Using Discrete Event Simulation to Model Multi-Robot Multi-Operator Teamwork

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With the increasing need for teams of operators in controlling multiple robots, it is important to understand how to construct the team and support team processes. While running experiments can be time consuming and expensive, the use of simulation models is an alternative method. In this study, we built a discrete event simulation model that represents multi-robot multi-operator teamwork. Preliminary results show that the model can generate performance measures consistent with experimental results.

INTRODUCTION

Visions for the usage of robots often involve the deployment of a team of robots working together to accomplish a common goal. For example, in search and rescue scenarios, distributing the exploration task to a team of low cost, easy-to-replace robots could reduce the time to complete the task. Such robot teams may also involve different types of robots or robots with different capabilities. Although using multiple robots could bring many benefits, the number of robots an operator can productively control is limited by the operator's cognitive abilities. When it is not possible for a single operator to control a team of robots, multiple operators are required to form a team to deal with the increased complexity.

Previous research (Nehme, 2009; Nehme, Crandall, & Cummings, 2008) has used queuing models for scenarios in which a single operator controls multiple robots. The teamwork of multi-robot and multi-operator teams can be modeled based on queuing theory as well. However, human behavior and teamwork usually bring more complexity than a basic queuing model. The objective of this research is to build a queuing model for multi-robot, multi-operator teamwork to understand its dynamics and outcomes.

BACKGROUND

Previous research (Mekdeci & Cummings, 2009; Nehme, 2009; Nehme, et al., 2008) has classified supervisory control of unmanned vehicles as a queuing problem where the vehicles requesting assistance are thought of as customers and the operators are thought of as servers. Schmidt (1978) used queuing theory to model the operator utilization of air traffic controllers. Divita et al. (2004) modeled a team performing supervisory control of an air defense warfare system using queuing theory. However, the model failed to predict the actual team performance observed when their proposed model was compared against empirical results. The authors concluded that discrepancy in predictions were due mostly to invalid assumptions they made about how tasks were allocated within the team and the fact that they did not account for the loss of situational awareness incurred by the team members.

Many of the interesting supervisory control problems cannot be solved analytically using queuing theory since some of the strict assumptions necessary for closed-form solutions do not hold. It is very difficult to get analytical solutions for queuing problems with non-Poisson arrival process, complex queuing network, reneging, and rework process. However, it is possible to use a discrete event simulation (DES) to overcome the limitations of analytical models and predict complex unmanned vehicle (UV) operator behavior. Discrete event simulation allows queuing problems to be solved in a "brute-force" manner, overcoming many of the strict assumptions required for elegant analytical solutions. DES models of a single human operator controlling multiple unmanned vehicles could be expanded to include the team composition and teamwork processes to model multi-robot multi-operator teamwork.

SIMULATION MODEL

In this section, a discrete event simulation model is introduced that includes: a) a queuing model of the human operator supervising multiple UVs; b) task assignment within the team of operators; and c) communication between operators.

Overview

The DES model was constructed under the assumption that the operator is acting in a supervisory control mode and the robots in the team are highly autonomous. Robots being supervised should function

independently of the human most of the time, and require human interaction only intermittently. Operators function as servers in the queuing model and serve the events generated from the robots. The overall framework is shown in Figure 1.
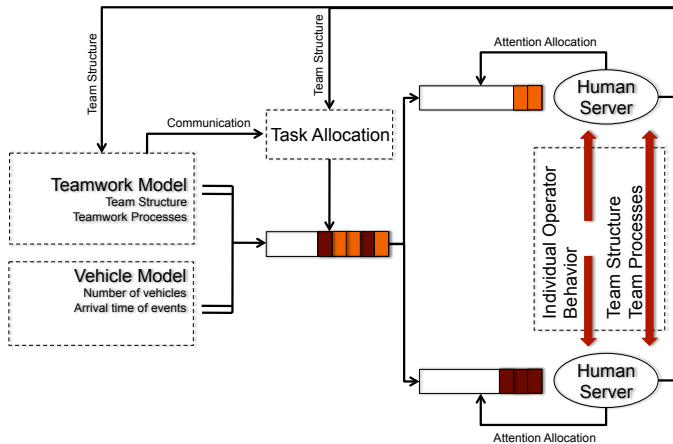

Figure 1: Discrete Event Simulation Model for Multi-robot Multi-operator Teaming

The events generated from the robots enter the queue and wait to be served when the operators are busy. Operators select from the queue for the next event to be served. This task assignment process is affected by the team structure of operators. After the events are served, the model generates performance outputs, which can be compared with empirical data. Certain scenarios can be modeled based on this basic model, such as putting limits on service time, changing queuing discipline, etc.

Arrival Process of Robot-Generated Events

Each robot has one event stream. An event arrives to the system and stays in the queue for a certain amount of time T. An event is then either served by the operator or exits the queue without being served if it waits longer than T. For each event stream, there is at most one active event in the system associated with it at any time. In other words, a new event is generated from this stream only if there is no event from stream in the queue or being served. The interarrival time of events are between the completion of service/reneging from queue and the arrival of the next event. These interarrival times are described by a random variable Λ_i, where i stands for event stream i.

Sometimes, events generated are not identical. In this situation, a random variable C following a multinomial distribution is used to describe the categories of events. New events are generated according to the interarrival time Λ_i and assigned an event category from C.

Service Process of a Single Operator

Each event is served by an operator via a service time described by random variable M. Sometimes, the service process involves several steps. In this case, the service time $M = \mu_1 + \mu_2 + ... + \mu_n$, with μ_i being the time required for step i.

The time an operator spends working on an event is associated with an opportunity cost of missing other important events waiting in the queue. Limiting the service time on one event may result in an increase of overall mission performance. This could be modeled by making the event exit from the server when the time limit is reached. In this situation, an output from processing this event may not be generated due to the shortened service time.

Task Assignment in Operator Teams

Task assignment in operator teams is affected by queuing network and queuing discipline. For queuing network, there are two possible ways of assigning tasks: 1) All the operators serve events from a common queue; 2) Each operator maintains a separate queue only for himself. In the first situation, events generated from all event streams enter this common queue. In the second situation, each event stream enters a specific operator's queue.

For queuing discipline, several common ways to pull an event from a queue include: First-Come-First-Serve, Last-Come-First-Serve and Random Selection. They can be used in the DES model according to characteristics of different task scenarios.

Communication in Operator Teams

Communication as a way of coordination is critical for team performance. Research about group decision making (Hirokawa, 1990) shows that in effective decision-making groups, communication serves both promotive functions that facilitate sound reasoning and critical thinking and counteractive functions that prevent a group from making errors. Salas et al. (2005) also discussed the importance of communication for teamwork processes such as mutual performance monitoring. In this study, the benefit of communication was modeled as a higher probability of correcting an error when there is communication. In addition, with communication, an operator is able to correct his teammate's errors, in addition to his own errors.

While communication is an essential component of teamwork, it also requires additional attention and

cognitive resources from the operators. Steiner (1972) refers to the differential between the performance of a team and the theoretical maximum achieved if the efforts of the individuals were combined ideally as "process losses". Based on this, communication is modeled as process losses in the model. When there is communication during the service process, the service time is extended by the duration of communication.

CASE STUDY

To validate the model, output from the model was compared to the results of an experimental study simulating an urban search and rescue mission. The experimental study and model parameters are discussed below.

Software Test-Bed

MrCS (Multi-robot Control System), a multi-robot communications and control infrastructure with an accompanying user interface built on USARSim (Lewis, Wang, & Hughes, 2007) was used as the control interface. Figure 2 shows the elements of the MrCS displayed on a dual display computer. Thumbnails of robot camera feeds are shown on the left screen. A video feed of interest is on the top left of the right screen. Under the video feed, a GUI element in the bottom left allows teleoperation and camera pan and tilt. The right window shows the area map and allows operators to mark the location of victims.

In MrCS, each robot is capable of updating a map, planning their routing and sending back video feed to operators. The operators' tasks were to explore the environment and identify as many positions of victims as possible. Robots were started in different regions and explored the environment automatically. The operators guided the robots in the environment in order to find the victims. The general workflow of a single operator is

shown in Figure 3. When a victim appeared in the camera of a robot and was detected by the operator, the operator's task was to select the robot, teleoperate the robot to bring the victim back into the camera view and mark the location of the victim on the map. This was the time the operator devoted to serve the robot, labeled as service time/service time out in Figure 3. After that, the operator continued monitoring all the robots and guided the robots to explore the environment. Most of the time robots were navigating using autonomous path planning, and the operator only needed to monitor the thumbnails of video feeds. Sometimes, the operator used teleoperation to manually control the robots to send them to a specific unexplored place. This free searching/teleoperation period stopped until a new victim appeared in a camera view, and the operator selected this robot to start a new task.
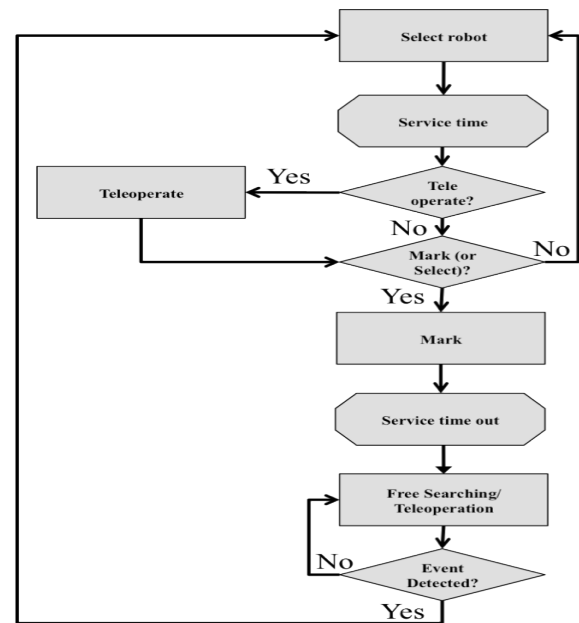

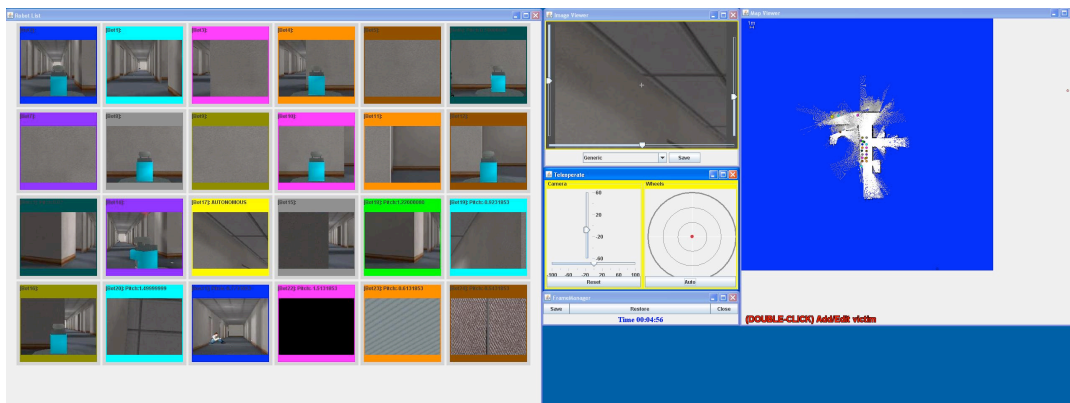**Figure 3:** Operation Procedure for Finding and Marking Victims

Figure 2: Interface for Operating Vehicles in a Search and Rescue Task

Experimental Procedure

The experiment had two independent variables: team structure and search guidance. Team structure had two levels: Sector and Shared Pool. Participants were grouped into teams of two operators. Each participant controlled 12 robots individually in the *Sector* condition, or the team shared the control of all 24 robots in the *Shared Pool* condition.

Search Guidance had three levels: Off, Suggested and Enforced. *Suggested* mode gives a recommendation to switch to another robot when the operator spends 30 seconds on a robot. *Enforced* mode gives a recommendation to switch at 30 seconds and switch automatically to another robot five seconds after the recommendation. *Off* mode provides no recommendation.

Performance was measured from several aspects: 1) number of victims found; 2) number of errors; 3) number of victims missed; 4) number of deletes. Communication time between the two operators was recorded as well. Detailed discussion about this experiment and results was presented in a previous paper (Gao, Cummings, & Bertuccelli, 2012).

Model Parameters

To compare the DES model output to the experimental results, several data sets were recorded in the experiment and used to fit probability distributions used in the model, as shown in Table 1.

Table 1: Parameters of the Model and Data Recorded during the Experiment

Parameters of the Model	Data Recorded during the Experiment
Interarrival time of victim-in-camera events	Arrival time of victim-in-camera events
Multinomial distribution for the type of victim-in-camera events	ID of each victim appearing in the camera
Service time of operator	Duration of teleoperation and marking of a victim
Probability of doing teleoperation	Number of operations involving teleoperation
Interarrival time and duration of communication	Time between communication and communication duration
Probability that a team has communication	Number of teams with communication
Distribution of probability to make an error = (Errors+Deletes)/(Found+Errors)	Number of victims found, errors and deletes
Distribution of probability to correct an error = Deletes/(Deletes+Errors)	

We also set parameters for the probability of noticing an event, the probability of following a system recommendation, and the probability of marking when the system recommends switching. Values of these parameters were set to be constant.

The DES model generates outputs consistent with the performance measure used in the experiment and total communication time.

RESULT

Using the parameters generated from the experiment data, 1000 trials were conducted using the DES model under each combination of team structure and search guidance mode.

To validate fit of the model to experiment, outputs from the DES model were compared with experiment data. Under all the conditions, outputs from the model are within the range of one standard error of experiment results. Figures 4-6 present the results for two kinds of team structure with no search guidance.
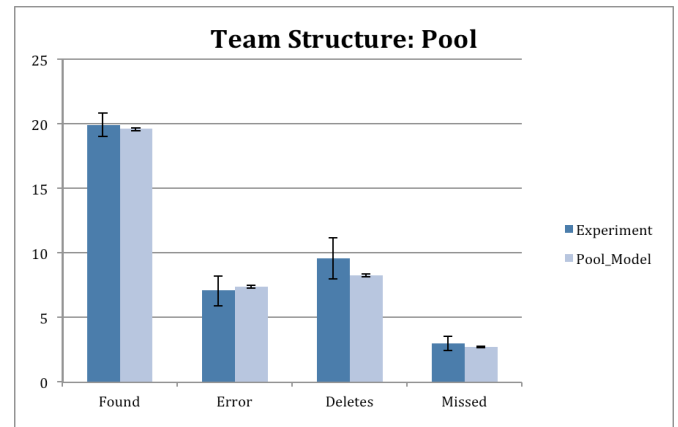

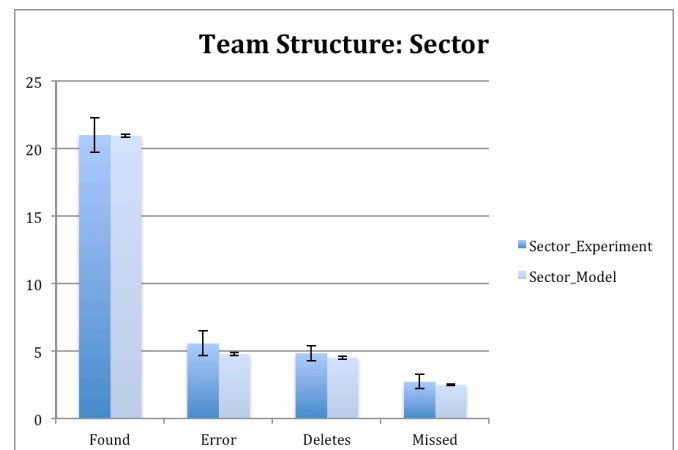**Figure 4:** Comparison of Results on Performance for Pool Teams

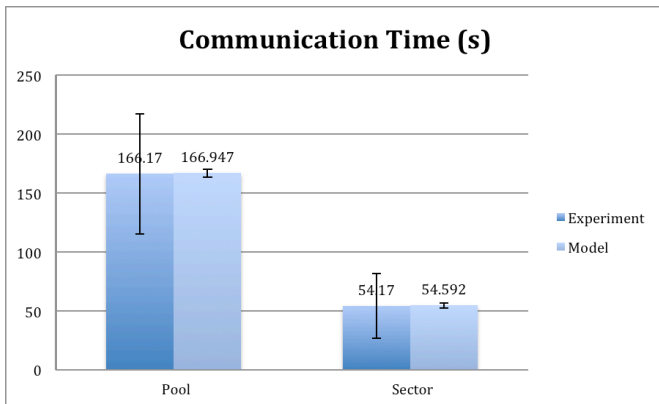**Figure 5:** Comparison of Results on Performance for Sector Teams

Figure 6: Comparison of Results on Communication

CONCLUSIONS AND FUTURE WORK

The queuing model appears to be a promising method to model a team of operators. By modifying the basic queuing model to include characteristics of operator behavior and team process, it is possible to generate accurate predictions of performance on multiple dimensions.

The current model has several limitations. First, communication was modeled as an exogenous process. In the real situation, communication is usually generated during the working process. Changing the exogenous communication events to endogenous could provide us more diagnostic power concerning the effectiveness and efficiency of communication. Second, the current queue principle is random selection. In the real situation, the task assignment is likely to be affected by the coordination and communication of team members.

Future work will include further validation using another independent data set, sensitivity analyses, and addressing the limitations listed above.

ACKNOWLEDGMENTS

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