Incorporating Human Input in Robotic Exploration

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***Abstract*—Robotic exploration is used to maintain an operator's situational awareness, scout unknown or dangerous environments, and search urban environments with many obstructions. Fully autonomous exploration enables the use of multiple robotic agents for better surveillance, but neglects the operator's task intuition and task goal evolution. We hypothesize that by including the human in the control loop, the autonomy will be more robust in adapting to unplanned changes and better able to assist the operator at the given task. We are incorporating a human input by asking the operator to shade, and thus locate, areas for exploration on a haptic tablet for minimal to no disturbance of operator's visual attention. An information density metric, ergodicity, will be used to generate decentralized control trajectories of the swarm of drones during a search and locate task in a virtual environment. Different levels of autonomy (direct control, shared control, and fully autonomy), environment complexity (rural vs. city), and number of drones (single drone vs. swarm) will be tested. We predict shared control will result in better perception augmentation of operator's environment, perception degradation of the outside observers, and overall, better task performance. A range of biometric data will be collected to evaluate the operator's ongoing situational awareness. Future work involves using the biometric data to create a machine learning model and adjust the level of control sharing in real time based on operator's cognitive state. If this method of shared control leads to improved task performance, it can be extended to other human-robot interaction and robotic exploration applications.**

I. Introduction

While a single drone can successfully track a dynamic target [1], in scenarios where time is critical and where vast regions of space need to be explored, such as in firefighting [2], ecological surveillance for conservation purposes [3], and humanitarian efforts in post-disaster management and research [4, 5], multiple drone deployment is necessary. As the number of drones increases, so does the cognitive complexity required to operate the swarm of drones [6]. Under high cognitive demands, individuals may experience mental overload at maximal task demand [7] and difficulty reallocating attention from one task to another [8, 7, 9]. This is problematic as operators often have to switch between drone operation, environmental surveillance, and task completion. Fully autonomous drones may relieve cognitive load, but neglect task intuition and goal evolution. The appropriate level of autonomy to improve task outcomes depends on a variety of factors including additional cognitive demands, swarm size, and the complexity of environment in which the human-swarm system is operating in [6].

Shared control is one way the capabilities of a person and robot such as a drone have been leveraged to result in better task outcomes [10, 11, 12]. During a target-hitting task with a joystick, giving the human operator high-level control over path planning and position while the robot maintained low-level control over aspects such as force management and reducing oscillation improved task performance [11]. While tasks in which the low-level execution may be unintuitive for a user, such as balancing a cart-pendulum, robotic intervention improves task outcomes [12]. Our method of shared control gives users the ability to provide high-level inputs by indicating or shading areas of exploratory interest while the autonomy uses ergodic control to specify decentralized trajectories and control inputs for each member of the swarm.

Ergodic control is used to generate trajectories according to the spatial statistics of information density so that the time spend exploring given area matches the expected information content of that area [13, 14, 15, 16]. User gestures on a haptic tablet are being mapped to a distribution over the region of interest and included in the spatial statistics of expected information content. Areas of high information can be also be found using sensors [13]. Trajectories are generated using ergodic control so that the amount of time the drone spends exploring given neighborhood matches the spatial statistics expected information content in that neighborhood. Together, the drones within a swarm will follow trajectories that are collectively more ergodic with respect to the spatial statistics than the individual drones [15], indicating that there are information-gathering and coverage benefits to using an ergodically controlled swarm as opposed to a single drone or a swarm formation.

During hardware challenges and unplanned events in extreme environments that prevent an individual drone from operating correctly, it is important that the remaining swarm population continues to explore optimally and augment the user's perception by providing an uninterrupted flow of information. Perception augmentation is important in maintaining an operator's situational awareness for surveillance purposes, and searching unknown, dynamic, or urban environments with many obstructions. Unlike hierarchical search and rescue control architectures [17, 18], ergodic control can be decentralized [16]. Ergodic control enables graceful degradation of individual drones while the remaining swarm population will continue to follow trajectories according to the spatial statistics.

The purpose of this study is to determine how to best leverage capabilities of the drones with the person to create more robust autonomy. We interpret the meaning of robust autonomy to be adaptive and effective in a variety of different, possibly extreme and changing environments. Robotic exploration may become more robust by thoughtfully incorporating operator knowledge and intuition. This extended abstract outlines our plans to begin to answer that question experimentally. In a virtual reality environment, participants will be asked to complete tasks in which perception augmentation through drone surveillance assists in task completion. Moreover, the effect of swarm movement on the perception of a third person observing the task will be tested. We hypothesize that a method of robotic exploration in between direct control (such as speech and gesture recognition [19], joystick, or a handheld controller) and fully autonomous control will result in greater perception augmentation of the operator and improved task performance.

II. METHODS

In this study we simulate the experience of operating swarm of drones in various environments. As part of experiment, subjects are asked to complete repetitions of two different tasks in virtual reality worlds created in Unity software.

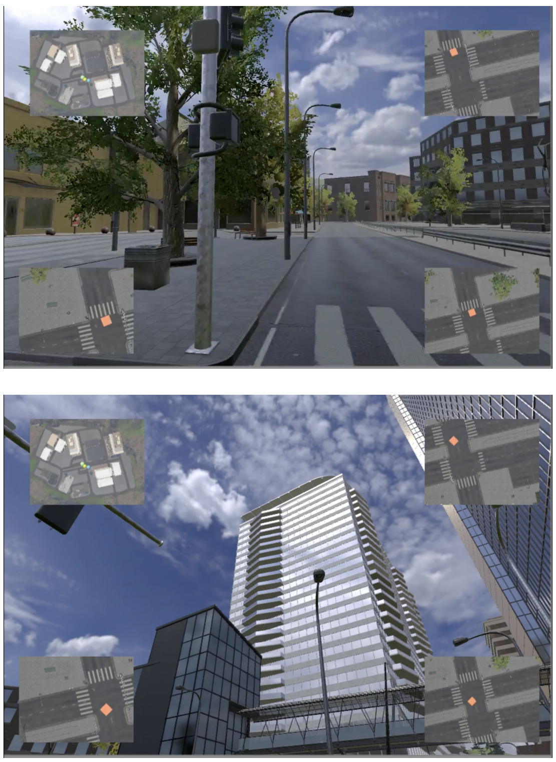

Fig. 1: Virtual reality environment created in Unity software.

The first task evaluates perception augmentation of the operator while the second task evaluates the effects of the different experimental factors on the perception of a third person observing the swarm. These tasks were chosen because increased information about the environment (i.e. perception augmentation) would assist in task completion. The participants are given different levels of control over the drone/swarm during different trials: direct control (the participant controls all movement of the drone), shared control (the participant will have control of high level surveillance goals), and no control (drone movements are fully autonomous). This study has been approved by Northwestern University's Institutional Review Board.

Each participant is completing one session lasting between 1-2 hours. Upon enrollment in the study, they are tasked with either identifying the target of interest based on the top down aerial view of the deployed swarm of drones or to race against a simulated operator to reach the object of interest. Then, they are going to participate in the search and locate task in the virtual reality setting. There is a total of 12 different trials shown in Table I testing for the following factors: number of drones, level of autonomy sharing, and environmental complexity. The order in which each condition is tested are randomized.

	Direct Control		**Shared Control**		**Full Autonomy**	
Single Drone	High	Low	High	Low	High	Low
Swarm	High	Low	High	Low	High	Low

TABLE I: Experimental design to test three independent factors: number of drones, level of autonomy, and environmental complexity.

A. Tasks

1) Search and Locate Task: Participants are being asked to search for and locate an object of interest in a virtual environment while avoiding potential hazards. Throughout this task, video feed from drone/s and the locations of the drone/s relative to the operator provide additional information about the environment to the user. The goal is to safely reach the target/s of interest in least amount of time.

We are testing different levels of drone autonomy. During direct control, the subject explicitly controls all drone movements (or leading drone in the case of a swarm) using the gaming joystick. During shared autonomy, the subject uses inferred information about the environment, to shade areas of expected information content on a TanvasTouch haptic tablet [20]. Landmarks in the environment correspond to textural and force feedback on the haptic surface and allow the user to orient themselves and locate areas of interest. The haptic tablet enables users to direct drones while continuing to visually monitor their environment. The user input is incorporated into the spatial statistics of expected information content and used to control the drones. During full autonomy, the drones ergodically explore the environment based on the expected information density generated from a measurement model of the user's visual field and sensor measurement of the environment. In cases where there are multiple drones, the video feed that is displayed to the user is chosen using image recognition of semantics [21].

2) Identification and Virtual Race Tasks: To quantify the effect of the experimental factors on the a third person's perception, we have created two test scenarios, an identification and a virtual race task.

In the identification task, participants are shown videos of simulated search and locate tasks. They are asked to identify the location of the object of interest based on the top down aerial view of the swarm formation in different complexity levels of environment and containing varying number of drones.

Order of videos shown are randomized and the correctness of their guess are not revealed to minimize any learning effects.

In the virtual race task, participants are placed in a prerecorded virtual reality of a simulated search and locate task. Based on their visual perception of the surroundings from ground level, they race to find the target before the simulated drone operator.

B. Exploration Algorithm

The exploration algorithm used for this study relies on a concept from information theory, ergodicity. A trajectory is considered ergodic if its time-averaged spatial statistics is equal to that of a reference distribution [22]. In other words, the trajectory $x(t)$ in Figure 2 is ergodic with respect to a distribution $\phi(x)$ if, for every neighborhood $N \subset X$, the amount of time $x(t)$ spends in N is proportional to the measure of N provided by $\phi(x)$, the reference spatial statistics [23]. In this case, the reference spatial statistics is the expected information density and can be determined using sensors [13] or a user input. In other work, ergodicity has been used to represent the information encoded in human movement [24] and perform drawing task [14]. The ergodic metric quantifies the similarities between the two spatial distributions [22] and is lower when the trajectory is more ergodic.

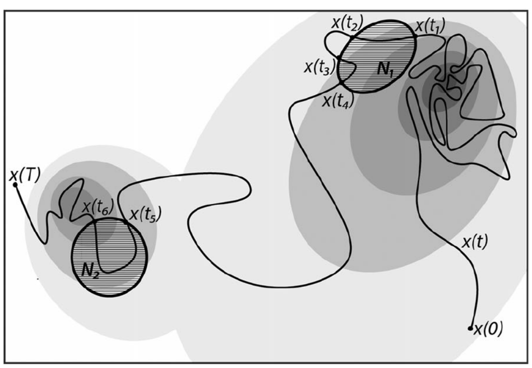

Fig. 2: An ergodic trajectory for a given probability density function from Miller and Murphey [23]. The amount of time $x(t)$ spends in N is proportional to the measure of N provided by the probability density function indicated by contour lines.

Ergodicity is computed by finding the sum of the weighted squared distance between the Fourier coefficients of the spatial distribution ϕ_k and the distribution representing the time-averaged trajectory c_k in Equation 1. Since we want the length of time a robot spends in a neighborhood to equal to the expected information content in that neighborhood, the optimal robotic trajectory will have the lowest value of the ergodic metric ε. Using Equation 1 as the objective function, ergodic control methods have been developed to generate trajectories so that the time-averaged spatial statistics approach that of a reference, either before execution of the trajectory or real-time [23, 16].

$$\varepsilon = \sum_{k_1=0}^{K} ... \sum_{k_n=0}^{K} \Lambda_k |c_k - \phi_k|^2 \tag{1}$$

where K is the number of coefficients calculated along each of the n dimensions, and k is a multi-index $k = (k_1, ..., k_n)$. The coefficients Λ_k weight the lower frequency information higher and are defined as $\Lambda_k = \frac{1}{(1+||k||^2)^s}$, where $s = \frac{n+1}{2}$. The reference Fourier coefficients and the Fourier coefficients of the trajectory $x(\cdot)$ are evaluated by Equations 2 and 3 where T is the final time of the trajectory.

$$\phi_k = \int_X \phi(x) F_k(x) dx \tag{2}$$

$$c_k = \frac{1}{T} \int_0^T F_k(x(t)) dt \tag{3}$$

The Fourier basis functions are determined by Equation 4 where h_k is a normalizing factor as defined in [22].

$$F_k(x) = \frac{1}{h_k} \prod_{i=1}^{n} cos(\frac{k_i \pi}{L_i} x_i) \tag{4}$$

C. Data Collection

The VR platform used for simulating different environments is the HTC Vive (Figure 3) with Unity software. Throughout the experiment, we are collecting various forms of biometric data that have been found to correlate with cognitive availability including eye tracking, electroencephalogram (EEG), blood pressure, and heart rate. The Pupil Labs' HTC Vive Binocular Eye Tracking has been unobtrusively installed on the HTC Vive to measure independent eye gaze, and pupil position and diameter.

Fig. 3: HTC Vive virtual reality platform [25].

Up to 32 channels of EEG signals will be gathered using Emotiv's EPOC Flex (Figure 4), a saline sensor EEG cap that participants will wear under the HTC VIVE headset.

Continuous blood pressure measurements and heart rate as well as one channel electrocardiogram (EKG) will be collected using the SOMNOtouch PSG (Figure 5) which uses a cuffless non-invasive method of data aquisition.

Fig. 4: Emotiv EPOC Flex EEG cap [26].

Fig. 5: SOMNOtouch NIBP, a cuffless solution for ambulatory blood pressure recording [27].

D. Analysis

Both tasks have been designed such that perception augmentation is crucial to task performance. Therefore, we are using task performance metrics to evaluate the effect of the autonomy allocation, number of drones, and environmental complexity on perception. In the search and locate task, we are using metrics such as time to completion and percent success. In the identification task, the perception of the third person observing the swarm movements aerially is measured by distance between the true location of the target and the predicted location by the observer. In the virtual race task, the perception of the third person observing the task within the environment while attempting to complete the same task as the operator is measured by time to completion.

For each of these metrics, a three-factor repeated measures ANOVAs will be used to evaluate significance. This statistical method will evaluate significance for each of the three independent variables: autonomy allocation, number of drones, and environmental complexity. It will also evaluate interaction effects between autonomy allocation, number of drones, and environment complexity, to determine how the optimal autonomy allocation changes in different situations. We will use the biometric data to build a machine learning algorithm to determine the cognitive availability of the user real-time in collaboration with Siemens.

III. Anticipated Results

Both the human and the autonomy have valuable knowledge about the environment and the areas in which it is most beneficial to explore. Combining the knowledge of expected information content from the human and autonomy into the shared control architecture will result in more helpful drone exploration, increased perception augmentation of the operator, and improved task performance. The level of control allocation is a spectrum that ranges from direct control (no control autonomy) to full autonomy. There is a region of optimal control allocation in which the system as a whole is most efficient at completing the task at hand as shown in Figure 6. Since our shared control method lands in between direct control and full autonomy, there will be significantly better task performance in the middle region compared to the end cases.

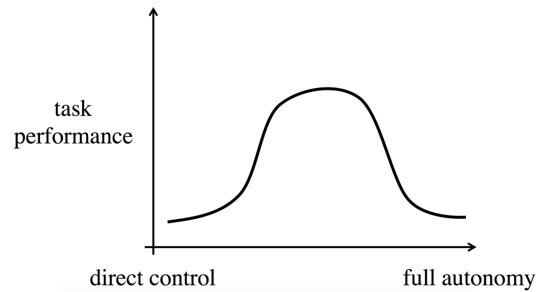

Fig. 6: Task performance vs. level of autonomy

The number of drones and complexity of the environment will have a significant effect on task performance and autonomy allocation. A swarm of drones as opposed to a single drone have greater sensing capabilities, and therefore will result in better perception augmentation and task performance. As the complexity of the environment and number of visual obstructions increase, perception augmentation through autonomy will have a greater benefit to task performance. Antithetical to perception augmentation, an outside observer will experience more perception degradation when drones are ergodically controlled compared to directly controlled scenarios.

IV. Future Work

Using the biometric data, we will build a machine learning model to determine the cognitive availability of the user real-time in collaboration with Siemens. The biometric data-driven model of cognitive availability in combination with ergodic control enables us to provide adaptable autonomy according to cognitive availability of the operator. With ergodic control, we can provide a continuous spectrum of autonomy allocation between direct control and full autonomy by weighing the user input, in this case according to cognitive availability of the operator. In later experiments, participants could complete similar surveillance tasks with the assistance of physical drones with an augmented reality surveillance system in which the level of autonomy changes according to cognitive availability.

As the cognitive availability of the operator changes during the completion of a task, the most appropriate level of control allocation will change as well. Figure 7 illustrates how we expect the autonomy allocation to relate to the cognitive availability of the operator to pursue other tasks. When cognitive

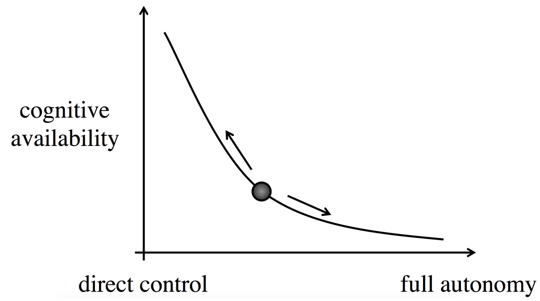

Fig. 7: Autonomy allocation update based on cognitive availability of the operator for optimal task performance.

availability of the operator is high, shifting control allocation in the direction of direct control is the better choice. However, when the cognitive availability is low due to the cognitive demands of other tasks, shifting the control towards full autonomy would be the preferred choice to distribute the workload. For individuals performing both a search and rescue task and a short term memorization task simultaneously, adapting the search and rescue autonomy according to the cognitive availability of the user leads to improved memorization task outcomes [9]. We expect this paradigm of adaptable autonomy to lead to similarly improves outcomes.

V. Conclusions

This paper presents a proposed method of shared human-swarm control and our experimental design to evaluate the effectiveness of incorporating a human input in robotic exploration. If our method of shared control leads to improved task performance, it would suggest that including an intelligent operator input directly into the control loop could improve the quality, efficiency, and robustness of robotic exploration. It would indicate that our approach is a useful way to leverage human's knowledge and strength of autonomous systems in order to create an interface that takes into consideration end goal requirements as well as real-time operator needs. In the future, it can be used to create adaptable autonomy according to the cognitive availability of the operator. This work and shared control paradigm can be extended to improve other applications of human-robot interaction and robotic exploration.

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