S_{mission} / T_{min}) = T_{min} / T_{actual}$$

$$MOE_{accomplishment} = N_{detected\_mines} / N_{total\_mines}$$

In this scenario, the USV start to move from the headquarter (P0) toward the mission area via pre-planned waypoints (PEZ, PT2). Then it performs the mine search mission by following the parallel search pattern with the planned track width. Note that the parallel search pattern is most desirable when the target (mines) is equally likely to occupy any part of the search area [5]. After finishing the mine search, it turns back to headquarter via planned waypoints (PB1, PB2, PB3, PSZ, PF). In this scenario, twenty mines are randomly located among $350\text{m} \times 350\text{m}$ mission area. The simulation is repeatedly continued to check all possible conditions between the USV speed, tracking width, and the sonar performance.

Fig 6 summarizes the simulation results. MOE_{time} is getting increased as the track width and speed increased. For instant, when the track width is 175m and the speed is 25knot, the MOE_{time} is calculated as 0.2. Note that the MOE_{time} is independent with the sonar performance. However, the $MOE_{accomplishment}$ is depending on the sonar performance. It increases when the sonar performance increase. The $MOE_{accomplishment}$ is also increased when the track width and speed decrease. For example, when the track width is 88m and the speed is 15knot equipped with low performance sonar, the $MOE_{accomplishment}$ shows 0.35. However when the same condition but with high performance sonar is applied, the result is 0.89 which is much higher than previous one. The planning strategy how to decide the searching speed and track width as well as how much degree of sonar performance attached is critical for the efficient USV mission operation. By analyzing the effectiveness of the mission plan in advance, the USV operator or mission designer maybe able to establish the desirable mission operation strategy. For example, the fuel limitation is one of critical factors to decide the mission plan. If the fuel is not enough in some reason, then the plan should be changed to increase the MOE_{time} by applying the wider track width and faster speed. Of cause, the $MOE_{accomplishment}$ should be decreased in this case as illustrated in Fig 6.

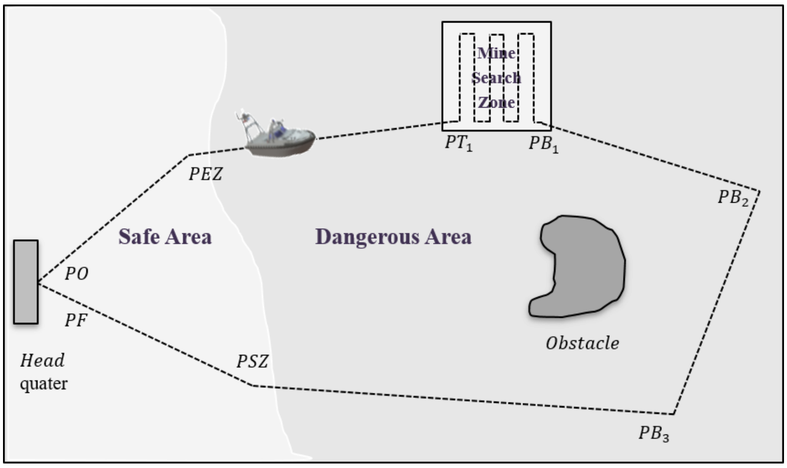
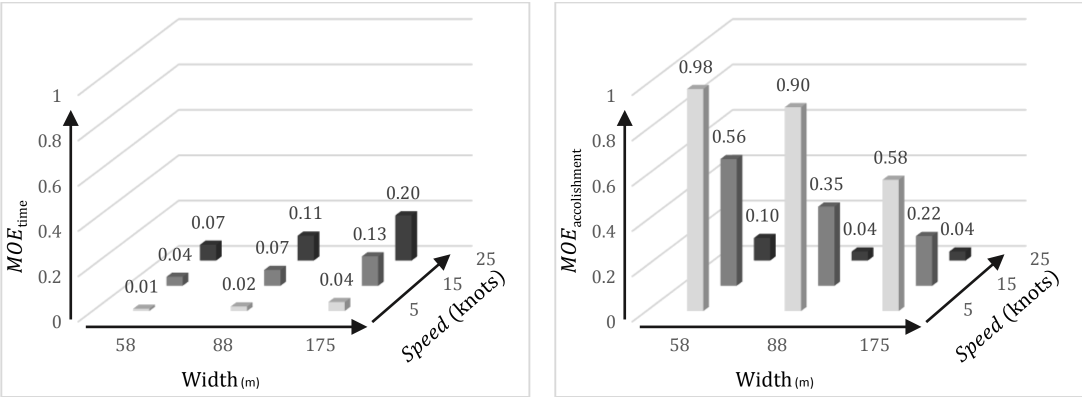
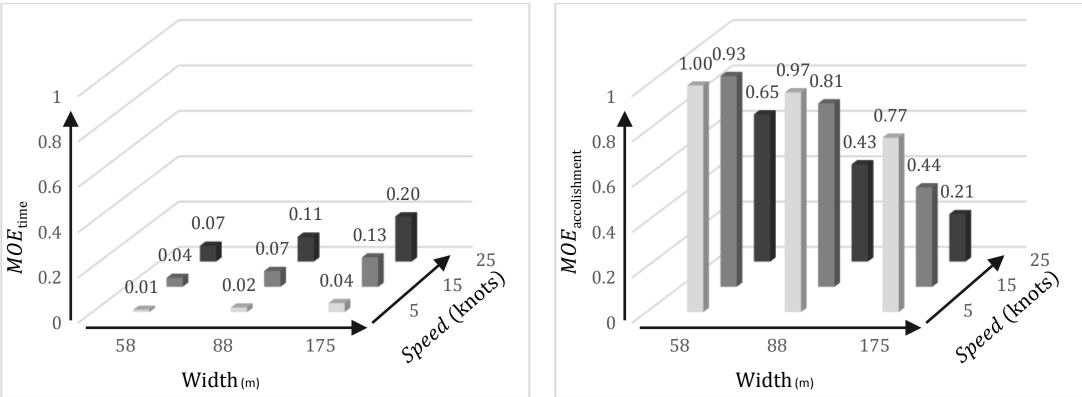


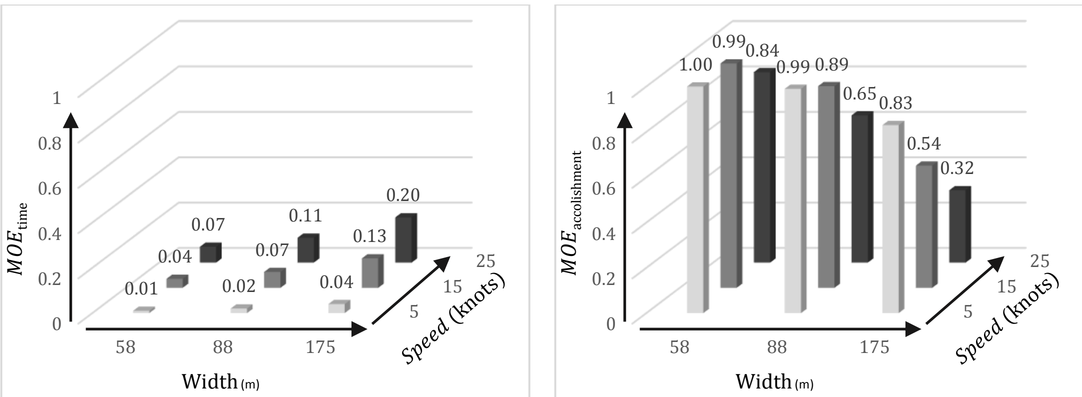
Fig 5 conceptual diagram of mine search mission



(a) case i: low performance sonar



(b) case ii: medium performance sonar



(c) case iii: high performance sonar

Fig 6 MOEs as a simulation result

V. CONCLUSION

A simulation-based analysis methodology for mission planning effectiveness of USV is successfully proposed. To deal with complex missions in complex environment, an autonomous systems requires integration of symbolic and numeric data, i.e., reasoning and computation. To do this, we have adopted the dynamics-based modeling formalisms as well as AI-based logical reasoning mechanisms to support both deliberative and reactive tasks necessary for dealing with the complex mission planning problem. Our approach is compared with others in that it supports (i) the simulation-based framework for analyzing the effectiveness of USV mission planning, (ii) highly autonomous multi-agent architecture that can identify objects, estimate self-states of USV, perceive the situation, decide the mission goal if necessary, plan/re-plan to achieve the goal, and allocate the resources, etc. (iii) the MOE model specially designed for USV mission planning. Simulation test performed on the mine search example has been successfully applied to illustrate the feasibility of our technique. In near future, USV researchers and engineers will be able to base their USV agent designs on the modelling and simulation analysis methodology proposed in this paper. They also will be able to employ our multi-agent architecture and simulation environment to verify such designs prior to their implementation.

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