2010 11th Int. Conf. Control, Automation, Robotics and Vision
Singapore, 7-10th December 2010

Magician Simulator - A Realistic Simulator for Heterogeneous Teams of Autonomous Robots

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***Abstract*—We report on the development of a new simulation environment for use in Multi-Robot Learning, Swarm Robotics, Robot Teaming, Human Factors and Operator Training. The simulator provides a realistic environment for examining methods for localization and navigation, sensor analysis, object identification and tracking, as well as strategy development, interface refinement and operator training (based on various degrees of heterogeneity, robot teaming, and connectivity). The simulation additionally incorporates real-time human-robot interaction and allows hybrid operation with a mix of simulated and real robots and sensor inputs.**

***Index Terms*—Simulation, Swarm Robotics, Multi-Robot Learning, Human Robot Interface.**

I. Introduction

Simulators reduce the costs of development and testing of control algorithms for mobile robots, providing estimates of the feasibility of a method by simulating various situations and environments and examination of algorithms prior to hardware implementation. The use of simulation reduces development time, avoids algorithmic and strategic failures, and reduces the number and severity of errors that arise during the implementation process [1]. Robot teaming and robotic swarm are active domains of research, with applications such as search and rescue, threat detection, patrolling, and counter terrorism. Real world problems are dynamic, uncertain, and time-dependent. The high level of complexities in such areas increases the need for simulators that take into account the environment, robots, and the dual aspects of robot-teaming and human-to-robot interaction. Simulations are used in a variety of scenarios, from individual robots to teams or swarms, from humanoid or wheeled mobile types to industrial based robots and robotic arms. We report ongoing efforts to develop a realistic, simulated environment for research on swarm robotics, multi-robot learning and robot teaming. In describing the simulator, we also emphasize development of a human-robot interface to meet design requirements, to train human operators, and to evaluate both robot-robot and human-robot strategies. The remainder of this paper is organized as follows. Related work and similar simulators are presented in Section 2. In Section 3, we introduce the urban challenge from which the current simulator is inspired. The Magician simulator, its units and capabilities are presented in Section 4. Section 5 is dedicated to the simulation application. Finally, we conclude and summarize in section 6.

II. Related Work

A. Simulation environments for multi-robot teams

Multi-robot simulation comprises diverse areas, such as sensing, exploration, mapping, localization, planning, coordination, formation, and task allocation. Deployment in the real world is the end-goal of robotics, but simulation environments provide significant advantages for design over using real robots due to four factors: ease of installation, lower cost, speed, and more convenience [2]. Kramer and Scheutz [3] developed a metric for the evaluation of simulation environments for robot development, determining five factors: platform, components, system architecture, agent, and programming environment. They concluded that researchers in the future would tend towards the adoption of autonomic systems with flexibility in infrastructure, ease of installation, and a mind to long term usage; on the other hand, their work does not consider higher-level operation of robots as members of teams, which we believe to be a crucial consideration. Optimizing global strategy considers the coordination of a team of heterogeneous robots in an environment towards completion of diverse tasks. Although each robot is autonomous, with responsibility for duties, communications between robots and the distribution of tasks across multiple robots leads to increased efficiency. For example, a team of robots can complete a mapping task faster than an individual robot, and work in optimization demonstrates that the information gained by a team is an improvement despite dynamism and uncertainty in the environment. Over the last decade, the field of robotic and robot autonomy attracted researches to introduce several educational-based simulators targeting machine learning and robot autonomy such as AMORsim [1], Simbad [4], SARGE [5], STAGE [6], USARSim [7], EyeSim [8], Webots [2], and Gazebo [9]. These simulators provide a limited degree of coherence between real world and the simulated one. In addition, few take heterogeneity and task/skill variation in account, but more importantly, human factors and human-robot interaction are addressed not at all, or only superficially.

B. Human input in real-time robot teams

Although a great deal of research seeks to demonstrate accurate fine-grained replica of robots in the real world, simulation is also able to provide a great deal of valuable information for the higher-level team-based scenario. The formation of a robot team is largely dependent on the control of each robot in regards to its teammates as reference points. Hsu and Liu [10] used simulation to test the strategies of maintaining formation by assigning inter-robot reference points, whether leader, predecessor or neighbor. In a hospital environment, simulation showed that a team of robots could provide a cost effective transportation and delivery service that was significantly faster than currently provided by humans [11]. This comparison was between human teams or robot teams, thus they did not consider a mixed team of humans and robots. Robot simulation environments often provide simulation of humans, but investigations largely consider task allocation, coordination and human interaction as isolated aspects [12]; Furthermore, simulation rarely integrates real-time human input as a factor. Through the implementation of a networked layer, Faust et al. [13] demonstrated that simulation environments support experiments into collaboration between man and machine, of particular interest because human behavior is often more difficult to simulate than the actions of robots. Furthermore, human input during a task can improve reliability, due to superiority of human judgments over those of robots at certain operations such as object identification that require higher-order concepts in some situations. Designed with these goals in mind, Magician is a simulation environment that allows us to test different strategies and for the training of operators, providing for real-time display of over twenty robots. The principles of this new simulator inspired from the rules of a novel competition called Multi Autonomous Ground-robotic International Challenge (Magic).

III. The Magic 2010 Competition

The Multi Autonomous Ground-robotic International Challenge[1] (MAGIC), organized and sponsored by the defense departments of Australia and United States, involves autonomous robotic teams that engage in an intelligence, surveillance and reconnaissance mission. Robots compete in three phases of competition over an accumulative maximum of 3.5 hours, each phase successively more difficult in terms of hostility and terrain complexity. The basic rules of the competition dictate that teams of robots are to map the challenge arena, including prescribed landmarks and features of interest, and to observe, identify and neutralize if necessary, objects of interest. Robots of two main types must maintain communication with a remote Ground Control Station at all times. Two human operators observe robot progress at the Ground Control Station (GCS); they may intervene with robot behavior to resolve situations, but are penalized for doing so. Robots must completely map and report features of the competition environment accurately to within 0.5 meters. Robots are required to enter buildings and negotiate terrain such as roads, sand and grass. The number and location of objects of interest and environment features are not known in advance. Robots should locate, identify, and neutralize if necessary, four types of objects of interest: i) static hostiles, ii) mobile hostiles, iii) non-combatants, and iv) competition referees. Neutralizations take 15 or 30 seconds for static and mobile hostiles, respectively. Robots are equally vulnerable to instantaneous neutralization by hostile objects of interest, including simulated sniper activity, whilst neutralization of non-combatants incurs heavy penalties. A further constraint is heterogeneity of robots. The rules define two types of robot, Disruptors and Sensors, that have different functions, and which cannot intercommunicate, i.e. Disruptors may not talk to Sensors and communicate only with human operators. There can be at most three Disruptors, and in addition, there must be at least twice as many Sensors as Disruptors at all times. Reliable communication is fundamental, in that data from each robot is to be provided each second across an area that comprises up to 500m by 500m of urban area (similar to previous simulated experiments in [14, 15]). At minimum, robots must communicate their position to the ground control station, and they must furthermore respond to emergency shutdown commands at all times. Distance and building characteristics are expected to have significant impact on 802.x wireless communication channels, especially when broadcasting from within buildings. Moreover, success in neutralization and mapping tasks is contingent on strong channels of communication. Neutralizations are complete only after maintaining an uninterrupted visual lock on a target for the required number of seconds, and this visual information must be displayed to judges at the Ground Control Station. Similarly, map annotations at the Ground Control Station are produced on the basis of reports and images sent by robots in the arena. Thus, a major task for robots is the coordinated formation of dynamic, self-repairing, wireless-mesh, relay networks to ensure that operators are able to see what their robots see. Other major issues included in the competition are as follows: Power limitations. Each robot carries a number of processors and cameras which are powered by onboard batteries. Battery capacity influences the need to return to base or designated service zone (DSZ, DSL) for refueling or service. Localization and Navigation. The imprecision of GPS relative to localization requirements for mapping and exploration tasks set by the competition organizers warrants a combined localization approach.. Human-Robot Interface (HRI). The HRI will be deployed at the Ground Control Station (GCS) for high-level control of teams of physical robots by two human operators. However, interactions with robots are penalized.

IV. The Magician Simulator

Flinders University's and Western Australia University's robotic team "Magician" is one of the top 6 teams in the Grand Challenge. Due to various degrees of complexity defined in the competition, there is a need for an environment for the assessment of strategies and methods. For the purpose of the challenge and the future education of students in the field of robot teaming, swarm robotics, and multi-robot learning, a simulator called Magician Simulator is implemented. An important use of the simulator is for pre-event training: human operators will be trained in the human robot interface via the simulation. Human control of objects of interest can also

[1] Official Magic 2010 website: http://www.dsto.defence.gov.au/MAGIC2010/

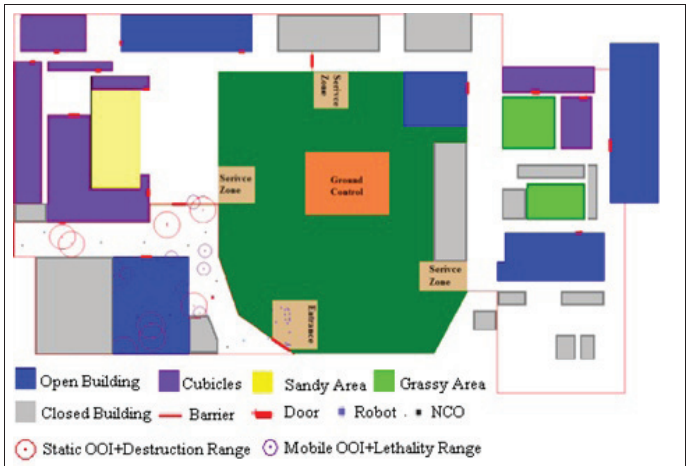

Fig. 1. A potential operator HRI configuration: configurable map display with autonomous talking agents relaying information via verbal message. Incoming images display below, and operators review potential actions in response. Colored squares on map indicate structure in simulated environment.

provide dynamic input to the evolution that is qualitatively different from the fixed or random programmed trajectories. The status of heterogeneous robots is presented to operators via the MAGICIAN Magic2010 simulator/HCI depicted in Figure 1. In addition to providing information about the robot teams, the interface indicates OOIs and their destruction/lethality ranges. Note that only a block diagram showing the approximate layout of the terrain is known. The numbers and locations of objects and doors are not known in advance, and thus are not displayed until they are detected by the system. The current version of the simulator (as depicted in Figure 2) loads each robot and runs the strategy all at one workstation, allowing operators to interact with robots using predefined messages during operation at the same workstation. An updated version of the simulator, currently under development, allows the interconnection of any number of computers via sockets architecture. In the new version, each workstation will act as a robot or subcomponent thereof, or a GCS/HRI unit. The goal of this increase in modularity is to allow investigation of complex behaviors between independent agents, including humans, through more substantial behavioral algorithms and use of actual hardware components. With regard to future applications, the following capabilities have been implemented in the simulator.

A. The Environment

The following issues are considered in the simulator: Number of phases. It is possible to define up to three phases, each with particular number of buildings, obstacles, robots, enemies, and roads. Experiments can be run in each phase separately or over all phases starting from the first, and moving into subsequent phases whenever predefined criteria are met. Environments. It is possible to define different environments, either by setting random numbers of buildings with randomly placed doors or by loading infrastructure from a coordinates file containing building dimensions and locations of entry points. Terrain. It is possible to define various types of terrains and ground materials, including grass and sand. In addition, ground elevation is considered inside the simulated landscape. Obstacles. Various types of obstacles are defined, including trees, fences, holes, and trenches. In general, any type of obstacle that can be represented with lines and circles can be defined inside the simulator.

B. The Robots

The possibility of defining various types of robots with various characteristics and capabilities is considered. In our simulator, it is possible to set following values for robots Robot type: Up to six different types of robots can be defined, which allows the reflection of various problems that arise with different degrees of heterogeneities. Hardware Devices. Each robot may have: i) between 6-10 cameras in corners or center of robots, ii) up to 5 different communication devices, iii) battery life, iv) maximum speed[2] , and v) GPS.

C. The Enemy

At current, up to three types of enemies are considered, each of which can be static or dynamic. Dynamic enemies follow either random movements or predefined patterns that contain a sequence of 10 locations inside the environment. It is possible to define up to 50 enemies in each phase of the simulation. The current version of simulator allows up to three phases to be defined, which can be used separately or all together. However, as with the other limits this can easily be increased if required.

D. The Ground Control Station (GCS)

Even though the competition designates the GCS as a place to set up the operators' infrastructures, in our implementation, the GCS also provides a higher-level strategy planner, which can send information directly to robots using wireless network. Decisions, first provided for human inspection, are forwarded to robots in the absence of human intervention.

[2]In the simulator, the speed of a robot is influenced by entities such as wheel slip and ground material (sandy and grassy areas). Therefore, two types of locations are defined, addressing actual and predicted position of the robot inside the environment. The presence of these two types of locations in each robots' memory provides the capability to assess various localization strategies.

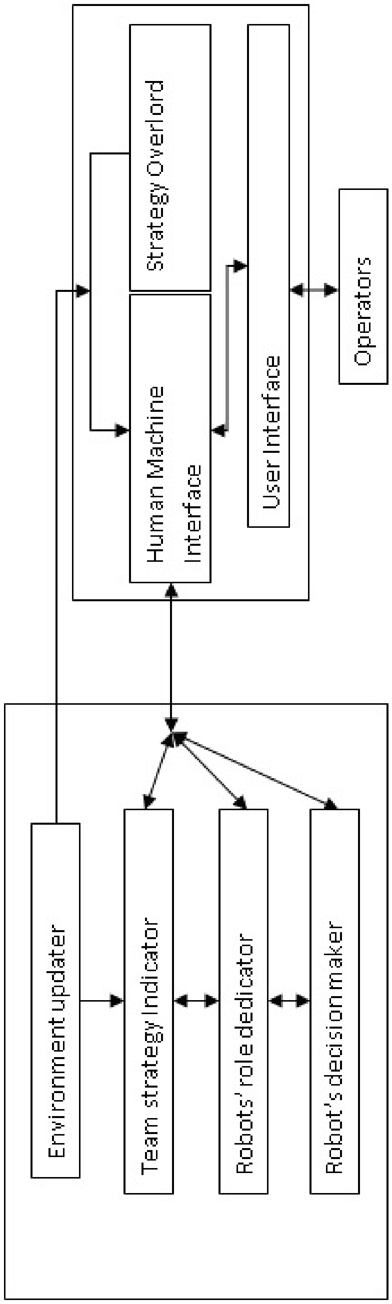

Fig. 2. The Magician simulator architecture. Operators can leave moment-to-moment operations to the strategy overlord, or override the strategy overlord when absolutely necessary.

E. The Vision

Based on the location of the cameras on a robot and the properties that are predefined for each type of camera (including resolution and zoom), it is possible to simulate vision by returning a fraction of the environment (which is defined as a matrix in robots). The output of each camera in each iteration is influenced by factors including the location of the camera on the robot, its current degree of zoom, the current resolution, and the direction and position of that robot.

F. The Network

The networking configuration of the simulator makes it possible to consider alternative strategies based on network constraints in a short-range multi-hop mesh networking architecture. The main networking challenge is to provide guarantees for unreliable wireless communications between mobile robots and the HRI unit such that periods of outage are at most seconds. Robots/computers that are out of communication range of other robots/computers (according to predefined networking ranges and simulated locations in the environment) or those that uses different networking channels cannot receive packets sent from other robots. To ensure that communications between mobile robots and the GCS are maintained at all times including hostile situations, we have developed redundancy in intermediate hops as a primary strategy, and are using the simulator to investigate effects of path planning and formation that prioritizes the positioning of relay vehicles behind the 'front line'.

V. Simulation applications

Traditionally, the primary benefit of simulators is that they can be run repetitively to contrast wide variations in parameter configurations, and so to examine optimal and sub-optimal outcomes. Such investigations require very little moment-to-moment input from the analyst. Contrasts are drawn from global metrics summated and tabulated at the conclusion of simulations. Our use of simulation goes beyond numerically comparing one simulation run with another. We extend the use of simulation for improvement of higher-level strategy, as guidance for robot autonomy, for the training of operators and in evaluation of HRI configuration. In our case, moment-to-moment observation is necessary and critical for real-time operator situation awareness. Without access to the challenge arena prior to the competition, the HRI and the robot fleet or ability of human operators cannot be tested inside the arena prior to the event. Training with a simulator is thus advantageous, in that decision-making under unfolding scenarios may be rigorously (re-)evaluated. By controlling environment parameters dynamically, we intend to explore the maximum operating limitations for individual operators, observe and record situation resolution, and explore innovative and alternative methods for workload assessment.

A. Evaluating Strategy

Teams who engage in goal-based activities employ a particular cache of cooperative strategies, whether playing a team sport or conducting a military mission. When strategy fails, the team's coach will often intervene to change the strategy, suggest why the current strategy is failing and how to prevent further strategic failures. Analogically, GCS operators are the coaches and robots the players, but our case coaches are penalized for intervening with team members. An optimal strategy may underperform within an unsupervised simulation. As the competition unfolds, the human operators will at their discretion intervene and control errors in the strategy of the autonomous fleet. Our goal in refining strategies in the simulated mission is to pick up as many problems as possible beforehand to reduce the number of human interventions during the competition.

B. Operator Training

Two human operators will passively observe the HRI during the 3-hour challenge. However, we anticipate unexpected situations to occur. Hence, operators must be capable of rectifying situations in which robot autonomy fails. Penalties apply for human interaction and intervention affecting any aspect of robot or interface autonomy. Clearly, on occasion, emergency interaction is necessary in that the penalty of not acting far outweighs the smaller interaction penalty; for example, the interaction penalty for ordering a robot to cease neutralization of a non-combatant (NCO) is far smaller than the penalty incurred for neutralizing an NCO. Operator proficiencies encompass many aspects of HRI information display including and not limited to robot configuration and troubleshooting, goal and strategy management, event and report management, and communications. While operators train to resolve situations explicitly and manually, operators also train to work long side HRI autonomy; this necessitates understanding how the interface is changing in response to events. Failing to do so will leave the operator wondering why the autonomous interface has changed some aspect of the configuration. The means to communicate steps taken by the interface's autonomy is clearly an interface design consideration, however, to work as team players, as suggested by Woods [16], the operator must take measures to understand the automated actions.

C. Interface Evaluation

The main design challenge of the HRI is ensuring that the arrival of robot messages capture operator attention and convey as much information as is relevant and needed for understanding and decision-making. The design motivations of perceptually salient and cognitively rich representations were introduced in an earlier paper [17]. Figure 3 depicts a potential display configuration. Colored squares indicate simulated environmental structures (satellite image is not consistent with the simulated structure). The virtual heads either side relay incoming information verbally to operators. Figure 4 depicts an alternative and complementary display configuration in which incoming images border a central map display and colored bars indicate robot health status. Situations that are more complex necessitate deeper integration of diverse information sources as well as status and activity of a number of robot teams. In situations involving moderate to high uncertainty (e.g. turning blind corners), the risk to the robot fleet is higher - operators must decide whether the risk is too great to allow the robot to make a particular given decision. It is not however; always true that more information about the situation is better; rather, the information that specifically alleviates uncertainty and promotes trust better. An increased awareness of the level of information to display to operators is likely only to come about through repeated deep analysis of scenarios under restricted time and operating conditions. In contrast with offline use-case analysis which is useful for preliminary design phases,

Fig. 3. A potential operator HRI configuration: configurable map display with autonomous talking agents relaying information via verbal message. Incoming images display below, and operators review potential actions in response. Colored squares on map indicate structure in simulated environment.

Fig. 4. A potential operator HRI configuration: incoming images appear around a central map display. Horizontal Colored bars indicate robot multiple battery and multiple communication link strengths.

simulation provides an environment for rigorous evaluation of appropriate presentation of information in later evaluative and research phases. The capture and analysis of operator training and performance data has greater overhead than a traditional simulation. Evaluation sessions involve two HRI operators, a simulation manager and HRI management software. Operators sit or stand back from the HRI display; their interactions with the system are recorded by video cameras. They periodically perform think-out-louds and produce reports on workload estimation, information that they need for decision making or situation awareness. The simulation manager initiates the simulation and controls environment parameters in real-time according to the evaluation or training goals. The HRI manager software controls the display of information presented on the HRI when operators report a need for it. Event logs timestamp the beginning and end of each event, the outcome and information configuration that operators request. Analysis of video data provides insight into the estimated operator workload for different event types and furthermore provides an estimation of eye-gaze during event resolution or in times of quiet operating conditions. A major outcome of the evaluation process is automatising aspects of the HRI and understanding the costs and benefits to operator situation awareness as a result of automation. Analysis of a rich data set will reveal where operators spend a majority of time observing HRI displays and the information that operators regularly rely on for situation awareness. These two insights alone will influence how and when information appears onscreen and when the information should disappear. Since operators cannot provide explicit feedback to indicate each time that they have received a given piece of information, we must refine basic time and state-based heuristics to control information presentation. The utility of such heuristics will rely closely on an understanding of anticipated events and doing so relies on some kind of rehearsal, simulation and experimentation.

VI. Conclusion

This paper has outlined a new simulation environment for use in areas such as Multi-Robot Learning, Swarm Robotics, and Robot Teaming. In addition to strategic planning and navigation-based studies with heterogeneous teams of robots and humans, the Magician simulator has the capability to be used for training operators, which will improve the human performance using the designated HRI unit. Whilst our current efforts are focused on extending the simulator's capabilities and fidelity, we will in the near future implement a distributed version of the simulator. Whereas a single workstation currently controls every individual facet of the simulation, separate workstations will be tasked to simulate specific robots inside a simulated environment connected via socket architecture. This introduces an additional level of convenience such that the exact control algorithms can be simulated and compared onboard the robot platform.

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