Human-in-the-loop Planning and Monitoring of Swarm Search and Service Missions*

Extended Abstract

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1 INTRODUCTION

In many anticipated applications of swarms, vehicles will work together to simultaneously search an area while servicing tasks (or jobs) as they appear. We call these Swarm Search and Service (SSS) missions.

As vehicles move in and out of the swarm, the amount of area seen by the swarm at any given time – coverage rate – changes dynamically. The dynamically changing coverage rate causes the arrival rate of jobs to also change dynamically. Since jobs appear only when they are sensed, predicting how and when the arrival rates change is challenging, making it difficult for operators to plan and manage SSS missions.

Research on planning swarm missions typically focuses on determining paths [1] or policies [2] for vehicles to service the expected jobs. Little to no work has focused on the resource allocation problem associated with determining the necessary number of vehicles needed to achieve mission success.

This paper presents a user study that explores the efficacy and ease-of-use of a prediction model – Hybrid Model – as an aid for operators tasked with planning and monitoring SSS missions where the arrival rate of jobs changes dynamically. By predicting the expected relationship between various mission parameters, the developed Hybrid Model allows operators to build a mental model of the trade-offs between different mission objectives. This mental model helps operators to effectively assign vehicles to the swarm during planning, as well as, maintain sufficient situation awareness during the mission to evaluate the performance of the swarm and distinguish between different issues that may arise.

2 METHOD

To model the performance of an SSS mission with dynamically changing coverage rates, a Hybrid Model is used [4]. The Hybrid Model uses a Markov chain to capture the dynamically changing swarm size, employing queuing theory to determine the transition dynamics between states.

2.1 Experimental Design

A user study with 24 participants (10 female) was conducted to evaluate the efficacy of the Hybrid Model as a planning and monitoring aid for SSS missions.

Each trial consisted of 2 parts: (1) a planning task and (2) a monitoring task. All trials presented missions comprised of 2 job types. The job parameters (expected number of jobs, required number of vehicles and service time) varied across trials.

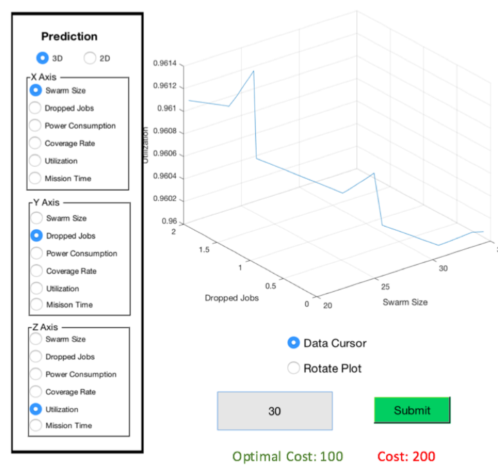

Figure 1: Planning panel of experimental interface showing non-monotonic relation between parameters.

One of the main challenges associated with planning and monitoring SSS missions is that the dynamically changing coverage rate of the swarm in open environments results in non-monotonic relationships between mission parameters. An example of the relationship between swarm size and dropped jobs is shown in Figure 1. Counter to intuition, there are regions where the number of dropped jobs increases as the swarm size increases. This is due to the fact that more vehicles have been added to the swarm, allowing the swarm to search the environment faster. However, until a certain threshold of additional vehicles is met, not enough extra vehicles are present in the swarm to service the additional jobs that arrive. In addition to the non-monotonic relationship between parameters and the conflicting trade-offs seen as a result of the various relationships between parameters, the causation between parameters is not bidirectional (i.e., one parameters may effect another, but that second parameter may not effect the first). Participants needed to evaluate and understand these complex relationships to effectively accomplish both tasks.

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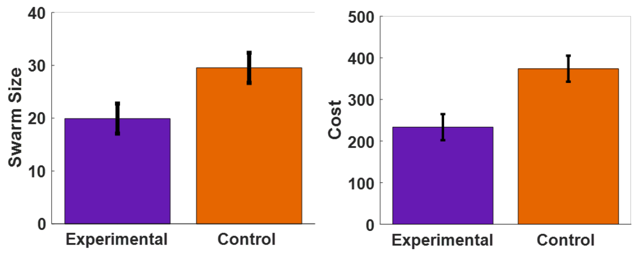

(a) Swarm Size **(b) Cost**

Figure 2: Comparison of planning results by group.

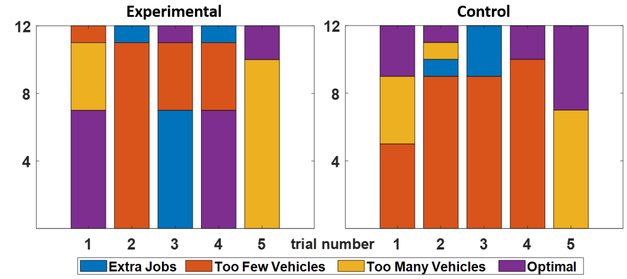

Figure 3: Participants' anomaly detection decisions.

Once participants had chosen a swarm size that they believed would minimize cost, their cost was shown in comparison to the optimal cost. For each trial, the optimal cost was found by running 100 missions comprised of the job types given for a variety of swarm sizes. The cost value associated with each swarm size was the average cost of the 100 missions run with that swarm size.

After completing the planning phase, participants moved to the monitoring task. In the monitoring task, participants were asked to watch a simulated mission. Their task was to determine whether the mission was running normally. One of three anomalies were possible: there were more jobs in the environment than expected, there were too few vehicles to handle the jobs needing service, or there were more vehicles than needed. If the participant thought an anomaly was occurring they were asked to click the corresponding button at the bottom of the interface.

3 RESULTS

The results shown here are compiled from the data collected from the 5 trials each participant completed. The data for the planning and monitoring portions of the trials will be reported separately. A one-way ANOVA with repeated measures was conducted using IBM SPSS version 25. The participants' group (experimental or control) was the independent variable. Input time, swarm size and cost were used as the dependent variables in the analysis of the planning data. The time to make a decision and the number of correct decisions made were the dependent variables used in the analysis of the monitoring data. All results are reported with a significance level of $p < 0.05$.

3.1 Planning Task

Figure 2 shows that the Hybrid Model allowed participants in the experimental group to plan missions with both a lower average swarm size and total overall cost. Both results were statistically significant. The results are consistent across job parameter changes between trials. However, participants in the control group only took 111.82 sec to choose a swarm size on average while participants in the experimental group took longer and averaged 154.04 sec.

3.2 Monitoring Task

In the monitoring portion of the trials, participants in the experimental group were able to correctly determine the performance and identify anomalies more accurately than their counterparts in the control group (3.5 trials versus 2 trials correct, respectively). However, they took longer to make their decision (209.65 seconds versus 124.45 seconds). The results are statistically significant. The group participants were in had an effect on the time participants took to make a decision ($\eta^2 = 0.143$).

Figure 3 shows the anomaly detection decisions made by subjects in each group. The ground truth decisions for the monitoring trials (in order) were: (1) optimal, (2) too few vehicles, (3) too many jobs, (4) optimal, and (5) too many vehicles. As shown, participants in the experimental group were able to not only determine if a mission was going well, but also distinguish between anomalies that occurred during the mission. In contrast, participants in the control group thought that all the missions presented had too few vehicles unless no jobs were missed (Trial 5).

4 DISCUSSION

The task given to human operators in charge of planning and monitoring SSS missions is quite complex. The task possesses 3 out of the 4 sources of complexity [3]: multiple desired states, conflicting dependence among data, and uncertainty in the data. The multiple desired states are described by the various costs that the operators must minimize. The complex interdependence between mission parameters results in conflicting trade-offs that operators must balance. In addition, SSS missions have inherent uncertainties associated with unknown locations of the jobs.

The analysis shows that in spite of the high task complexity and the lack of training trials participants in the experimental group were able to plan missions more effectively than their counterparts in the control group. This was apparent in their ability to choose smaller swarm sizes that produced lower overall missions costs. The results were consistent across all trials. The control group weighed the trade-off between cost parameters less, thereby producing a lower average time to plan. The control group's higher overall cost and lower time to plan indicates that they developed a flawed mental model that may have been too simplistic to represent the actual interaction between mission parameters.

When monitoring SSS missions, participants in the experimental group were not only able to identify when a mission was progressing normally, but also distinguish between causes of sub-optimal mission performance than participants in the control group. This indicates that participants in the experimental group were able to effectively cross-reference expected mission performance given by the Hybrid Model with the real-time mission parameter tracking to maintain a better situational awareness of the mission, leading to a better understanding of how the relationships between mission parameters affect the performance of the swarm.

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