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AGENT-BASED HARDWARE-IN-THE-LOOP SIMULATION FOR UAV/UGV SURVEILLANCE AND CROWD CONTROL SYSTEM

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ABSTRACT

An agent-based hardware-in-the-loop simulation framework is proposed to model the UAV/UGV surveillance and crowd control system. To this end, a planning and control system architecture is discussed first, which includes various modules such as sensory data collection, crowd detection, tracking, motion planning, control command generation, and control strategy evaluation. The modules that are highly related with agent-based modeling (focus of this paper) are then discussed, which includes the UAV/UGV motion planning considering multi-objectives, crowd motion modeling via social force model, and enhancement of simulation environment via GIS 3D coordinates conversion. In the experiment, Repast Simphony is used as the agent-based modeling tool, which transmits sensory data and control commands with QGroundControl as hardware interface that further conducts radio communications with ArduCopter as a real UAV. Preliminary results show that finer grid scale and larger vehicle detection range generate a better crowd coverage percentage. Finally, conclusions and future works are discussed.

1 INTRODUCTION

Many applications of Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs) as multi-vehicle systems have been emerging in recent years such as surveillance, reconnaissance, information gathering in mapping, wildfire fighting, and border patrol (Jones 2009). To study such multi-vehicle systems, various researchers have utilized agent-based simulation (ABS) in recent years, which is a bottom-up modeling technique used to simulate real system components (e.g. vehicle, people and their interactions) in an integrated environment. These agent-based models have been then used by various experiments to investigate the simulated behavior of the real system under various settings to gain benefits such as cost saving and performance enhancement (e.g. time, travel distance, energy consumption). In ABS, agents interact with each other and the environment, where the environment may place constraints on agent activities (Macal and North 2010). One important feature in our work is that the environment location information is incorporated into the attribute of an agent. For this purpose, GIS (Geographical Information System) information is utilized for acquiring elevation/height information of UAVs/UGVs to achieve more accurate modeling of them.

In addition, incorporating real hardware using hardware-in-the-loop simulation (HILS) techniques, which is another major task in our work, is a crucial step to perform system-level development and real-time testing considering various issues such as time, cost, and safety (Ledin 1999). Various studies have been conducted to apply agent-based HILS for UAV and UGV systems. For example, Chen and Chang (2008) discussed an ABS platform for UAV missions involving emergent formation and behaviors. Later, Cicirelli, Furfaro, and Nigro (2009) proposed an agent-based infrastructure for distributed simulation over HLA/RTI, under which various UAV coordination and control topics were studied such as agent behaviors, message interaction, time management, system load-balancing, and reconfiguration. Chandhrasekaran, Eunmi, and Min (2009) proposed a model using HILS to react to failures in UAV system in real-time and designed a control mechanism with dual-loop architecture to analyze the system performance. Later, Yang and Li (2012) proposed a HILS system based on right angle robot to verify dynamic control, object detection, object tracking, localization and image mosaic algorithms for a UAV system. The HILS system in their study was two-dimensional robot lead rails, constituting a right-angle robot to build a flight simulation system.

The goal of this paper is to propose a comprehensive and coherent agent-based HILS for UAV/UGV surveillance and crowd control. It focuses on modeling UAVs/UGVs, people/crowd, as well as enhanced simulation environment. In addition, ABS is integrated with a real UAV through the hardware interface (middleware) to achieve both monitoring (sensory data updates) and execution (control command generation) functions for the UAV/UGV system control. Preliminary experiments are also conducted to test the effect of various factors (e.g. number of grids used in the simulation environment and detection range of vehicles) on crowd converage performance.

The rest of this paper is organized as follows: Section 2 discusses an overview of simulation-based planning and control framework first. Then, the three sub-sections in Section 2 explain details on UAV/UGV motion planning, crowd motion modeling via social force model, and conversion of GIS to 3D Cartesian coordinates. Section 3 discusses the development of test-bed involving hardware and software, followed by preliminary experimental results. Section 4 concludes the paper and discusses the future works.

2 PROPOSED SIMULATION FRAMEWORK AND COMPONENTS

Figure 1 depicts the overview of simulation-based planning and control framework, which provides the vision for leveraging the usage of agent-based HILS platform discussed in this paper. In Figure 1, integrated controller, integrated planner, and real system are systematically combined for mission planning and crowd control via UAVs and UGVs. The loop connecting the integrated controller and the real system depicts the flow of sensory data collection and processing, command generation including crowd detection, tracking, motion planning modules, and control command transmission via hardware interface. The integrated controller and the real system are self-contained to function if the observed system variance is small. In case of deteriorated system performance, the integrated planner is invoked to incorporate the most current data collected from the integrated controller into the strategy maker, to evaluate the various control strategies against future uncertainties, and then to select the best one to be used by the command generator. The control strategy can involve various aspects including preferences of sensory data processing units, look-ahead time units in tracking, weights of different motion planning objectives. Due to the space limit of this paper, the discussion of this topic (control strategies) is not included. It is noted that the proposed ABS can be further extended to incorporate other functionalities including computer vision for crowd detection, dynamic data driven feature for steering measurement, which are left for future study. A similar framework was presented in Wang et al. (2013), and a detailed discussion of the current framework with the dynamic data driven adaptive multi-scale simulation (DDDAMS) enhancement is also available in Khaleghi et al. (2013). It is noted that our current paper focuses more on the ABS and HILS compared with them.

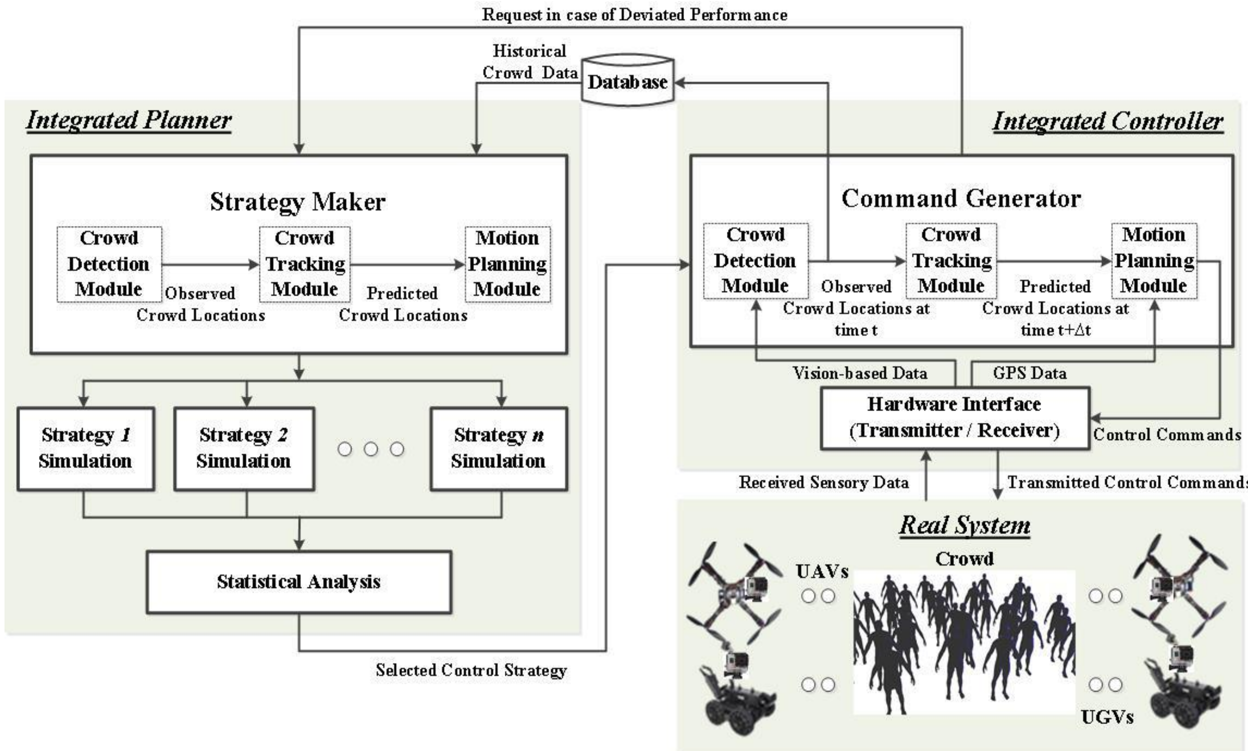


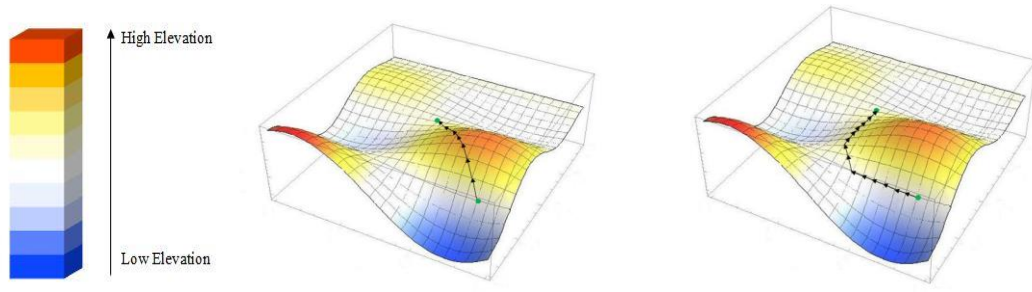
Figure 1: Simulation-based planning and control framework for UAV/UGV surveillance and crowd control system (Wang et al. 2013; Khaleghi et al. 2013).

In this framework, crowd detection, crowd tacking and motion planning are three major missions for unmanned vehicles. Instead of discussing every component of Figure 1, this paper will emphasize the components related with ABS. Specifically, we will discuss the UAV/UGV motion planning, crowd motion modeling via social force model, and conversion of GIS to 3D Cartesian coordinates (environment in ABS).

2.1 Motion Planning for Unmanned Vehicles

Motion planning is an important aspect in autonomous operation of UAVs and UGVs, with the goal of finding the optimal path given a pair of the current location and destination. Successful motion planning of UAV/UGV system is subject to various factors such as energy consumption and range of operation. Graph search methods such as A* (Hart, Nilsson, and Raphael 1968) and its variants, D* (Stentz 1994) and Theta* (Nash et al. 2007), have been widely used in the literature by discretizing the operational environment and then creating the corresponding path.

In this work, we use A* algorithm to select the optimal trajectories of a vehicle utilizing an eight-point connectivity graph, which determines eight directions that the vehicle can move. Each vehicle's location is represented by a triple set $[x(t), y(t), z(t)]$, where the first two elements are calculated based on the latitude and longitude of UAVs and UGVs, and the third element is the altitude of UAVs/UGVs from Mean Sea Level (MSL) which is defined as the summation of terrain elevation of environment and the Above Ground Level (AGL) altitude. For UGVs we consider AGL as zero. Furthermore, the world is assumed to be static with known terrain elevation represented by $elev(x(t), y(t))$. In our work, selection of the vehicle optimal trajectory is concerned with respect to two objective criteria: travel distance and energy consumption. Exemplary results under the two different objectives are demonstrated in Figure 2 considering the same simulation environment.



(a) (b)

Figure 2: Optimal paths by (a) minimizing travel distance and (b) minimizing energy consumption

The formulations for the Euclidian traveling distance of UAVs and UGVs are shown in (1) and (2), respectively.

$$f_1^{(A)} = \sum_{t=t_0}^{T-1} \{[x(t+1)-x(t)]^2 + [y(t+1)-y(t)]^2 + [elev(x(t+1),y(t+1)) + AGL(t+1) - elev(x(t),y(t)) - AGL(t)]^2\}^{0.5} \tag{1}$$

$$f_1^{(G)} = \sum_{t=t_0}^{T-1} \{[x(t+1)-x(t)]^2 + [y(t+1)-y(t)]^2 + [elev(x(t+1),y(t+1)) - elev(x(t),y(t))]^2\}^{0.5} \tag{2}$$

It's known that changing UAV's altitude or moving UGVs downhill/uphill affects their energy consumption (Sauter et al. 2008). To deal with this issue, the elevation penalty (Wichmann, and Wuensche 2004) is considered based on the angle of two traveling locations as shown for UAVs and UGVs in (3) and (4), respectively. Table 1 shows sample elevation penalties considered in this work. Summation of all elevation penalties in a path for UAVs and UGVs are defined in (5) and (6), respectively; and they are associated with the energy consumption (the second objective).

$$\beta^{(A)}(t) = \arctan\left(\frac{|elev(x(t+1),y(t+1)) + AGL(t+1) - elev(x(t),y(t)) - AGL(t)|}{[[x(t+1)-x(t)]^2 + [y(t+1)-y(t)]^2]^{0.5}}\right) \tag{3}$$

$$\beta^{(G)}(t) = \arctan\left(\frac{|elev(x(t+1),y(t+1)) - elev(x(t),y(t))|}{[[x(t+1)-x(t)]^2 + [y(t+1)-y(t)]^2]^{0.5}}\right) \tag{4}$$

$$f_2^{(A)} = \sum_{t=t_0}^{T-1} elevPenalty\big(\beta^{(A)}(t)\big) * \{[x(t+1)-x(t)]^2 + [y(t+1)-y(t)]^2 + [elev(x(t+1),y(t+1)) + AGL(t+1) - elev(x(t),y(t)) - AGL(t)]^2\}^{0.5} \tag{5}$$

$$f_2^{(G)} = \sum_{t=t_0}^{T-1} elevPenalty\big(\beta^{(G)}(t)\big) * \{[x(t+1)-x(t)]^2 + [y(t+1)-y(t)]^2 + [elev(x(t+1),y(t+1)) - elev(x(t),y(t))]^2\}^{0.5} \tag{6}$$

Table 1: Sample elevation penalties

Range of $\beta(t)$	$[0, \frac{\pi}{18})$	$[\frac{\pi}{18}, \frac{\pi}{9})$	$[\frac{\pi}{9}, \frac{\pi}{4})$	$[\frac{\pi}{4}, \frac{\pi}{2})$	$\frac{\pi}{2}$
$elevPenalty\beta(t)$	1	1.5	3	5	6

2.2 Crowd Motion Modeling

According to FHWA (2004), human crowd behavior has been studied by models in three major categories:

- Microscopic models, in which pedestrians' motions as discrete agents were studied and the crowd behaviors resulted from this self-organization process. Models belonging to this category include 1) stochastic formulation (Helbing 1992b), 2) cellular automation model (Mrowinski, Gradowski, and Kosinski 2010), and 3) social force model (Helbing and Molnár 1995).
- Macroscopic models focus on the whole crowd as one or more groups of individuals to seek their specific goals (destinations) and their collective behaviors. Examples of such models include fluid dynamic approach (Helbing 1992a) and regression models (Milazzo, Rouphail, and Allen 1998).
- Mesoscopic models include hybrid approaches of the above two categories. In this category, individuals' behavior is examined and at the same time, their interactions are considered based on macroscopic relationships and goals of the crowd. Studies have been also conducted on gas-kinetic formulation (Helbing 1992b) and agent-based microscopic model (Musse and Thalmann 1997).

Among available models, social force model conforms to our goals in simulating crowd motion. This physics-based model focuses on the effects of the environment on individual and crowd interactions (Helbing and Molnár 1995). The individual behavior and collective pattern of crowd motion have also been examined by the social force model. For example, considering scape panic phenomenon, Helbing, Farkas, and Vicsek (2000) entered psychological effects into their social force model to design a generalized model for characterizing the crowd behavior. Later, based on a cognitive model approach and visual information, two behavioral heuristics were proposed to determine the desired walking directions and speeds of individuals, which were then combined with body collision to model crowd disaster at extreme densities (Moussaïd, Helbing, and Theraulaz 2011).

In this paper, since each individual moves based on the social force model while being part of a goal-directed crowd and interacting with other individuals and the environment, we have employed the agent-based approach and applied it to the mesoscopic model. For this purpose, we adopted the model proposed by Moussaïd, Helbing, and Theraulaz (2011), where two heuristics have been defined based on visual data. Each human has a field of view between $-\varphi$ and φ with maximum range of $d_{\max}$ and direction/angle of destination is represented by α_0 (see Figure 3). In addition, each person has a comfortable walking speed, defined as v_0, which he would like to take in the case with no obstacles. The first heuristic formulated in (7) determines the direction/angle (α) of each human to minimize the distance to its destination and also takes into account the presence of obstacles and other humans in his field of view.

$$min_\alpha\, d(\alpha) \quad \text{where } d(\alpha) = d_{max}^2 + f(\alpha)^2 - 2d_{max}\, f(\alpha)\cos(\alpha - \alpha_0) \tag{7}$$

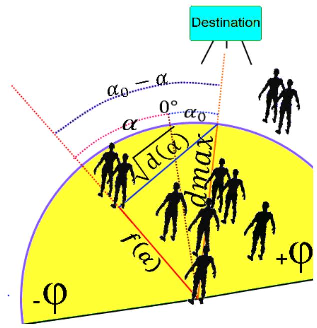


Figure 3: Motion of human crowds in the case with obstacles

The second heuristic changes the walking speed of humans to avoid collisions. In this case, if a person has an obstacle in direction α and distance d_h, his speed would be:

$$v = min\left(v_0, \frac{d_h}{\tau}\right),$$

where τ is the relaxation time (i.e. time required to adopt a new behavior).

2.3 Mapping the Geographical Location to 3D Cartesian Coordinates

Any point in the globe, which is described by latitude ϕ, longitude λ and ellipsoid height (elevation) h, could be uniquely described in the 3D Cartesian coordination (x, y, z) as the following equations shown (Drake 2002):

$$x = \left(\frac{a}{\sqrt{1-e^2\sin^2\phi}} + h\right)\cos\phi\cos\lambda,$$
$$y = \left(\frac{a}{\sqrt{1-e^2\sin^2\phi}} + h\right)\cos\phi\sin\lambda,$$
$$z = \left(\frac{a\,(1-e^2)}{\sqrt{1-e^2\sin^2\phi}} + h\right)\sin\phi;$$

where $e^2 = \frac{a^2-b^2}{a^2}$ is the eccentricity squared, a is the semi-major axis, and b is the semi-minor axis.

To estimate the distance between two points described in latitude-longitude coordination that is referred to as *The Great Circle Distance* (the shortest distance over the earth's surface), we use the haversine distant equation in Sinnott (1984). This equation assumes a perfect spherical world and was widely used in GPS systems due to its capability in making good estimate of the spherical distance between two points. The distance is defined by $d = Rc$, where d is the great circle distance between two points, R is the earth's radius ($E(R)$=6,371,135 m) (Dave and Richard 1999), and c is the angular distance in radians calculated using (8) and (9).

$$c = 2\arctan\left(\frac{\sqrt{\mathrm{hav(c)}}}{\sqrt{1-\mathrm{hav(c)}}}\right) \tag{8}$$

$$hav(c) = \sin^2\left(\frac{\phi_2-\phi_1}{2}\right) + \cos\phi_1\cos\phi_2\sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right) \tag{9}$$

Since the elevation of the two points should also be considered in order to have a more accurate estimate of the distance, in this paper, we use the NASA World Wind library (Maxwell et al. 2006) to obtain the terrain elevation of a point specified only by latitude and longitude, referencing the sea level.

Compared with Spherical Law of Cosines, which is also used in some literature to compute c, haversine formula has a better performance for numerical computation even at small distance (Veness 2010), since the necessity of inverting the cosine magnifies the rounding errors for small c. These findings motivated us to use haversine formula in this work.

3 SYSTEM IMPLEMENTATION AND EXPERIMENTS

3.1 Hardware and Software Test-bed

Figure 4 demonstrates the hardware and software test-bed that has been developed in this work. Different agents (UAV, UGV and crowd) and their behaviors are implemented using Java in Repast Simphony, and motion planning algorithm (A*) has been implemented in python. During the simulation run, agent-based model and python-based motion planning algorithm communicate using Jython, which is python for java platform (http://www.jython.org/).

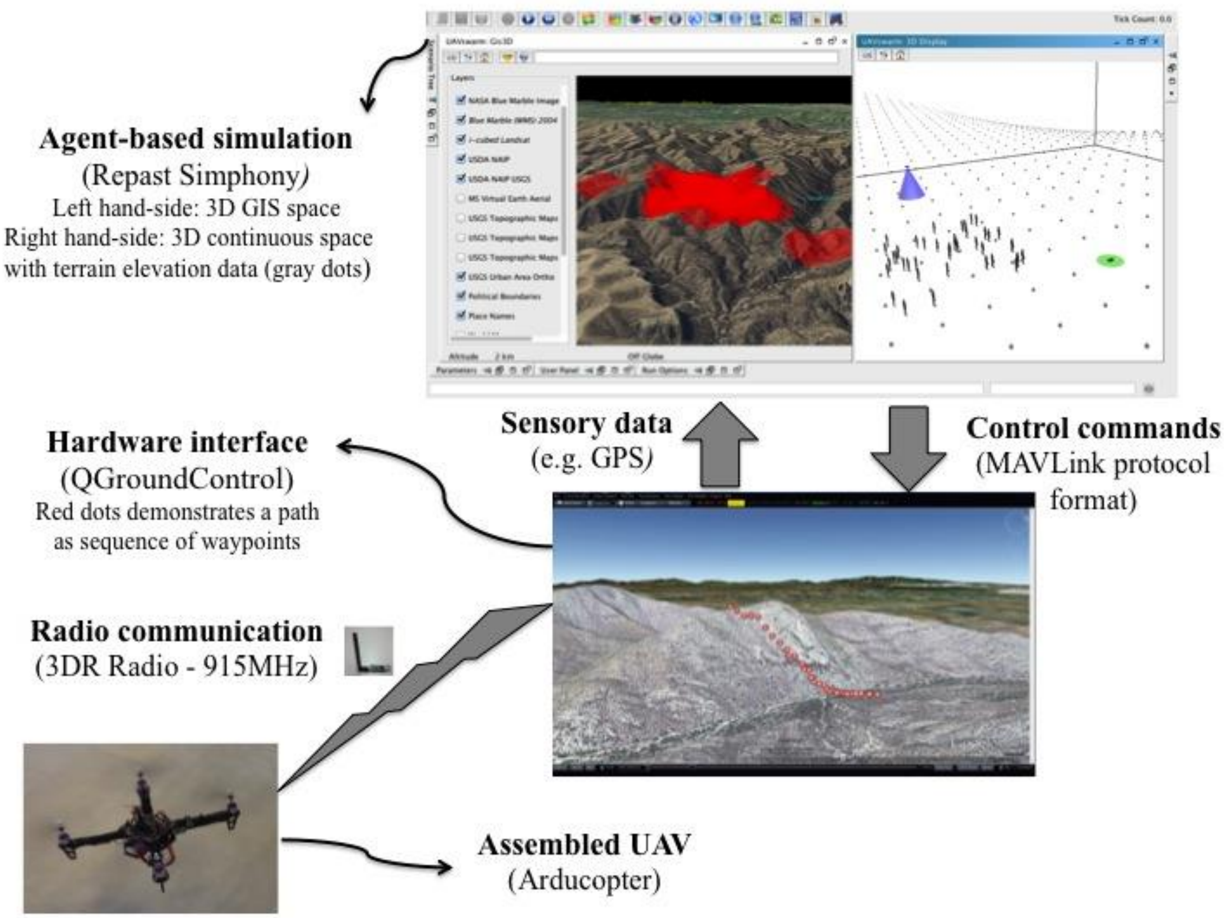


Figure 4: Hardware and software test-bed (ABS (running both in fast-mode as well as in real-time), hardware interface, and real UAV)

Geographical coordinate (latitude and longitude) of a desired location is determined in the 3D GIS space and using the formula described in Section 2.3, the selected location has been mapped in 3D continuous space where agents are capable to move along X, Y and Z axes. Furthermore, by this mapping a grid has been generated where each node contains terrain elevation data which has been used in motion planning of vehicles. To control a real system, ABS running in real-time generates commands for UAVs and UGVs where these control commands are written in MAVLink format for use in QGroundControl (Meier 2010) as hardware interface. This tool provides radio communications with UAVs such as ArduCopter (https://code.google.com/p/arducopter/) by sending control commands and receiving sensory data.

3.2 Preliminary Results

Based on the implemented system in Section 3.1, experiments have been conducted to examine the effects of various factors (e.g. number of grids and detection range of vehicles) on system performance. The system performance considered in this work is crowd coverage percentage. As mentiond in the previous section, each node of the environmental grid contains terrain elevation data gained from GIS and has been used in motion plannig of unmanned vehicles. Our experiments consider one UAV, one UGV, and a crowd of forty people. It's assumed here that the human walking speed equals to 1.5 m/s in the crowd. Figure 5 shows the three experimental results, where the number of grids under the same simulation environment gradually increases from 20 by 20 to 60 by 60 (a larger number of grids indicates the smaller grid size).

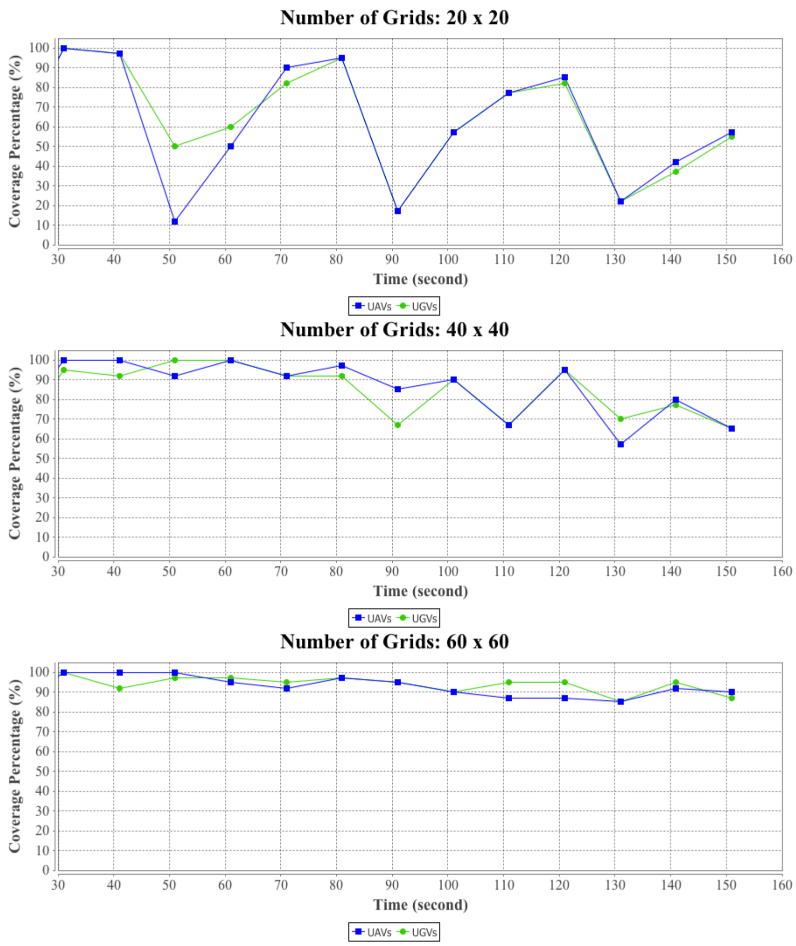


Figure 5: Impacts of number of grids (under the same simulation environment) on system performance

As the experimental results show, the system performanc fluctuates a lot when the number of grids equals to 20 by 20, which is due to the large grid size resulting in location inaccuracy. Continuing to increase the number of grids under the same simulation environment (the other 2 graphs in Figure 5), the system performance improves, and the fluctuation gets diminished over time, which demonstates the critical role of grid size (the smaller is better) in maintaining system performance. However, it has been observed that involving a smaller size of grid in simulation requires more computational resources (e.g. CPU and memory usage), as motion planinig algorithm will need to search a larger graph in terms of the number of grids and more GIS data is required to be imported in the simualtion environment.

Figure 6 shows impact of vehicle detetion range on system performance involving three detection range settings (i.e. 5m, 10m, 15m). Depending on the resolution of camera mounted on the UAVs/UGVs and their other properties, detection range of them will vary. In this experiment, however, the same detection range has been assumed for UAVs and UGVs. Involving real detection capability using camera images is left for a future research. It is observed from the results, that as the detection range becomes larger, the crowd coverage percentage is increased and smoother over time. The results also show that a larger detection range will enhance the system performance, as in each time stamp, more people are supposed to be covered by UAVs and UGVs. We also noticed that the impact of the detection range on system performance is related with crowd tracking horizon and motion planning frequency. In our work, fixed numbers are used, however, and investigation of its impact is left for future study. Furthermore, establishing mathematical relationships between system performance and various important factors could be helpful to gain insightful suggestions to the considered UAV/UGV systems.

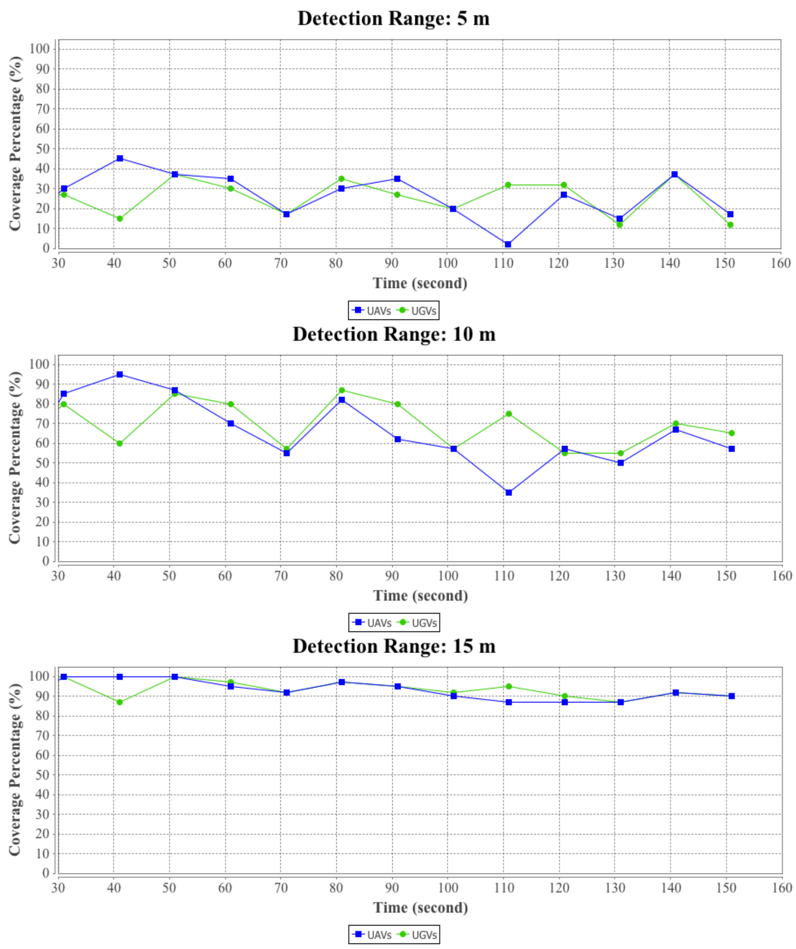


Figure 6: Impacts of detection range (under the same simulation environment) on system performance

4 CONCLUSIONS AND FUTURE WORKS

In this research, we have proposed an agent-based HILS framework to study the UAV/UGV surveillance and crowd control system. UAV/UGV motion planning, crowd motion modeling via social force model, GIS 3D coordinates conversion were three major focuses of this work. The implementation of the proposed framework has been also discussed, and experiments were also conducted to test the impacts of environmental grid size and the UAV/UGV detection range on the system performance (coverage percentage). Preliminary results have showed that the finer grid scale and a larger UAV/UGV detection range generate better crowd coverage results than the coarser grid scale and a smaller vehicle detection range.

Future works involves the following aspects: 1) investigating other missions such as crowd detection and crowd tracking based on the proposed simulation framework, 2) analysis of the planning functions (planning horizon, control strategies) under the proposed framework, 3) incorporating dynamic data collected from the real UAVs/UGVs into the simulation system for dynamically changing the modeling scale (simulation fidelity) as well as steering the measurement process over time.

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