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DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs

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14. ABSTRACT
The main goal of this project was to investigate algorithmic approaches to create scalable, robust, multi-scale, and effective urban surveillance and crowd control strategies using UAVs and UGVs. To achieve the goal, a comprehensive planning and control framework was designed and developed based on dynamic-data-driven, adaptive multi-scale simulation (DDDAMS), where dynamic data is incorporated into simulation, simulation steers the measurement process for data update and system control, and an appropriate level of simulation fidelity is selected based on the time constraints for evaluating alternative control policies using simulation. An information-aggregation approach was developed for crowd dynamics modeling by incorporating multi-resolution data, where a grid-based method is used to model crowd motion with UAVs' low-resolution global perception, and an autoregressive model is used to model individuals' motion based on UGVs' detailed perception. Also, a vision-based target detection and localization via a team of cooperative UAV and UGVs was developed. Finally, a testbed was successfully developed, involving hardware (UAVs and UGVs), software (agent-based simulation, GIS), and human components, and used to demonstrate the proposed framework.

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Section 1: Cover Sheet

Final Report

Period of Performance: 05/01/12 – 09/30/15

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Section 2: Objectives and Overall Approach

Goal: The main goal of this project was to investigate algorithmic approaches to create scalable, robust, multi-scale, and effective urban surveillance and crowd control strategies using UAVs and UGVs.

Overview of Approach: In order to achieve the goal, a comprehensive planning and control framework was designed and developed based on dynamic-data-driven, adaptive multi-scale simulation (DDDAMS) (see Figure 1), where dynamic data is incorporated into simulation, simulation steers the measurement process for data update and system control, and an appropriate level of simulation fidelity is selected based on the time constraints for evaluating alternative control policies using simulation. In this project, the DDDAMS framework that was developed and demonstrated by PI Son's group for the case of extended manufacturing enterprise have been leveraged and further developed to address scalable, robust, multi-scale, and effective urban surveillance and crowd control via UAVs and UGVs. The research outcomes (e.g. DDDAMS framework, information aggregation framework, underlying algorithms, and experiments involving simulation-based testbed) developed in this project have been published in multiple journals and conference proceedings (see Section 6 for a complete list of publications). More details on the proposed planning and control framework will be explained in Section 3.

Detailed Objectives (Tasks): The proposed approach is composed of the following three major tasks:

- Development and refinement of coherent planning and control framework (DDDAMS) for effective and efficient control of UAV/UGVs
- Development of algorithms to improve performance of coordinated UAV and UGVs in tracking and controlling human crowd
- Development of a hardware-in-the-loop simulation/control framework and testbed for crowd control

The progress made to date for each of these tasks is described in Section 3.

Section 3: Summary of the Efforts

This section provides details on the efforts that were made for three major tasks defined in Section 2.

3.1. Task 1: Development and refinement of coherent planning and control framework (DDDAMS) for effective and efficient control of UAV/UGVs

Figure 1 shows an overview of the proposed DDDAMS-based planning and control framework for surveillance and crowd control via UAVs and UGVs that was developed and refined in this project. The major components of the framework include 1) real system

(UAVs, UGVs, human crowd, and environment), 2) integrated planner, 3) integrated controller, and 4) decision module for DDDAMS. The proposed framework was aimed to enhance the surveillance and crowd control capability of UAVs and UGVs in terms of their performance on crowd detection, tracking, and motion planning. In particular, the crowd coverage percentage was considered as the measure of effectiveness (MOE) in this work. An overview of different components is provided in the following paragraphs, and more details on the proposed framework can be found in the following journal paper:

- A. Khaleghi, D. Xu, Z. Wang, M. Li, A. Lobos, J. Liu, Y. Son, A DDDAMS-based Planning and Control Framework for Surveillance and Crowd Control via UAVs and UGVs, *Expert Systems with Applications*, 40, 2013, 7168-7183.

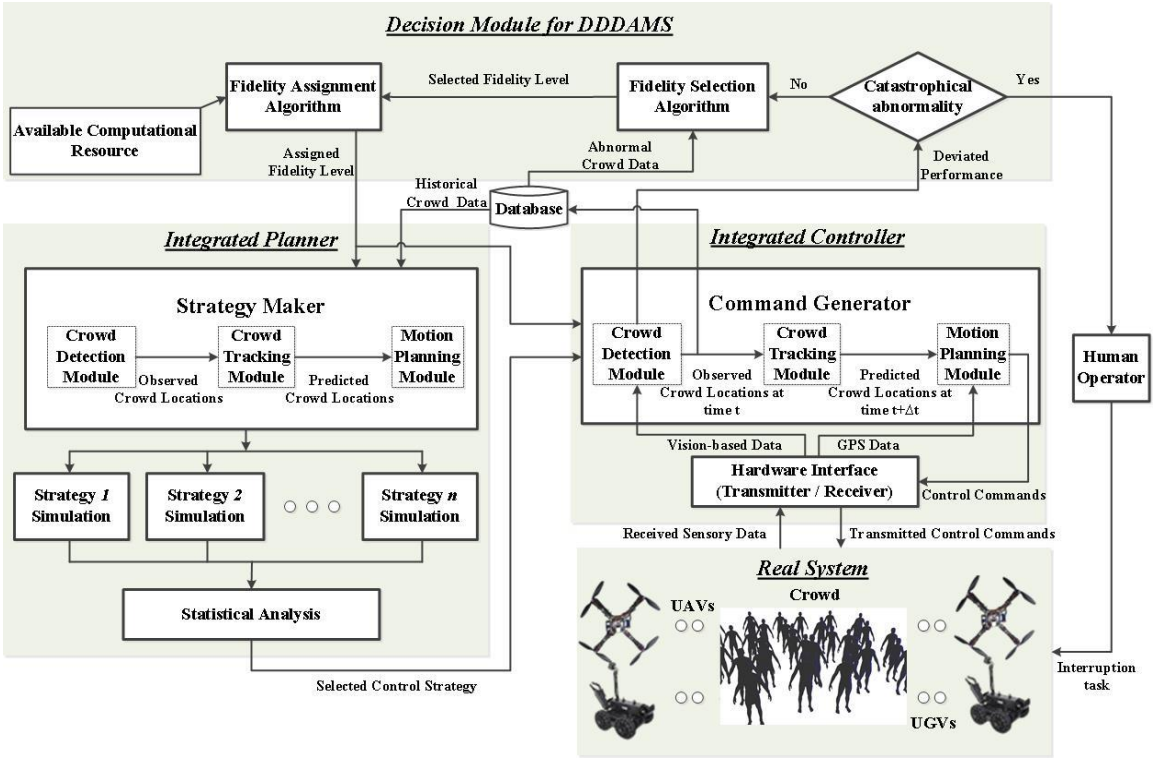


Figure 1: Proposed DDDAMS-based planning and control framework for surveillance and crowd control via UAVs and UGVs (Khaleghi et al., 2013)

Integrated Controller: The integrated controller is in charge of effective and efficient control of UAVs and UGVs, where the effectiveness is supported by the integrated planner, and the computationally efficiency is supported by the decision module for DDDAMS. To control UAVs and UGVs, the integrated controller performs four major functions: 1) crowd detection, 2) crowd tracking, 3) motion planning of UAV/UGV, and 4) interaction with the real system. To achieve interactions with the real system, the hardware interface in the integrated controller acts as a medium to collect sensory data (e.g. vision data and global positioning system (GPS) data) from the real system, passes them to the command generator, receives control commands from the motion planning module, and sends the corresponding control commands to the real system. Among received sensory data, the vision-based data (e.g. images and video streams) are utilized in the crowd detection

module, and the GPS data are used by the motion planning module. Given the vision-based data, the crowd detection module 1) processes them for crowd detection and location identification purposes, 2) invokes the decision module for DDDAMS if actual and predicted system performances (crowd coverage in this work) have a significant deviation, and 3) passes the analyzed crowd data (e.g. locations and crowd coverage) to the database periodically. Based on the crowd location identified at time stamp t, the crowd tracking module predicts the crowd locations at time stamp $t+\Delta t$, where Δt is an interval that users must define depending on the intended frequency of control (10 seconds were used in this work). The predicted locations are then used in the motion planning module as destination locations of the UAVs/UGVs, from which control commands (e.g. waypoints) for next Δt are generated for the UAVs/UGVs. This process (i.e. data collection – crowd detection – crowd tracking – motion planning – control command generation) continues in an iterative manner until the real system performance deviates enough from the predicted performance (event basis) or the predefined planning horizon is elapsed (temporal basis), which then invokes the integrated planner.

Integrated Planner: The integrated planner, when invoked, devises an optimal control strategy for UAVs/UGVs based on predicted system performance and passes the updated control strategy to the integrated controller. The integrated planner in the proposed work was implemented in an agent-based simulation (ABS) environment, where the strategy maker selects optimal strategies for each of the same components in the command generator (i.e. crowd detection, crowd tracking and motion planning) based on simulation-based evaluation of alternative strategies against different scenarios. This work mainly focuses on 1) evaluation of alternative estimation methods of UAV/UGV locations in Δt, and 2) evaluation of multi-objective weights in UAV/UGV motion planning. For estimation of UAV/UGV location, the crowd shape and boundary are characterized first via clustering technique, followed by the simulation-based evaluation on UAV/UGV locations contingent to different control strategies. For the evaluation of multi-objective weights in UAV/UGV motion planning, agent-based simulation is used in the similar way for evaluating different weight combinations of placed on the multiple objectives (e.g. shortest travel distance, least elevation change) over different scenarios. Under both cases, each control strategy only corresponds to one simulation instance, and the best strategy can be sorted out (via statistical analysis) after all simulation instances are completed. At last, the selected best control strategy is stored and then used by the integrated controller for adjusting the corresponding vehicle parameters.

Interactions among Components: At a given time point t, when the decision module for DDDAMS is invoked, the checking condition (catastrophic abnormality block) is processed first. The checking condition determines whether the current control system has severe problem or performance deviations (predicted vs. real) are too extreme to recover. Under these circumstances, the human operator should participate for interrupting the real system run. These fatal abnormalities are due to system malfunctions, human errors, and other issues, which are out of the scope of our analysis in this work. We are interested in the abnormalities, where the actual and predicted system performances deviate significantly yet every components still work in the normal condition. Under the ordinary abnormality case, the fidelity selection algorithm is invoked next. The outputs of the

fidelity selection algorithm are a combination of different fidelity levels at all considered crowd regions/cells in terms of information details (collected via UAV or UGV) to be incorporated into simulation. In general, simulating group level behaviors involves coarse scale and requires less information and computational resource (and time), while the simulation of detailed individual behavior needs finer scale of modeling, more detailed information and more computational intensive (and time-consuming). Given that the deployment of fidelity selection results in simulation faces computational constraints, the fidelity assignment algorithm adjusts optimum system performance against computational resources available in the system. The fidelity assignment algorithm is formulated as a 0-1 knapsack problem, and the assigned fidelity levels are provided to the integrated planner and integrated controller for the simulation fidelity update, control strategy evaluation and control command generation.

Framework Implementation: The proposed planning and control framework (see Figure 1) was implemented employing a number of state-of-the-art software tools: 1) Repast Simphony® (Agent-based simulation tool) for command generator and strategy maker (see Figure 2), 2) QGroundControl for hardware interface. It is noted that the same simulator used in the strategy maker (running in fast-mode) is used as the command generator (running in real-time mode). To represent a real system to demonstrate the proposed planning and control framework, both real hardware components as well as simulated components were used under the real-time hardware-in-the-loop (HIL) simulation environment in this work: 3) manually assembled Aducopter and parrot AR.Drone 2.0 for UAVs and manually assembled Adurover for a UGV, 4) social force model implemented in Repast Simphony® running in real-time for simulated crowd behaviors, 5) simulated UGVs in Repast Simphony®, 6) GIS 3D data from NASA for simulated environment (i.e. elevation data) in Repast Simphony®, and 7) radio communications (915MHz) by 3DR. More details on the hardware components (UAVs and UGVs) and their integration with the real-time HIL simulation will be described in Section 3.3.

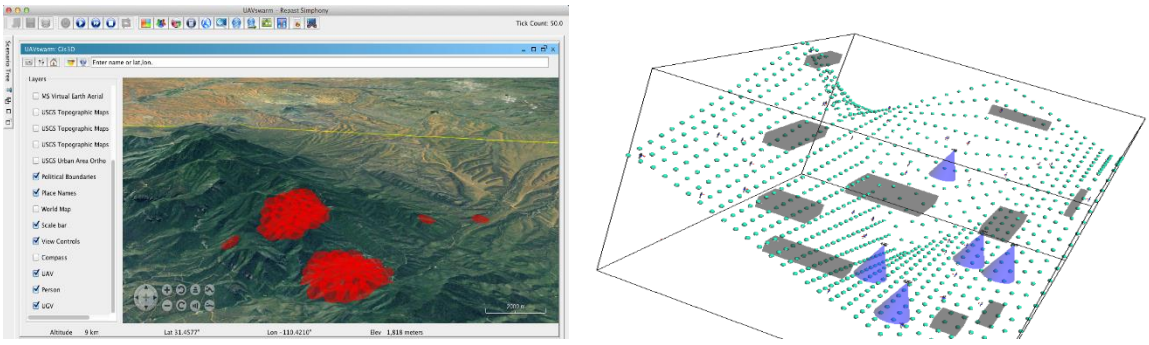


Figure 2: Sanpshot of agent-based simulation in contionous 3D environment and GIS 3D projection in Repast Simphony

3.2. Task 2: Development of algorithms to improve performance of coordinated UAV and UGVs in tracking and controlling human crowd

This section provides details on the models and algorithms that were developed for three major modules (crowd detection, crowd tracking, and motion planning) pertaining to the proposed control framework (see Figure 1).

Crowd Detection: To address crowd detection by UGV and UAV, we considered both real image/stream data from the camera in a real UAV (see Figure 3(a)) and from the camera in a real UGV (see Figure 3(b)) as well as models of them. Key characteristics considered in the models illustrated in Figures 3(a) and 3(b) are provided in Table 1.

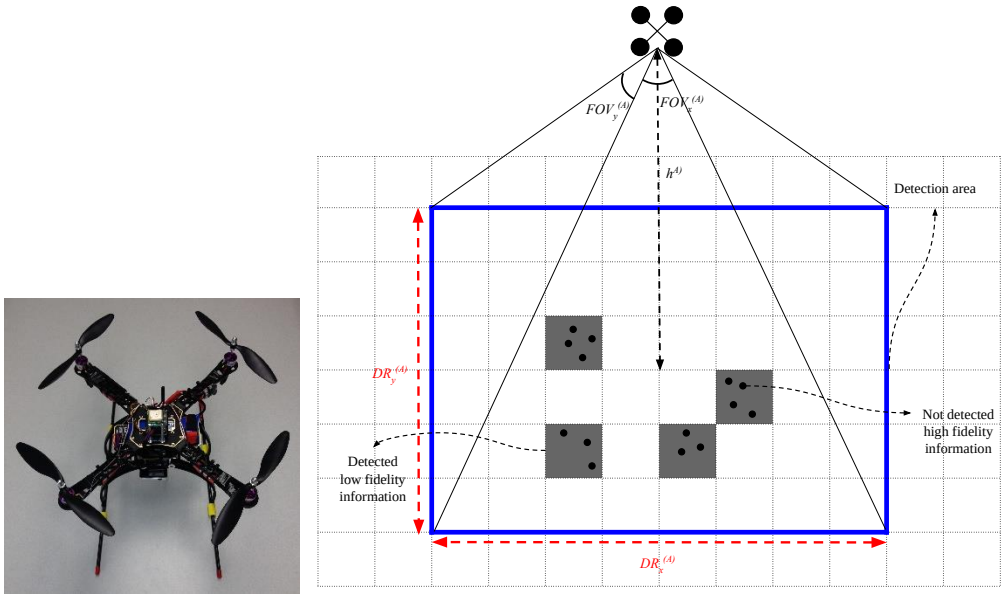


Figure 3(a): Illustration of UAV detection and associated parameters

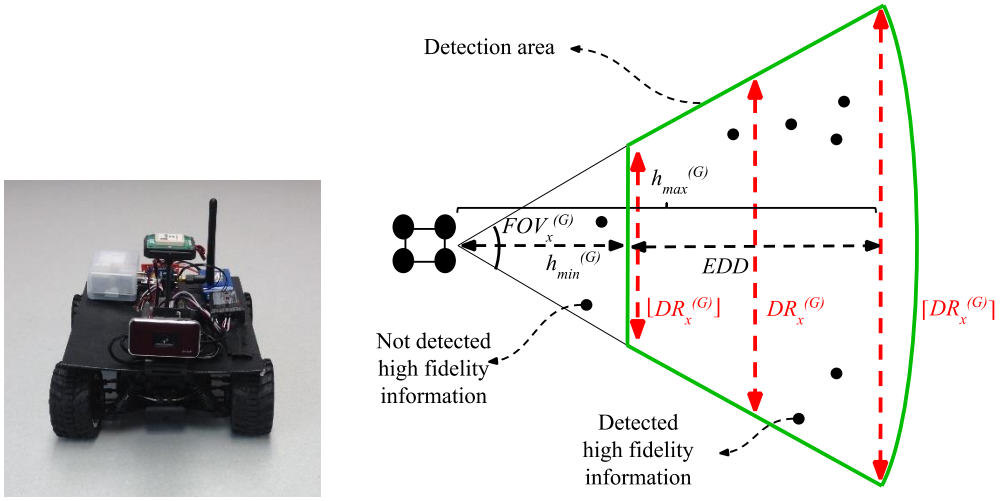


Figure 3(b): Illustration of UGV detection and associated parameters

Table 1: Parameters for UAV and UGV for their detection module

Notation	Explanation	Notation	Explanation
$FOV_x^{(A)}$	Horizontal field of view of UAV's camera	$FOV_x^{(G)}$	Horizontal field of view of UGV's camera
$FOV_y^{(A)}$	Vertical field of view of UAV's camera	$h_{min}^{(G)}$	UGV's safety distance
$h^{(A)}$	AGL altitude of UAV	$h_{max}^{(G)}$	Longest detection distance of UGV's camera
$DR_x^{(A)}$	Detection range of UAV in the horizontal direction	$DR_x^{(G)}$	Detection range of UGV in the horizontal direction
$DR_y^{(A)}$	Detection range of UAV in the vertical direction	EDD	UGV's effective detection depth

In terms of models of detection capabilities of UAV/UGV (having cameras) during their surveillance, the complementary role of them was considered in this research, where UAVs with less accurate detection capability are used to localize crowd as groups by flying over obstacles to keep the entire group in their FOV, and UGVs are used for detection of individuals in crowd due to their accurate localization (see Figure 4). This assumption considered in our modeling was based on the visual comparison in Grocholsky et al. (2006) that has demonstrated uncertainties in localization of detected objects between air and ground vehicles. For the crowd track module (discussed in the next section), we considered different scenarios based on the data quality of UAV and UGV (see Table 2).

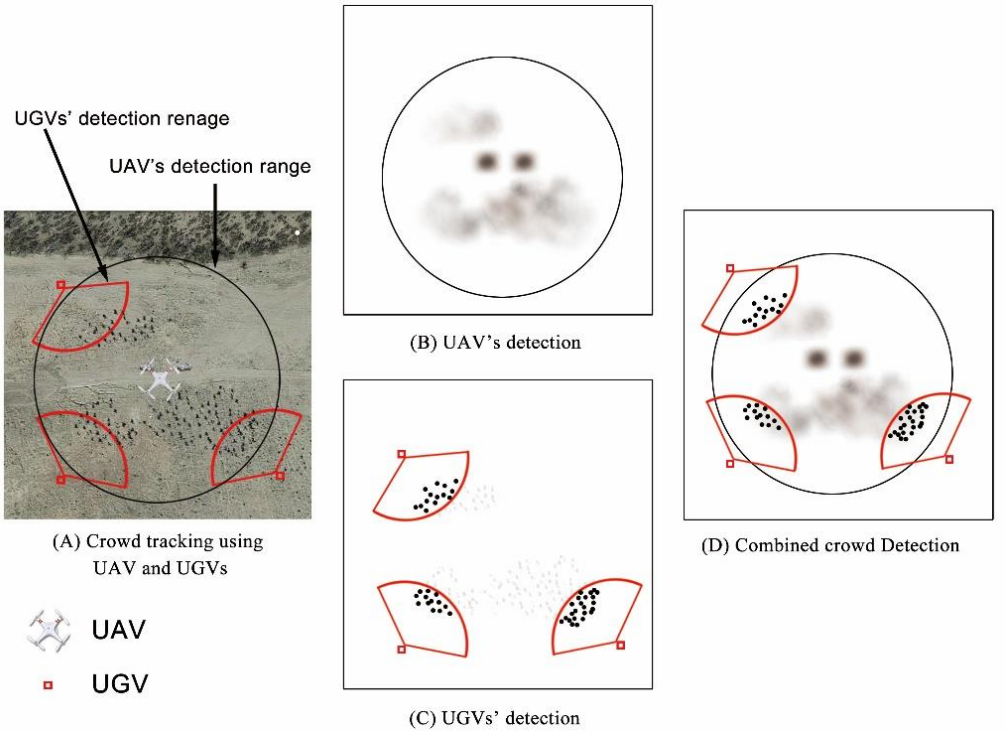
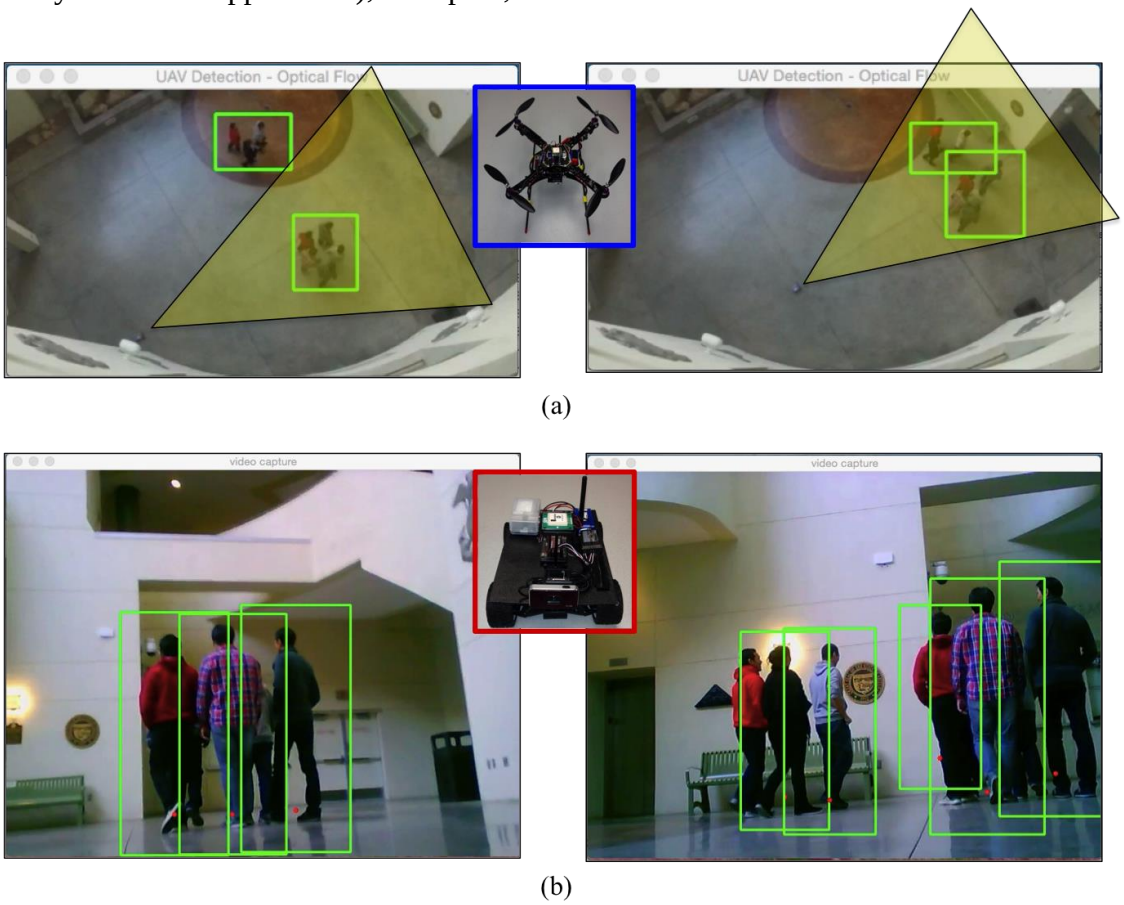


Figure 4: Detection capability of UAVs and UGVs (Yuan et al., 2015)

In addition to the models on crowd detection, a novel vision-based target detection and localization system was also developed as part of this project to make use of different detection capabilities of UAVs and UGVs. A customized motion detection algorithm was applied to follow the crowd from the moving camera mounted on the UAV. Due to UAV's lower resolution and broader detection range, UGVs with higher resolution and fidelity were used as the individual human detectors, as well as moving landmarks to localize the detected crowds with unknown independently moving patterns at each time point. The UAV's localization algorithm, proposed in our project, then converts the crowds' image locations into their real-world positions, using perspective transformation. A rule-of-thumb localization method by a UGV was also developed, which estimates the geographic locations of the detected individuals. The algorithms were developed and customized using open source computer vision libraries (OpenCV). Figure 5 depicts the detection results by a UAV and UGV for a scenario of two moving crowds. More details on the vision-based target detection and localization system can be found in the following journal paper:

- S. Minaeian, J. Liu, Y. Son, Vision-based Target Detection and Localization via a Team of Cooperative UAV and UGVs, *IEEE Transactions on Systems, Man, and Cybernetics: Systems* (Special Issue on Biomedical Robotics and Bio-mechatronics Systems and Application), Accepted, 2015.



(a)

(b)

Figure 5: The detection results for a scenario of two moving crowds: (a) detected crowds by UAV at two different time stamps including UGV's projected detection range; (b) detected individuals by UGV at two different time stamps (Minaeian et al., 2015)

In addition, we developed two camera motion planning algorithms to enhance the computational efficiency as well as target detection performance. Local motions necessary for the camera to maximize its visibility of the human crowd are considered. It is noted that the camera motion is to locally adjust the camera locations/directions to achieve the best observations of the crowd. In most of the existing methods available in the literature, it is assumed that that maintaining the visibility of a single reference point (e.g., the center of mass) will provide the visibility to the entire target. However, it usually is not the case in the real world.

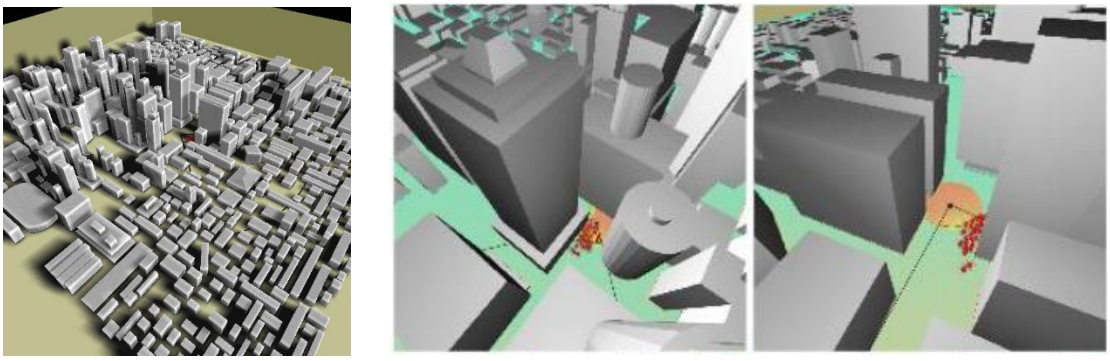


Figure 6: (a) A virtual city with 161 building; (b) Snapshots of CIOg camera following 30 targets in the city environment in (a)

Among widely known methods, the Intelligent Observer (IO) camera provides a high success rate, but is extremely inefficient. The Visibility-Aware Roadmap (VAR) (Oskam et al. (2009)) camera provides fast online tracking strategy through the use of pre-computed visibility information, but it performs worse than IO in terms of visibility. To address this issue, we propose two camera planning methods called Cached Intelligent Observers (CIO): CIOg and CIOc (Vo et al. (2012)). These new methods provide comparable performance to both IO and VAR while reducing the offline computation and maintaining efficiency in determining camera motions online. The main idea is to incrementally build and cache the visibility information in the vicinity of the targets and the camera. These new methods can be viewed as an improved IO camera that reduces the visibility computation complexity to almost constant. The CIOg method begins by creating a two dimensional grid. For each grid point, CIOg caches a certain amount of information about not only itself (such as its distance from the nearest obstacle), but also about other grid points in the network (such as its visibility to other points). Like its predecessor, IO (Becker et al. (1997)), at each time step, CIOg uses prediction and evaluation of camera and target positions to try and find an ideal location for the camera to maintain visibility of the as much of the flock as possible for the next time step. In CIOc, a slightly different approach is taken to storing visibility information in the space. First, using disc-like partitions, a graph is computed as well as a visibility graph among overlapping partitions of the workspace. As with CIOg, these data structures are used with successive cycles of prediction and evaluation of future target and camera positions to make decisions about where to move next. Figure 6(b) shows an example of CIOg successfully following 30 targets in the city environment shown in Figure 6(a).

Crowd Tracking: Upon the detection of individual agents in a crowd by UAVs or UGVs, movement tracking of these individual agents is initiated. The goal is to predict the location of individual agents at next time stamp based on current and historical observations. Based on these predicted locations, UAVs and UGVs can decide their optimal control strategy of the crowd quantified by certain performance measure.

In tracking crowds using both UAVs and UGVs, the type of tracking methods can be selected based on the data quality of observations from UAVs and UGVs. For UAVs and UGVs, the data quality issue is reflected in different aspects. For UGVs, the observation data are assumed to be either error-prone or error-free, depending on the sensor capability of cameras on-board. When the UGVs are distant from the crowd, or there are occlusions between the individuals and UGVs, the observations of individual location may contain large errors. In contrast, when UGVs are close to the individuals and no obstacles block the view of UGVs, the observations from UGVs will likely to have ignorable errors.

In our project, without loss of generality, observations of individuals collected from UAVs were assumed to have two levels of resolutions (see Figure 4). When the altitudes of UAVs are high, it is assumed that UAVs will receive image data with low resolution. This means UAVs will not be able to differentiate individual's location if they stand close to each other. In this sense, UAVs perceive a group of individuals like a blob without further detailed location information of each individual. In addition, only individuals who form into a dense region will be captured by UAVs and dispersed individuals will not be captured. A higher resolution image can be obtained when the altitude of UAVs become lower. However, since the role of UAV is to provide an overall view of the crowd, altitude of UAVs may not be set low enough to clearly observe individuals. Therefore, the high resolution observations from the UAV are still assumed to be able to only capture blobs formed by dense region. For either UAV or UGV, the data quality issue corresponds to two scenarios, i.e. high/low resolution observation from UAV and error-free/error-prone observation from UGVs respectively. These scenarios can be summarized in a two-by-two table as shown in Table 2.

Table 2: Summary of tracking scenarios regarding data quality

	Error-free observation (UGV)	Error-prone observation (UGV)
Low resolution (UAV)	Scenario 2 (current work)	Scenario 3
High resolution (UAV)	Scenario 4	Scenario 1 (current work)

As explained in Table 2, the current work considers two scenarios, scenarios 1 and 2. As the methods are chosen based on how the motion dynamics are modeled, the modeling procedure is explained first below followed by different methods developed for scenarios 1 and 2.

Modeling of crowd motion dynamics: To track the motion of individuals in the crowd, the model regarding the motion dynamics of the individuals needs to be assumed. In current work, the state space model is adopted. The state vector contains state information of an individual agent, including its preference state, such as moving speed and direction, and

geographic state, such as locations. Thus the preference state vectors are used as elements to model the complex spatial/temporal problem. As an individual person in a civil crowd, its preference and geographic states at time *t* are mainly affected by three types of factors: 1) the preference of crowd individuals, including itself, at time stamp *t*-1; 2) the environmental factors that affect crowd preferences; and 3) the impacts of the controlling units, such as UAVs and UGVs. Different formats of the matrixes in the proposed model can be specified to model the motion dynamics of the crowd under different scenarios. The common scenarios include crowd moving towards a direction; shrinking or spreading of the crowd, change of movement direction and speed, crowd split, or merge. More details on the proposed model for crowd motion dynamics can be found in the following journal paper:

- Yifei Yuan, Zhenrui Wang, Mingyang Li, Young-Jun Son, Jian Liu, DDDAS-based Information-Aggregation for Crowd Dynamics Modeling with UAVs and UGVs, *Frontiers in Robotics and AI* (Sensor Fusion and Machine Perception Section), 2:8, 2015, 1-10.

Tracking Scenario 1: Tracking scenario 1 corresponds to the case that UAVs observe the high resolution data and UGVs capture individual location with observation errors. Under this scenario, the crowd tracking from both UAVs and UGVs can be achieved by Kalman filter. For tracking using UGVs, the locations of all crowd individuals detected by UGVs are used as input. A Kalman filter is constructed with a state vector that is a stack up of state vectors of all the detected individuals. In current work, it is assumed that the values of the matrix used in Kalman filter have been specified. In case that the values of these matrices are unknown, system identification must be performed to determine their values and then the tracking of crowd can be implemented with Kalman filtering. For tracking using UAVs, the location of crowd center is estimated from the collected low resolution data; then the crowd center is used as the input to Kalman filter. As compared with the Kalman filter used in tracking from UGV, the state vector used in tracking from UAV has a state vector of only four dimensions, i.e. the location and speed of the crowd center. By tracking the motion of crowd center, a highly aggregated information regarding the motion of the crowd is obtained.

Tracking Scenario 2: Tracking scenario 2 corresponds to the case that UAVs observe the low resolution data and UGVs capture individual location without observation errors. Under this scenario, the crowd tracking from UAVs cannot be achieved with Kalman filter due to low resolution observation. An alternative approach to prediction crowd motion involving an aggregated model is proposed. More details on the proposed aggregation model can be found in Yuan et al. (2015). Given that UAV observes low resolution data and UGV observes very accurate information of certain individual's location, it is possible for UAV to improve its prediction by receiving information aggregated from UGV. Figure 7 the UAVs' crowd prediction with UGVs' information aggregation, where there is a discrepancy between predictions by UGV (predicting that the cell in the 3rd row and 4th column will be occupied by the crowd) and UAV (predicting that the same cell will not be occupied by the crowd). More details on the aggregation process can be found in Yuan et al. (2015). As for tracking using UGVs, when observations errors are ignorable, the state space model can be reformulated as an autoregressive (AR) model. Therefore, the tracking

of individuals using UGVs is achieved by fitting an AR model. More details on the tracking using UGVs can be found in in Yuan et al. (2015).

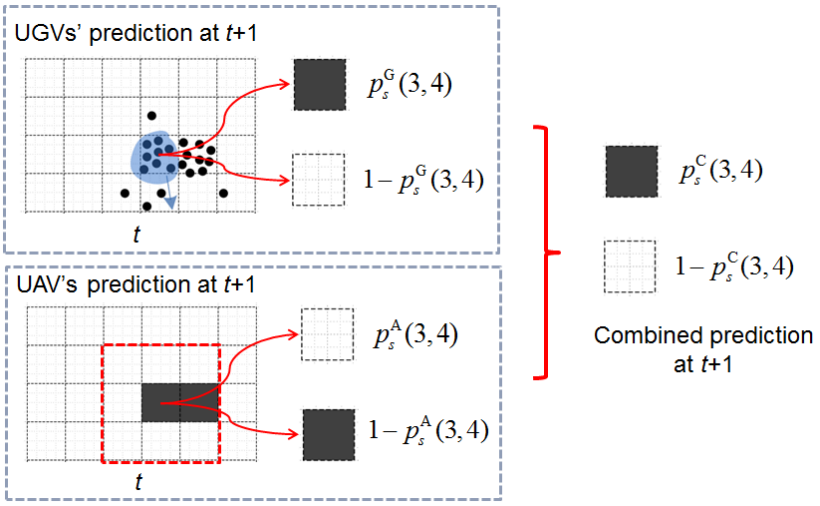


Figure 7: Overview of UAVs' crowd prediction with aggregated UGVs' information

Motion Planning: In our project, A* algorithm was used for motion planning of UAVs/UGVs to find their optimal trajectory from start location to the destination location, where the destination location is defined based on the output of the crowd tracking module. A* is a well-known graph search algorithm where the optimality and efficiency of chosen path depends on the chosen heuristic. It combines concepts of Dijkstra (least cost from the initial location) and Best-First Search on a heuristic basis (least cost to the destination) to guarantee the optimal path with minimum cost in a reasonably short time (Patal, 2013).

Similar to other graph search algorithms, a grid is generated by discretizing the environment and a graph is defined where each node of graph represents one block of grid. In this work, eight-point graph connectivity was considered to represent eight different motions that UGV can perform. In addition, it was assumed the world is static and prior geographical information about the environment (e.g. terrain elevation) is known. In case of insufficient prior knowledge about the environment and existing obstacles, vision-based sensory data (e.g. video streams) can be used to provide such dynamic data in use. In our project, the terrain information was obtained by the GIS data available in the NASA world wind map (http://worldwind.arc.nasa.gov/java/).

In our project, two objectives were considered in motion planning, where the first objective was to minimize the Euclidian distance of vehicles from the start location to the destination location, and the second objective was to minimize the energy consumption of UAV/UGV by providing penalty for the paths involving elevation changes. In addition, the weight of each objective is defined based on their relative importance. Figure 8 depicts resultants paths based on the shortest path, the least elevation change, and combination of both objectives, respectively. More details on the motion planning algorithm can be found in Khaleghi et al. (2013).

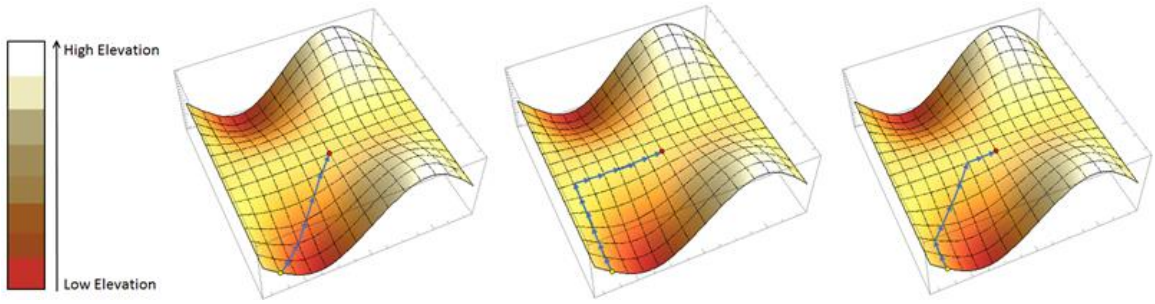


Figure 8: Three motion planning paths with minimal travel time, minimal energy consumption, and a linear combination of both objectives

3.3. Task 3: Development of a hardware-in-the-loop simulation/control framework and testbed for crowd control

This section provides details on the hardware-in-the-loop simulation/control framework and testbed for crowd control.

Testbed: To test the proposed DDDAMS planning and control framework (see Figure 1), a testbed representing a real system (3 UAVs, 1 UGV, human crowd, environment such as terrain and location) was developed. The testbed in our project is composed of both real hardware components as well as simulated components: 1) manually assembled Aducopter (UAV), parrot AR.Drone 2.0 (UAV), X8+ UAV by 3DR, and manually assembled Adurover (see Figure 9), 2) simulated crowd and simulated UGVs implemented in Repast Simphony® agent-based simulation, 3) GIS 3D data from NASA for simulated environment (i.e. elevation data) in Repast Simphony®, and 4) radio communications (915MHz) by 3DR.

Figure 9: Aducopter, Parrot AR. Drone 2.0, and Adurover used in the testbed

To accomplish the testbed involving both hardware components as well as software components, we developed hardware-in-the-loop (HIL) real-time simulation platform using Repast Simphony® agent-based simulation tool. To provide a communication network between the ground control station and the vehicles (see Figure 10), we evaluated various technologies. 3DR® Radio developed by 3dRobotics® (http://3drobotics.com/) was our first choice, which can provide 915 MHz radio communication with air data rates up to 250 kbps and approximate extended range of 1 mile. This radio module was specially designed to transmit telemetry data using MAVLink® (Micro Air Vehicle Link).

MAVLink® (http://www.qgroundcontrol.org/mavlink/start) is an open source protocol for communication between the ground control station and unmanned vehicles, which provides a standard message format for sending waypoints. It is noted that the same message format is generated using the agent-based simulation of our testbed as the control commands. More details of the MAVLink® message format can be found in http://mavlink.org/messages/common. While 3DR® radio module has been used in a variety of unmanned vehicles to provide a one-to-one communication network between a vehicle and the ground control station, a network is required in our testbed with a hybrid control architecture to provide communication between multiple vehicles and the ground control station. In this regard, our second choice of communication network in our project was Xbee® Pro 900 by Digi®. Even though this module has the capability of providing a mesh network, it has not been designed for working with MAVLink®, which causes a delayed communication in transmitting telemetry data. To overcome this challenge, we selected Wi-Fi using MAVLink® as our third choice of the communication network in the project.

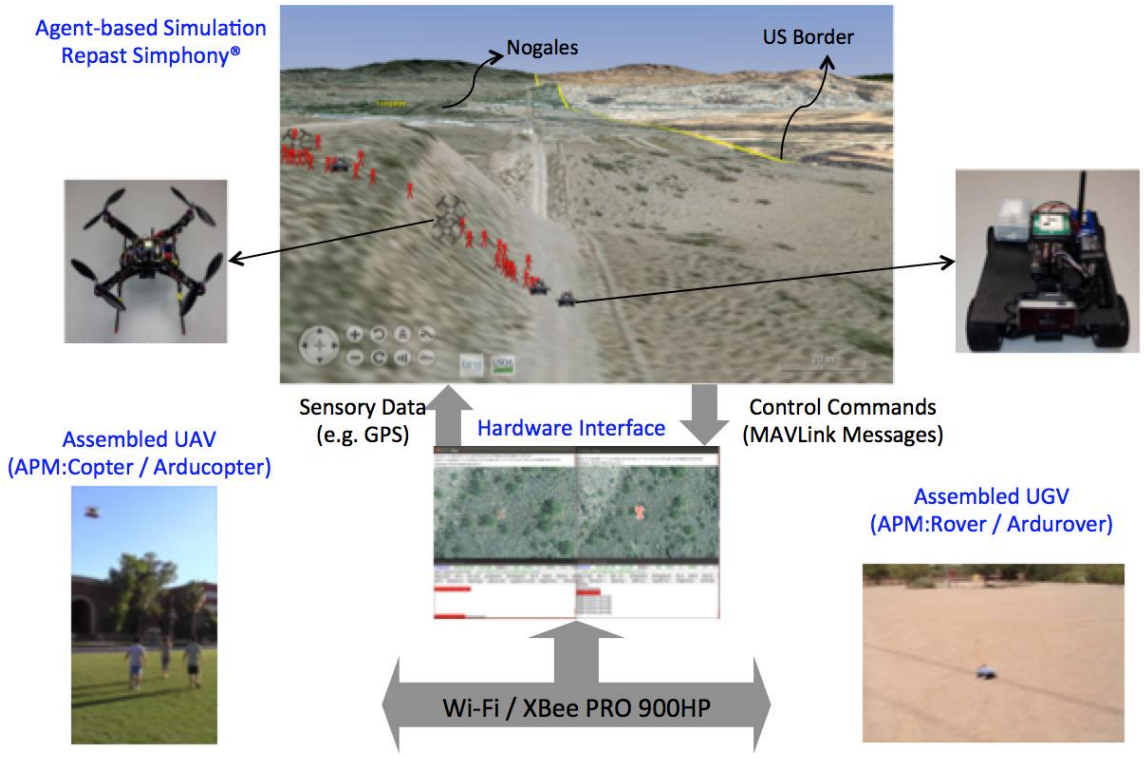


Figure 10: Hardware-in-the-loop integration

UAVs (Aducopter and Parrot AR. Drone 2.0): This section provides details on three types of UAVs (Aducopter, Parrot AR. Drone 2.0, X8+ from 3DR) that were acquitted to develop the proposed testbed.

Aducopter and Adurover (see Figure 9): The hardware for the aircraft including battery and autopilot system costs less than $300 USD and is modular, consisting entirely of off-

the-shelf and open-source parts. The airframe is a customized quad-rotor helicopter with a fiberglass body and removable ABS plastic arms. With a diameter of 450mm and weight of 800g without battery installed (1200g with a 5000 mAh lithium polymer battery installed), this small UAV can be operated indoors safely and navigate small spaces. Each arm is fitted with a brushless outrunner direct-current motor (RCTimer HP2217) with 10-inch diameter carbon fiber fixed-pitch propellers installed. Each motor is controlled by an electronic speed control (ESC) circuit (RCTimer 40A OPTO ESC) that accepts speed commands at 490 Hz from an autopilot module called the ArduPilot Mega 2.5 (APM 2.5). The ArduPilot is an open-source aircraft control board based on ATmega 2560 microprocessor. It handles input from the on-board sensors (3-axis gyro, 3-axis accelerometer, 3-axis magnetometer, barometer, and GPS unit) and sends pulse-width-modulation (PWM) signals to the ESCs. By itself, it can perform automated stabilization, GPS-based autonomous navigation, and radio control input from a 2.4GHz band handheld transmitter. However, for this project, we are interested in controlling the aircraft using our own algorithms. Therefore, we will use the autopilot board for low level control of the aircraft, and command it via serial (MAVLink protocol) from a quad-core ARM Cortex-A9 embedded PC on-board. This on-board PC will process the images captured via on-board camera and then send commands to the autopilot to execute. For hardware-in-the-loop operation, (i.e. in the absence of the embedded PC), the ArduPilot may also accept commands wirelessly using a ISM-band (915 Mhz) radio receiver on-board. An Adurover (see Figure 9) was custom built in a similar manner as well.

Parrot AR. Drone 2.0 (see Figure 9): Parrot AR. Drone 2.0 is equipped with 1) a front camera (CMOS sensor with a 90 degrees angle lens, video frequency of 30 fps, resolution of 1280*720 pixels), 2) ultrasound sensor (emission frequency of 40 kHz and range with 6 meters), 3) embedded computer system (CPU OMAP 3630 1GHz ARM cortex A8, DDR SDRAM 128MB, NAND Flash memory 128M, Wi-Fi /g/n, Linux OS), and 4) battery (Lithium polymer battery (3 cells, 11.1V, 1000 mAh; Charging time: 1.5 hours; running time of 12 minutes). With WIFI N, it can fly as far as 165 feet, and it is controllable from any client device supporting Wi-Fi Communication. It uses different ports: UDP port 5556 for controlling and configuring, TCP port 5555 for video stream, and, TCP port 5559 (control port) to transfer critical data, by opposition to the other data that can be lost with no dangerous effect.

X8+ UAV by 3DR (see Figure 9): X8+ from 3DR is equipped with 1) a controller with live on-screen flight data, 2) flight battery, 3) 8 APC propellers (4 SF and 4 SFP), 4) 3DR u-blox GPS with Compass, 5) Ground station radio (3DR Radio v2 -915 MHz), and 6) Advanced Pixhawk v2.4.5 autopilot system. Some major features include 1) maximum altitude of 100 m (328 ft), 2) range (300 m (984 ft) from launch point), 3) max flight time of 15 minutes, 4) payload capacity of 800 g (1.7 lbs), 5) GPS lock required at all times, 6) autonomy by a Mac, PC or Android device, 7) smooth and reliable flight dynamics, 8) flight Protection(land itself automatically, or return to launch), 9) automatic mission planning software, and 10) compatible with gimbal stabilizer.

Section 4: Accomplishments / New Findings: Research Highlights

This section provides details on the results and accomplishments that we have obtained for three major tasks (see Section 2) based on the approach and detailed methods discussed in Section 3.

4.1. Task 1: Development and refinement of coherent planning and control framework (DDDAMS) for effective and efficient control of UAV/UGVs (Ta)

The proposed DDDAMS framework (see Figure 1) was successfully demonstrated for the testbed based on agent-based real-time simulation (including three types of real UAVs, one real UGV, radio communications, simulated UGVs/UGVs, real crowd, simulated crowd, and simulated environment) (see Figure 10). In addition, as mentioned in Section 2, the research outcomes (e.g. DDDAMS framework, information aggregation framework, underlying algorithms, and experiments involving simulation-based testbed) developed in this project have been published in multiple journals and conference proceedings (see Section 6 for a complete list of publications).

4.2. Task 2: Development of algorithms to improve performance of coordinated UAV and UGVs in tracking and controlling human crowd

This section provides details on the numerical simulation studies that were conducted for two scenarios (see Table 2) to evaluate the performance of the developed crowd tracking and motion planning methods.

Scenario 1: As mentioned earlier, scenario 1 corresponds to the case that UAVs observe the high resolution data and UGVs capture individual location with observation errors. In this scenario, a case study was conducted for a hypothetical surveillance and crowd control scenario considering two different fidelities, where in low fidelity two UAVs perform tracking by observing crowd as group and in high fidelity tracking has been done using two UGVs by observing all individuals in the crowd. A border environment in the state of Arizona in U.S. was selected and a crowd of 80 individuals in two separate groups were considered in Repast Simphony, where their comfortable walking speed was assumed to be around 1.5 m/s. Crowd locations were observed in each 1 time stamp in simulation. The crowd tracking module utilized these observations and predicted the crowd locations after 10 time stamps in both fidelities. In the motion planning module, the high and low simulation fidelities utilize the predicted locations from UGV and UAV, respectively. Furthermore, different spatial resolutions (grid sizes) have been considered to perform motion planning in high and low fidelities due to different specifications of real hardware.

Figure 11 demonstrates the performance of the two fidelity scenarios as crowd coverage percentage in intervals of 10 time stamps. As seen in the figure, high fidelity has higher performance due to the utilization of individual observations in tracking module as well as more accurate locations of vehicle motion planning under finer grid. However, more system computational resources are needed in the high fidelity. Figure 12 illustrates CPU

usages of the tracking module under situations with the high and low simulation fidelity, and such difference mainly lies in the dimension of state vectors used in the tracking algorithm. In the case with low fidelity, the center of the crowd dense region was collected and inputted to the tracking algorithm, which leads to a state vector of dimension of 4. In contrast, under the case with high simulation fidelity, under which every individual agent was tracked in the crowd tracking algorithm, the state vector has a dimension that is a product between 4 and the total number of individual agents. For our experiments with 40 individuals in the crowd, the state vector has a dimension of 160, which consumed more computations during the tracking.

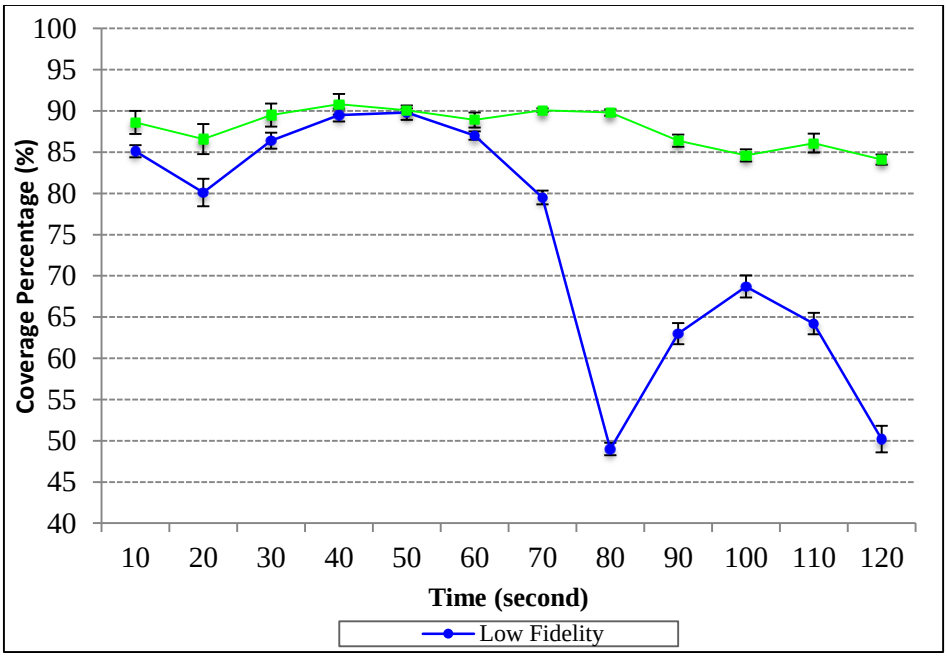


Figure 11: System performance for two fidelity cases with 95% confidence interval

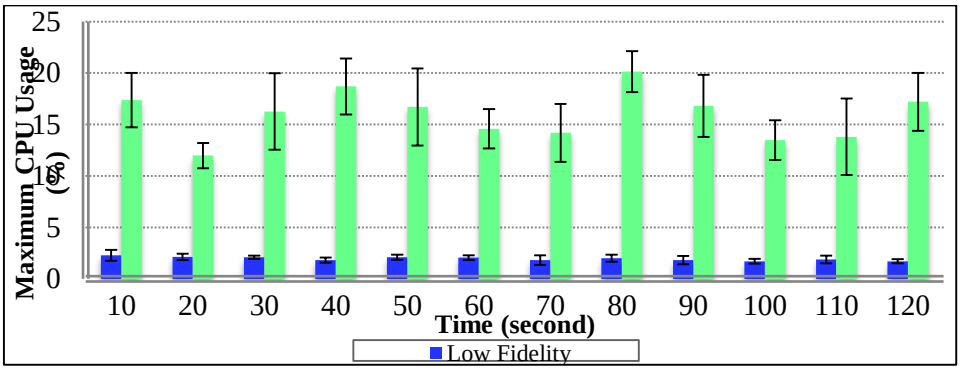


Figure 12: CPU usage for tracking module under two simulation fidelity cases with 95% confidence interval

As Figure 12 shows from time stamps 10 to 120, the two fidelities result in similar performance, which justifies the low fidelity case can maintain similar system performance

with high fidelity case under certain circumstances. Then, a hypothetical event (i.e. some people start to lead the entire group) was purposely created at time stamp 70, which causes 4 individuals in each group increase their comfortable walking speed from 1.5 m/s to 1.7 m/s. As the results show, due to this event the low fidelities performance has been decreased dramatically after some delay (this delay is the time for the leaders separating from the major group). As the result shows, the performance in high fidelity has also been reduced, but compared with that of the case with low fidelity, the effect of the event is much less due to tracking individuals instead of that of crowd. By adopting high fidelity, the required performance (80% coverage percentage) is maintained, but more computational resources are consumed.

Scenario 2: As mentioned earlier, scenario 2 corresponds to the case that UAVs observe the low resolution data and UGVs capture individual location without observation errors. In this scenario, fifty individuals with changing motion dynamics are simulated within a time duration of 15 time instances. The fifty individuals are monitored by one UAV and two UGVs. The UAV observes the overall crowd, and obtains low resolution data that only capture the dense region. Each UGV monitors one subgroup of ten individuals. The motion dynamics of the crowd is illustrated in Figure 13. The figure shows that from time 1 to 4, all fifty individuals (denoted as black solid dots) move towards the right. The blue curves represent the detection range of two UGVs. From time 5 to 6, two subgroups of individuals leave the majority of the crowd. One subgroup moves towards the northeast direction and the other subgroup moves towards the southeast direction. From time 7 to 15, the subgroup in the northeast corner of the crowd keeps moving toward to the right. The subgroup in the southeast corner of the crowd concentrates and a dense region is formed. Before concentration, the subgroup has low density and UAV fails to observe these data.

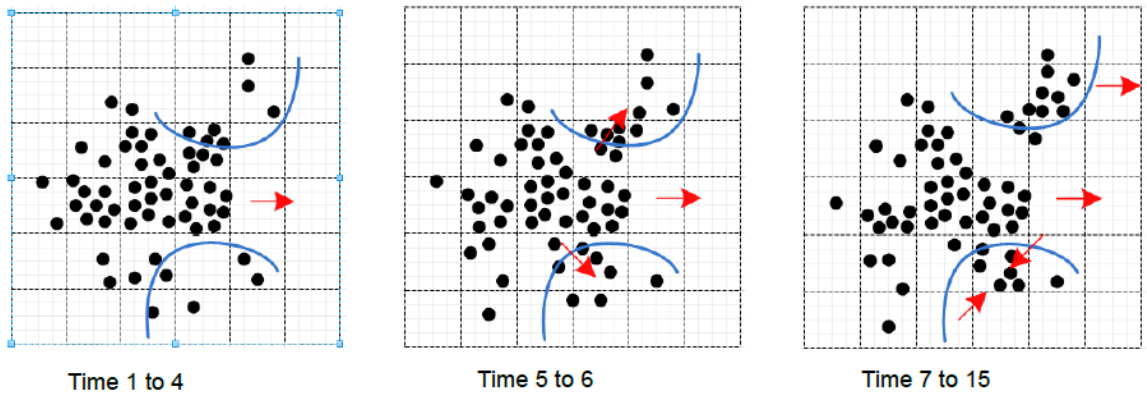


Figure 13: Motion dynamics at different time instances

The proposed crowd motion prediction approach is adopted in predicting the motion of dense region captured by UAV. The observations of individuals from UGV are assumed error-free and autoregressive model is used to estimate motion dynamics and predict future locations. Given the predicted location of dense region and individuals in two subgroups, two prediction outcomes are considered. The first one is solely based on the UAV prediction and the second one combines prediction outcomes from both UAV and UGV through information aggregation.

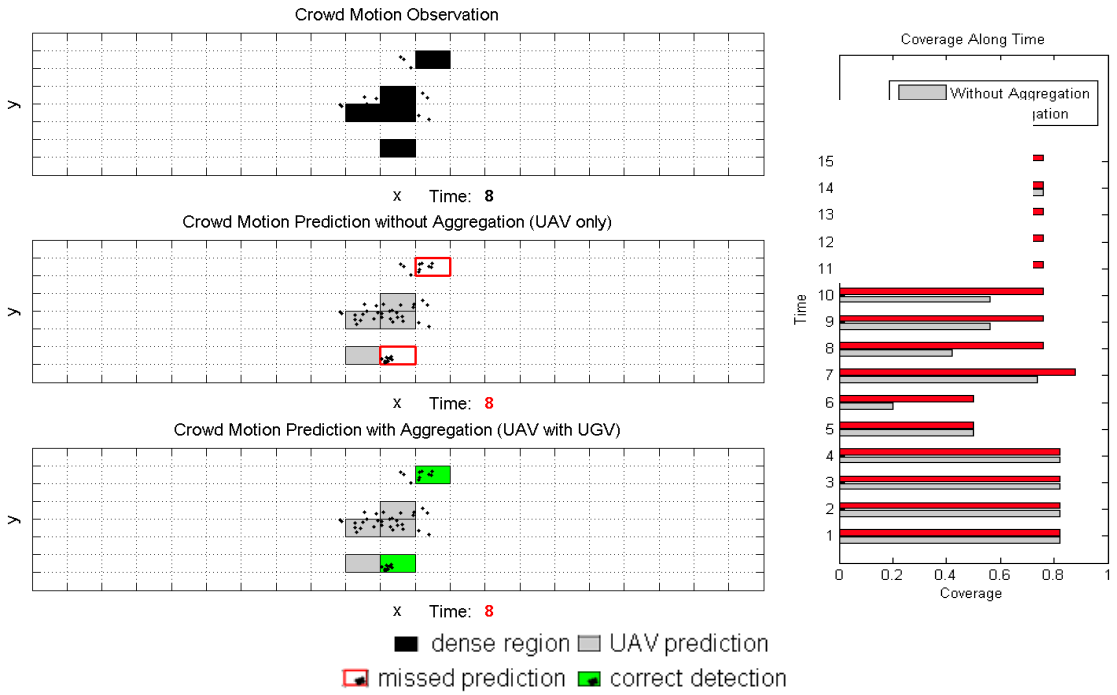


Figure 14: Tracking results illustration at time 8

The example tracking results are illustrated in Figure 14 and Figure 15. The first panel in Figure 14 shows the location of individuals at time 8, where the dense regions with more than 10 individuals in the cell are illustrated with black filled square. The second panel shows the prediction solely based on UAV. The true locations of individuals are plotted. The predicted locations are illustrated with gray squares. Two subgroups of individuals, each forming a dense region, are not correctly predicted by UAV. The cells corresponding to these two subgroups of individuals are highlighted with blank squares having red edges. The third panel shows the combined prediction. To emphasize the benefit of using combined prediction, the extra cells added in combined prediction that correctly predicts two subgroups are highlighted in green squares. The tracking performance is evaluated as the coverage value (i.e., proportion of individuals captured by UAV and UGVs). The coverage of using UAV alone is compared with combined prediction. The right panel shown in Figure 14 shows the coverage value up to time 8.

Figure 15 shows the snapshot of tracking outcome at time 15. Again both the tracking illustration and the coverage value indicate that using combined prediction outperforms prediction based on UAV alone. This shows the effectiveness of the proposed information aggregation approach in improving the tracking performance.

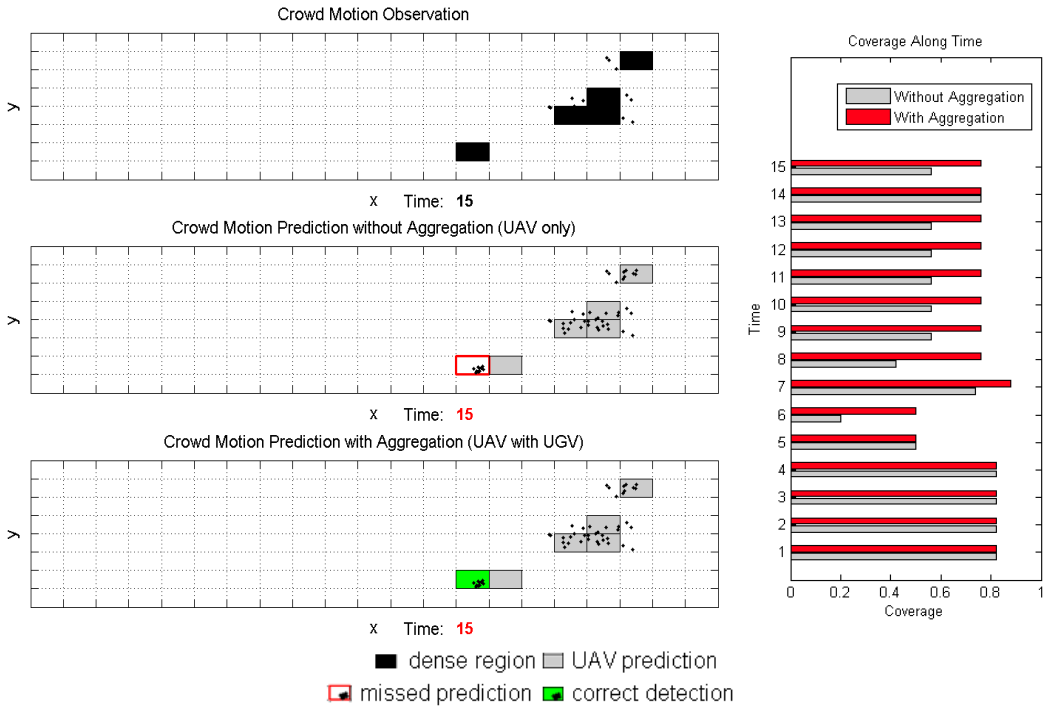


Figure 15: Tracking results illustration at time 15

4.3. Task 3: Development of a hardware-in-the-loop simulation/control framework and testbed for crowd control

Flight Test of UAVs: Both the UAVs (Aducopter and Parrot AR. Drone 2.0 in Figure 9) and UGV (Adurover in Figure 9) were successfully tested in the field. Our tests revealed that Aducopte was able to remain stable while carrying an additional payload of up to 1200g, and can remain in the air for up to 30 minutes with one 5000 mAh 11.1V lithium polymer battery. Using the GPS unit on-board and the autopilot unit, the UAV can autonomously navigate to given waypoints outdoors with an accuracy of about +/- 2 meters despite wind and other environmental influences. With the addition of a high-accuracy sonar unit, the UAV can hold altitude and position with centimeter accuracy and autonomously takeoff and land. Live telemetry data from the UAV including GPS position, compass orientation, and pitch/roll orientation is streamed to a ground station PC where it can be viewed online or saved to a log file. The test with Parrot AR. Drone 2.0 and Adurover provided similar performance results. Figure 16(b) shows a snapshot of recorded path (a series of waypoints) from Google map, where physical flights based on the provided waypoints were successfully demonstrated.

Testbed: The proposed testbed based on agent-based real-time simulation (including three types of real UAVs, one real UGV, radio communications, simulated UGVs/UGVs, simulated crowd, and simulated environment) (see Figure 10) were successfully established. Figure 16(a) shows a snapshot of demo of the proposed hardware-in-the-loop testbed. The constructed testbed is modular, so additional hardware equipment and/or software modules can be appended to the current testbed easily.

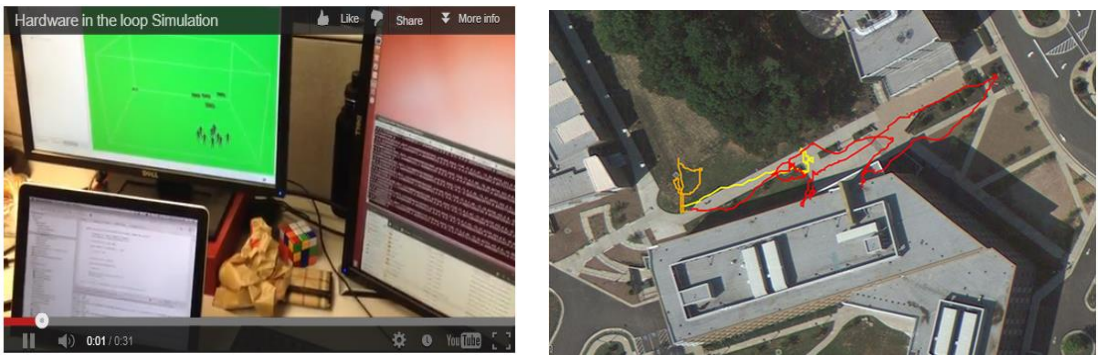


Figure 16: Snapshot of demo of Hardware-in-the-loop testbed; snapshot of recorded path from Google map (GPS waypoint flights)

Section 5: Personnel Supported

The following is a list of faculty and students who were supported by this grant in the reporting period.

Faculty:	Graduate Students:
Young-Jun Son	Amirreza M. Khaleghi
Jian Liu	Zhenrui Wang
Jyh-Ming Lien	Dong Xu
	Sara Minaeian
	Christopher Vo
	Hoyoung Na
	Seunghan Lee
	Yifei Yuan
	Haomiao Yang
	Sara Minaeian

Section 6: Publications

Section 6.1 lists submitted, accepted, or published papers for the project period. And, Section 6.2 includes other references cited in the report.

6.1. Submitted, Accepted, Published Publications

- (PhD Dissertation) A. Khaleghi (supervised by Young-Jun Son), Hardware-In-The-Loop Dynamic Data Driven Adaptive Multi-Scale Simulation (DDDAMS) System For Crowd Surveillance Via Unmanned Vehicles, Systems and Industrial Engineering, The University of Arizona, August 2015.

- (PhD Dissertation) M. Li (supervised by Jian Liu), A Multi-Level Information Aggregation for Reliability Assurance Of Hierarchical Systems, Systems and Industrial Engineering, The University of Arizona, May 2015.
- (PhD Dissertation) C. Vo (supervised by Jyh-Ming Lien), Algorithms for Shepherding and Visibility-based Pursuit, Computer Science, George Mason University, August 2014.
- A. Khaleghi, D. Xu, Z. Wang, M. Li, A. Lobos, J. Liu, Y. Son, A DDDAMS-based Planning and Control Framework for Surveillance and Crowd Control via UAVs and UGVs, *Expert Systems with Applications*, 40, 2013, 7168-7183.
- Yifei Yuan, Zhenrui Wang, Mingyang Li, Young-Jun Son, Jian Liu, DDDAS-based Information-Aggregation for Crowd Dynamics Modeling with UAVs and UGVs, *Frontiers in Robotics and AI* (Sensor Fusion and Machine Perception Section), 2:8, 2015, 1-10.
- S. Minaeian, J. Liu, Y. Son, Vision-based Target Detection and Localization via a Team of Cooperative UAV and UGVs, *IEEE Transactions on Systems, Man, and Cybernetics: Systems* (Special Issue on Biomedical Robotics and Bio-mechatronics Systems and Application), Accepted, 2015.
- A. Khaleghi, D. Xu, S. Minaeian, M. Li, Y. Yuan, C. Vo, A. Mousavian, J. Lien, J. Liu, and Y. Son, UAV/UGV Surveillance and Crowd Control via Hardware-in-the-loop DDDAMS System, Darema, F., Douglas, C (Eds.), Springer (under review)
- Online Collision Prediction Among 2D Polygonal and Articulated Obstacles, Yanyan Lu, Zhonghua Xi and Jyh-Ming Lien, *International Journal of Robotics Research (IJRR)*, Accepted, 2015.
- Minaeian, S., Yuan, Y., Liu, J., and Son, Y., 2015, "Human-in-the-Loop Agent-based Simulation for Improved Autonomous Surveillance using Unmanned Vehicles," *Proceedings of 2015 Winter Simulation Conference*, Savannah, GA, Accepted (extended abstract for poster presentation).
- Continuous Visibility Feature, Guilin Lu, Yotam Gingold, and Jyh-Ming Lien, in the *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2015, Boston, MA, USA
- Semantically Guided Location Recognition for Outdoors Scenes, Arsalan Mousavian, Jana Kosecka and Jyh-Ming Lien, *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, May 2015, Seattle, WA, USA
- Khaleghi, A., Xu, D., Minaeian, S., Yuan, Y., Liu, J., and Son, Y., 2015, "Analysis of UAV/UGV Control Strategies in a DDDAMS-based Surveillance System," *Proceedings of 2015 IIE Annual Meeting*, Nashville, TN.
- Minaeian, S., Liu, J., and Son, Y., 2015, "Crowd Detection and Localization Using a Team of Cooperative UAV/UGVs," *Proceedings of 2015 IIE Annual Meeting*, Nashville, TN.
- Khaleghi, A., Xu, D., Minaeian, S., Li, M., Yuan, Y., Liu, J., Son, Y., Vo, C., and Lien, J., 2014, "A DDDAMS-based UAV and UGV Team Formation Approach for

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- Vo, C., McKay, S., Garg, N., and Lien, J., "Following a Group of Targets in Large Environments", *Proceedings of the Fifth International Conference on Motion in Games*, Springer, 2012.
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- C. Vo, S. McKay, N. Garg, and J.-M. Lien, "CIO: Cached Intelligent Observer," in Motion in Game, 2012.

Section 7: Interactions / Transitions

The following is a list of significant seminars, conference participation, and outreach activities relevant to this grant.

- S. Minaeian, J. Liu, and Y. Son, 2015, "Cooperative Unmanned Vehicles for Vision-based Detection and Real-World Localization of Human Crowds," INFORMS Annual Meeting 2015, November, Philadelphia (presented by a student).
- A. Khaleghi, D. Xu, S. Minaeian, M. Li, Y. Yuan, J. Liu, Y. Son, 2014, "DDDAMS-based System for Surveillance and Crowd Control via UAVs and UGVs," INFORMS Annual Meeting 2014, November, San Francisco (presented by students).
- Y. Son, 2014, "DDDAMS-based Planning and Control: 1) Manufacturing Enterprise and 2) Surveillance and Crowd Control," DDDAS Panel at ASME 2014, August, Buffalo.
- Y. Son, UAV/UGV simulation as part of simulation applications, Summer Engineering Academy (Outreach program at University of Arizona), 2013, 2014, 2015.
- Son, Y., "An Extended Belief-Desire-Intention (BDI) Model for Human Behaviors", Industrial Engineering, University of Houston, Oct. 16, 2015.
- Son, Y., "An Extended Belief-Desire-Intention (BDI) Model for Human Behaviors", Mathematics and Computer Science, Emory University, Feb. 28, 2014.
- Son, Y., "An Extended Belief-Desire-Intention (BDI) Model for Human Behaviors", Industrial Engineering, University of Pittsburgh, Oct. 30, 2014.
- Son, Y., "An Extended Belief-Desire-Intention (BDI) Model for Human Behaviors", Industrial Engineering, SungKyunKwan University, Seoul, Korea, July 29, 2014.
- Son, Y., 2013, "Distributed federation of multi-paradigm simulations and decision models for planning and control: from shop floor to top floor," International Symposium on Modeling and Simulation of Complex Management Systems, June, 2013, Shenzhen, China (Keynote Speech).
- Son, Y., "Distributed Federation of Multi-paradigm Simulation and Decision Models for Extended Manufacturing and Service Enterprises", Texas A&M University, Nov. 18, 2013.
- Son, Y., "DDDAMS-based Surveillance and Crowd Control via UAVs and UGVs, School of Design and Human Engineering", UNIST, Ulsan, Korea, July 25, 2013.

- Son, Y., “Distributed Federation of Multi-paradigm Simulations and Decision Models for Planning and Control”, Department of Industrial and Systems Engineering, Northern Illinois University, May 2, 2013.
- Son, Y., “Distributed Federation of Multi-paradigm Simulations and Decision Models for Planning and Control”, Department of Industrial and Systems Engineering, Lehigh University, Jan. 30, 2013.
- Son, Y., Liu, J., and Lien, J., 2013, “DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs,” DDDAS Program PI Meeting, October, 2013, Arlington.
- Khaleghi, A., Xu, D., and Son, Y., 2013, “DDDAMS-based Surveillance and Crowd Control via UAVs and UGVs,” INFORMS Annual Meeting 2013, October, Minneapolis (presented by students).
- Y. Son, Distributed Federation of Multi-Paradigm Simulations and Decision Models for Planning and Control, School of Design and Human Engineering, UNIST, Ulsan, Korea, July 12, 2012.
- S. Kim, H. Xi and Y. Son, Scalability of Modeling Driver's Behavior under the Extended Belief-desire-intention Framework, INFORMS Annual Meeting, Phoenix, USA, October 14~17, 2012.
- Y. Son, Belief-Desire-Intention (BDI) Agent-Based Simulation Modeling for Transportation Systems, TRB ABJ70 Summer Webinar Series, August 3, 2012.
- Y. Son and Y. Chiu, Belief-Desire-Intention (BDI) Agent-Based Simulation Modeling for Transportation Systems, Workshop on Agent-based Modeling and Simulation at TRB, Washington DC, USA, January 22~26, 2012.
- Y. Son, Incorporating Social and Human Behavior into Engineering Models, UA and Sandia Symposium, Tucson, AZ, February 21, 2012.
- Y. Son, Multi-Paradigm Simulation Innovations for Manufacturing and Service Enterprises, da Vinci Circle Meeting, Tucson, AZ, March 22, 2012.
- Y. Son, Multi-Paradigm Simulation Innovations for Manufacturing and Service Enterprises, IIE Western Regional Student Conference, Feb. 23rd, 2013.
- C. Vo, PBS News Hour segment on building a do-it-yourself drone, Apr 18, 2013 (http://www.pbs.org/newshour/rundown/2013/04/do-it-yourself-drones-tech-enthusiasts-create-drone-user-group.html).
- C. Vo, Capital News Service Article and Video, May 9, 2013 (http://cnsmaryland.org/2013/05/09/the-drones-are-here-regulators-struggle-to-react/).
- C. Vo, Development of inexpensive drones, Nova Labs, Dec. 2012, Jan 2013, March 2013, May 2013.
- C. Vo, Indoor flight demonstration at UMD, DC Area Drone User Group, Dec. 2012.
- C. Vo. and J, Lien, Engineer's Week Demonstration at GMU, Feb 21, 2013.
- C. Vo. and J, Lien, UAV Demo for STEM at Howard University, Mar 9, 2013.
- C. Vo. and J, Lien, RobotFest Demonstration, Apr 27, 2013.
- C. Vo. and J, Lien, The Drone Next Door Conference, May 7, 2013.
- C. Vo. and J, Lien, Tech demo at Hamfest, June 9, 2013.
- C. Vo. Christopher quoted about STEM volunteering at the local Maker Faire, March 2014

- C. Vo. was featured in Washington Post / Associated Press Article about drones, March 2014
- An article about Christopher on InTheCapital, April 2014
- C. Vo appeared in Season 2, Episode 4 of the CNN documentary show Inside Man, hosted by Morgan Spurlock, about Big Data and Privacy, May 2014
- MASC UAV appeared on CBS This Morning held by Jeff Pegues during the broadcast, June 2014
- C. Vo quoted in Scholastic Science World article about the many uses of drones, Sep. 2014

An overview of our project on "DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs" was presented as part of Young-Jun Son's overall research on "Multi-Paradigm Simulation Innovations for Manufacturing and Service Enterprises" for the following industry and government groups either during their visits to The University of Arizona or PI Son's visits to them.

- Simulation engineers at LG Electronics, August 10, 2015
- Engineering managers from Sensintel, September 18, 2013
- Engineering managers from Northrop Grumman, Feb. 12, 2013
- Systems engineering researchers from Sandia National Lab on Nov. 20, 2012
- Systems engineering director at Lockheed Martin on Oct. 23, 2012
- Simulation engineers from Raytheon Missile Systems on Nov. 9, 2012

In addition, as part of community outreach, our project members were heavily involved with Washington D.C. Area Drone Users Group, a group of more than 200 professionals and hobbyists that are committed to promoting the use of flying robots for recreational, humanitarian, and artistic purposes. In particular, we taught several guided tutorial sessions to educate members on how to build our inexpensive and modular UAV design, and the group has purchased and built over 25 UAVs using our same design. These users come from many disciplines such as law enforcement, aerial photography, military, and engineering backgrounds and owing to the modularity of the platform, have developed their own modifications and tweaks to serve their purposes with the UAV platform.

Furthermore, Young-Jun Son and Jian Liu co-chaired an invited session on "Dynamic Data Driven Modeling and Analysis of UAVs and UGVs" at INFORMS Annual Conference 2013 on Oct. 6~9 in Minneapolis, which is co-sponsored by INFORMS Simulation Society and INFORMS Quality, Statistics, and Reliability Section. The following three presentations were presented at the conference.

- Khaleghi, A., Xu, D., and Son, Y., 2013, "DDDAMS-based Surveillance and Crowd Control via UAVs and UGVs," Abstract accepted in May 2013 and to be presented at INFORMS 2013.
- Li, M., Wang, Z., and Liu, J., 2013, "Information Aggregation/Disaggregation based Crowd Tracking using UAVs and UGVs," Abstract accepted in May 2013 and to be presented at INFORMS 2013.

- Lien, J., Vo, C., and McKay, S., 2013, "Following a Group of Targets in Large Environments," Abstract accepted in May 2013 and to be presented at INFORMS 2013.

Section 8: New Discoveries

Nothing to report (outside of the various technological advances reported earlier).

Section 9: Honors/Awards

The following is a list of honors and awards that the project members received during the project period.

- Young-Jun Son was selected as a Fellow of Institute of Industrial Engineers (IIE) in 2014.
- Young-Jun Son received the 2013 Outstanding Mentor of Graduate/Professional Students Award (the Graduate and Professional Student Council at the University of Arizona selects only one UA faculty member each year).
- Young-Jun Son was selected as da Vinci fellow for 2012 by the University of Arizona College of Engineering da Vinci Circle, the giving society of the college (Only one UA Engineering faculty member per year is selected)
- Young-Jun Son was selected for the inaugural University of Arizona College of Engineering Fellowship (2011~2014) (Three top performing faculty members were selected to receive 3 year Fellowship)
- Jian Liu received honorable mention for best paper award at 2012 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Hong Kong, Dec. 10-13, 2012.
- Srinivas Sai (Young-Jun Son's advisee) received the best MS thesis award at Institute of Industrial Engineers (IIE) Annual Meeting 2012, Orlando, FL, May 21, 2012 (IIE grants this award to at most one MS student each year; Young-Jun Son's advisees received the award in 2009 (Nurcin Celik) and 2011 (Hui Xi) as well).
- Mingyang Li (advisee of Jian Liu) joined the University of South Florida as an Assistant Professor in the Department of Industrial Engineering and Management Systems Engineering in Fall 2015.
- Mingyang Li (advisee of Jian Liu) received the 2014 INFORMS Quality, Statistics, and Reliability Section's Best Student Paper Finalist Award based on the paper entitled "Bayesian Modeling and Inferencing of Heterogeneous Time-to-event Data with an Unknown Number of Sub-populations" that was co-authored by Jian Liu.

1.

1. Report Type

Final Report

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Primary Contact Phone Number
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1-520-275-6717

Organization / Institution name

The University of Arizona

Grant/Contract Title
The full title of the funded effort.

DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs

Grant/Contract Number
AFOSR assigned control number. It must begin with "FA9550" or "F49620" or "FA2386".

FA9550-12-1-0238

Principal Investigator Name
The full name of the principal investigator on the grant or contract.

Young-Jun Son

Program Manager
The AFOSR Program Manager currently assigned to the award

Frederica Darema

Reporting Period Start Date

05/01/2012

Reporting Period End Date

09/30/2015

Abstract

The main goal of this project was to investigate algorithmic approaches to create scalable, robust, multi-scale, and effective urban surveillance and crowd control strategies using unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs). To achieve the goal, a comprehensive planning and control framework was designed and developed based on dynamic-data-driven, adaptive multi-scale simulation (DDDAMS), where dynamic data is incorporated into simulation, simulation steers the measurement process for data update and system control, and an appropriate level of simulation fidelity is selected based on the time constraints for evaluating alternative control policies using simulation. Under the DDDAMS framework, an information-aggregation approach was developed for crowd dynamics modeling by incorporating multi-resolution data, where a grid-based method is used to model crowd motion with UAVs' low-resolution global perception, and an autoregressive model is used to model individuals' motion based on UGVs' detailed perception. Various simulation experiments were conducted to illustrate and test the effectiveness of the information-aggregation approach. Experimental results revealed that the proposed information aggregation approach can achieve a higher crowd coverage in crowd tracking compared with the approach without involving aggregation. In addition, a vision-based target detection and localization via a team of cooperative UAV and UGVs was developed, and its effectiveness (i.e. reduced maximum and mean errors in localizing the crowds) has been demonstrated.

Finally, a testbed was successfully developed, involving hardware (three types of UAVs and one UGV), software (agent-based simulation, geographic information system (GIS) data), and human components, and used to demonstrate the proposed DDDAMS-based planning and control framework.

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Archival Publications (published) during reporting period:

• (PhD Dissertation) A. Khaleghi (supervised by Young-Jun Son), Hardware-In-The-Loop Dynamic Data Driven Adaptive Multi-Scale Simulation (DDDAMS) System For Crowd Surveillance Via Unmanned Vehicles, Systems and Industrial Engineering, The University of Arizona, August 2015.

• (PhD Dissertation) M. Li (supervised by Jian Liu), A Multi-Level Information Aggregation for Reliability Assurance Of Hierarchical Systems, Systems and Industrial Engineering, The University of Arizona, May 2015.

• (PhD Dissertation) C. Vo (supervised by Jyh-Ming Lien), Algorithms for Shepherding and Visibility-based Pursuit, Computer Science, George Mason University, August 2014.

• A. Khaleghi, D. Xu, Z. Wang, M. Li, A. Lobos, J. Liu, Y. Son, A DDDAMS-based Planning and Control Framework for Surveillance and Crowd Control via UAVs and UGVs, Expert Systems with Applications, 40, 2013, 7168-7183.

• Yifei Yuan, Zhenrui Wang, Mingyang Li, Young-Jun Son, Jian Liu, DDDAS-based Information-Aggregation for Crowd Dynamics Modeling with UAVs and UGVs, Frontiers in Robotics and AI (Sensor Fusion and Machine Perception Section), 2:8, 2015, 1-10.

• S. Minaeian, J. Liu, Y. Son, Vision-based Target Detection and Localization via a Team of Cooperative UAV and UGVs, IEEE Transactions on Systems, Man, and Cybernetics: Systems (Special Issue on Biomedical Robotics and Bio-mechatronics Systems and Application), Accepted, 2015.

• A. Khaleghi, D. Xu, S. Minaeian, M. Li, Y. Yuan, C. Vo, A. Mousavian, J. Lien, J. Liu, and Y. Son, UAV/UGV Surveillance and Crowd Control via Hardware-in-the-loop DDDAMS System, Darema, F., Douglas, C (Eds.), Springer (under review)

• Online Collision Prediction Among 2D Polygonal and Articulated Obstacles, Yanyan Lu, Zhonghua Xi and Jyh-Ming Lien, International Journal of Robotics Research (IJRR), Accepted, 2015.

• Minaeian, S., Yuan, Y., Liu, J., and Son, Y., 2015, “Human-in-the-Loop Agent-based Simulation for Improved Autonomous Surveillance using Unmanned Vehicles,” Proceedings of 2015 Winter Simulation Conference, Savannah, GA, Accepted (extended abstract for poster presentation).

• Continuous Visibility Feature, Guilin Lu, Yotam Gingold, and Jyh-Ming Lien, in the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2015, Boston, MA, USA

• Semantically Guided Location Recognition for Outdoors Scenes, Arsalan Mousavian, Jana Kosecka and Jyh-Ming Lien, Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), May 2015, Seattle, WA, USA

• Khaleghi, A., Xu, D., Minaeian, S., Yuan, Y., Liu, J., and Son, Y., 2015, “Analysis of UAV/UGV Control Strategies in a DDDAMS-based Surveillance System,” Proceedings of 2015 IIE Annual Meeting, Nashville, TN.

• Minaeian, S., Liu, J., and Son, Y., 2015, “Crowd Detection and Localization Using a Team of Cooperative UAV/UGVs,” Proceedings of 2015 IIE Annual Meeting, Nashville, TN.

• Khaleghi, A., Xu, D., Minaeian, S., Li, M., Yuan, Y., Liu, J., Son, Y., Vo, C., and Lien, J., 2014, “A DDDAMS-based UAV and UGV Team Formation Approach for Surveillance and Crowd Control,” Proceedings of 2014 Winter Simulation Conference, Savannah, GA.

• Khaleghi, A., Xu, D., Minaeian, S., Li, M., Yuan, Y., Liu, J., and Son, Y., 2014, “A Comparative Study of Control Architectures in UAV/UGV-based Surveillance System,” Proceedings of 2014 IIE Annual Meeting, Montreal, Canada.

• Wang, Z., Li, M., Khaleghi, A., Xu, D., Lobos, A., Vo, C., Lien, J., Liu, J., and Son, Y., 2013, “DDDAMS-based Crowd Control via UAVs and UGVs,” Procedia Computer Science 18, 2028–2035, Proceedings of 2013 International Conference on Computational Science, Barcelona, Spain.

• Khaleghi, A., Xu, D., Lobos, A., Minaeian, S., Son, Y., and Liu, J., 2013, “Agent-based Hardware-in-the-Loop Simulation for Modeling UAV/UGV Surveillance and Crowd Control System,” Proceedings of 2013 Winter Simulation Conference, Washington DC.

• Vo, C., McKay, S., Garg, N., and Lien, J., “Following a Group of Targets in Large Environments”, Proceedings of the Fifth International Conference on Motion in Games, Springer, 2012.

• Vo, C., and Lien, J., 2012, “Group Following in Monotonic Tracking Regions”, Proceedings of the 22nd Fall Workshop on Computational Geometry, 2012.

Changes in research objectives (if any):

NA

Change in AFOSR Program Manager, if any:

NA

Extensions granted or milestones slipped, if any:

The original project end date was April 30, 2015, which was in the middle of Spring 2015. And, the Research Assistantship (RA) contracts for the graduate students continued till May, 2015. So, no cost extension was requested till Sep. 30, 2015, and it was granted. The remaining balance was used to continue to support graduate students for the rest of Spring 2015 RA contract as well as summer 2015. The project scope remained unchanged. During the extended project periods, graduate students under the guidance of PIs refined the testbed that the project team had developed, and conducted experiments using the testbed.

AFOSR LRIR Number

LRIR Title

Reporting Period

Laboratory Task Manager

Program Officer

Research Objectives

Technical Summary

Funding Summary by Cost Category (by FY, $K)

	Starting FY	FY+1	FY+2
Salary			
Equipment/Facilities			
Supplies			
Total			

Report Document

Report Document - Text Analysis

Report Document - Text Analysis

Appendix Documents

2. Thank You

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