Mission Planning for Coupled Human-Robot Teams Using

Adaptive Human Performance Models

by

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Abstract

The increasing prevalence of autonomous robots in a variety of domains has motivated
the development of task allocation and scheduling algorithms which enable cooperative
multi-robot teams to execute missions in a coordinated fashion. These missions
often entail completing discrete tasks in distinct locations to maximize reward (e.g.
information) while minimizing cost (e.g. fuel and time) and adhering to spatial and
temporal constraints (e.g. vehicle dynamics and task time windows). Traditional
problem formulations typically assume the team to be composed entirely of independ-
ent, autonomous vehicles. However, many current and future applications require
tight coordination between humans and autonomous systems.

Existing algorithmic approaches to multi-agent planning do not extend well to
operations in which humans cooperate closely with robotic teammates due to the
dynamic and stochastic nature of human performance. Reliable prediction of human
task execution is challenging, and even proven models are subject to time-varying
characteristics (e.g. fatigue and distraction) as well as differences between individuals
(e.g. experience and skill). The difficulty of accurately modeling human performance
demands a planning architecture that is highly responsive to heterogeneous, hard-to-
predict agents.

This thesis presents fast algorithms that integrate humans into the planning prob-
lem using well-established models from the human factors community to produce task
allocations and schedules for tightly coupled human-robot teams. Humans are treated
as dynamic agents, and feedback from their realized performance is leveraged to adapt
agent models in real-time. The efficacy of this approach is investigated through mul-
tiple experiments involving human interaction with simulations of unmanned aerial
vehicles (UAVs). Results indicate that adaptive human performance modeling pro-
vides distinct advantages in the context of mission planning for human-robot teams.

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Man is not as good as a black box for certain specific things. However he is more flexible and reliable. He is easily maintained and can be manufactured by relatively unskilled labour.

Wing Commander H. P. Ruffell Smith, RAF, 1949
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Chapter 1

Introduction

1.1 Motivation

The increasing prevalence of autonomous robots in a variety of domains has motivated the need for task allocation and scheduling algorithms to enable multi-robot teams to execute missions in a coordinated fashion [43]. Modern examples of these missions – particularly with the recent proliferation of unmanned aerial vehicles (UAVs) – include commercial package delivery [51], precision agriculture [123], forest fire response [24], and intelligence, surveillance, and reconnaissance (ISR) operations [1, 44]. Such missions can often be represented as accomplishing a set of discrete tasks in distinct locations (e.g. servicing customers or surveying points of interest) to maximize reward (e.g. revenue or information) while minimizing cost (e.g. fuel and time) and adhering to spatial and temporal constraints (e.g. vehicle dynamics and task time windows).

Existing algorithmic approaches typically assume the team to be composed entirely of independent, autonomous vehicles. However, many current and future applications require tight coordination between humans and autonomous systems [38].

A conceptual scenario for a human-robot team performing an ISR mission is depicted in Figure 1-1. UAVs autonomously fly to areas of interest and acquire real-time on-site sensor imagery without human involvement [17]. Human operators then immediately classify the provided imagery and handle overall mission supervision and high-level goal specification [63]. The multi-agent team is coordinated by an au-
tonomous planner that assigns both the human and vehicle tasks in order to optimize mission efficiency. This collaborative effort leverages the strengths of humans (e.g. perceiving visual imagery and flexible problem solving) as well as autonomous systems (e.g. distributed sensing and optimizing complicated processes) to facilitate an effective approach to this operation [22, 40]. However, there are several key research challenges associated with achieving such a level of human-machine cooperation.

Multi-agent task allocation itself is computationally demanding, as it involves solving complex combinatorial decision problems (NP-hard) [15]. Requiring human operator cooperation with robotic teammates for the completion of tasks adds additional layers of complexity by thrusting coupled agent constraints and stochastic, dynamic performance into the planning problem. Reliable prediction of human task execution is difficult, and even proven models are subject to time-varying characteristics (e.g. fatigue and distraction) as well as differences between individuals (e.g. experience and skill) [26]. Consequently, the difficulty of accurately modeling humans demands a planning architecture that is responsive to hard-to-predict agents.

This thesis presents a planning framework that efficiently and effectively assigns cooperative tasks to a heterogeneous human-robot team. Humans are treated as dynamic, unpredictable agents whose performance must be modeled using flexible closed-loop strategies. Finally, all innovations undergo comprehensive human-in-the-loop testing to analyze their potential in realistic situations.
1.2 Literature Review and Analysis

Several areas of research address various aspects of mission planning for coupled human-robot teams. These include human-machine collaboration, multi-agent task allocation and scheduling, and human performance modeling. Relevant state-of-the-art strategies and their corresponding unsolved challenges are outlined in this section to motivate the efforts of this thesis, and a technical background on each topic is presented in the next chapter.

Recent trends in research have highlighted the notion that many applications require a shift in perspective away from designing autonomy to fully replace humans to a more synergistic approach in which human and autonomous elements complement one another [38, 73]. A significant effort towards effective human-machine collaboration has been the design of flexible autonomy to interact with humans at appropriate levels and with robustness [36, 49]. Studies have produced planners that enable a single robot to dynamically execute a shared plan with a human teammate [45, 102], but they have not been extended to missions with multiple robots. Other efforts have developed intelligent task management strategies for human operators that regulate and optimize over human workload parameters throughout mission execution [97, 108]. However, these queuing policies do not consider multi-agent applications with coupled constraints or dynamic parameters. Additional work has enabled human operators to dynamically modify mission goals for automated planners in human-robot missions, but humans are treated as supervisors rather than having direct roles in mission tasks [28]. Lastly, several strategies focus on adjusting levels of automation (i.e., autonomous system roles in relation to human roles) for addressing dynamic mission demands, but they too approach the problem from a human supervisory control standpoint rather than a coupled multi-agent planning perspective with flexible human performance modeling [61, 62, 120].

Multi-agent task allocation and scheduling has been considered through a variety of approaches [88], but the challenges of integrating humans into the planning problem have not been addressed. The basic problem formulation can be reduced to a
mixed-integer program with binary decision variables for the allocation of tasks and continuous decision variables for task scheduling [88]. Exact optimization methods for these mixed-integer programs generally exhibit poor scalability, as computation time increases exponentially with the size of the problem space (i.e. number of agents and tasks) [41]. Thus optimal solution strategies are usually deemed intractable for the large, dynamic, highly-constrained problems that are associated with human-robot teaming applications. This inability to handle most realistic situations has led to the creation of a number of approximation techniques [15]. One such approach that incrementally assigns tasks, referred to as sequential planning, has been shown to be viable for many problems of interest, producing provably-good approximate solutions in polynomial time [27]. But while efficient sequential algorithms with the ability to handle time-varying score functions and coupled constraints do exist [86, 116], they do not optimize well over tight agent coupling or consider the dynamic and stochastic agent performance that is addressed in this thesis. Additionally, task allocation for a relatively static, uncoupled human-robot team has been considered previously [87], but a framework for strictly coupled planning between dynamic humans and multiple robotic teammates has not yet been developed.

Accurate modeling of human performance is a necessary condition for effective planning in applications involving human agents. The field of human information processing has produced a variety of models concerning the evaluation of perceptual imagery, context switching between taskings, situational awareness representations, and workload considerations [37, 117]. Probabilistic models of trade-offs between speed and accuracy can provide useful tools for predicting human task duration as it relates to accurate imagery classification [21, 85]. Other efforts demonstrate that providing time between perceptual tasks improves overall human performance [75, 95]. Finally, studies involving human interaction with multiple UAVs establish quantitative workload thresholds for human operators [32, 33]. These models are all relevant to the allocation and scheduling of coupled human-robot tasks, as they predict time needed for successful human task completion and the rate at which new demands can be presented. Still, such modeling techniques have important limitations when
viewed in light of heterogeneous, dynamic human agent behavior [26]. Rather than fully relying on the predictive power of these simple models, the work in this thesis aims to demonstrate that their inclusion as priors in an adjustable framework is an effective approach to planning for human-robot teams.

There are many unresolved challenges to address before human-robot teaming missions like the one illustrated in Figure 1-1 can be fully realized. The goal of this research is to create effective approaches to mission planning for highly coordinated human and autonomous agents. An efficient, polynomial-time sequential planner is developed to enable task allocation and scheduling for coupled human-robot teams. Performance models from the human factors community are incorporated into the planning problem to generate solutions that conform to human heuristics and constraints. Instead of relying fully on the models’ predictive power, an efficient closed-loop planning framework is utilized. Flexible agent models that recognize and adapt to varying human performance and operator input throughout complex missions are used to alleviate the challenges of heterogeneous, dynamic human behavior.

1.3 Thesis Contributions and Layout

The remaining chapters of this thesis proceed as follows:

- Chapter 2 provides a technical background to ground this research in the fields of human-machine collaboration, multi-agent task allocation and scheduling, and human performance modeling.

- Chapter 3 addresses mission planning for coupled human-robot teams. Methods are discussed for integrating human operators into the traditional task allocation and scheduling problem using well-established human factors models, developing a sequential, polynomial-time planner to generate solutions quickly for heterogeneous, highly-coupled human-robot teams, and designing a closed-loop planning framework to adapt to dynamic and stochastic human agent parameters in real-time.
• Chapter 4 presents a pilot study to evaluate the interactions between a single human operator and multiple simulated UAVs. The construction of a user interface to enable human-robot teaming is also discussed. Results show that flexible human models which leverage realized task execution information to adapt planning parameters in real-time can improve overall mission performance for tightly coordinated human-robot teams.

• Chapter 5 showcases a human-in-the-loop experiment in which multiple human operators interact with multiple UAVs. Improvements to the interface, modeling approaches, and experiment procedure are explained. Results demonstrate that flexible human models which leverage actual performance and allow operator adjustment can lead to more effective (and enjoyable) human-robot teaming.

• Chapter 6 presents this effort’s conclusions, summary of contributions, and avenues for future work.

• In addition, Appendix A provides the script for the multiple-operator experiment discussed in Chapter 5, Appendix B presents questionnaires from Chapter 4’s single-operator pilot study and Chapter 5’s multiple-operator experiment, and Appendix C gives in-depth data acquired from both experiments.

A portion of this thesis’s content is based on work published in the following conferences:


Chapter 2

Background

This chapter presents a review of human-machine collaboration, cooperative multi-agent planning, and human performance modeling in order to ground this research in the relevant fields. Existing ideas are examined and synthesized to provide a technical basis for the contributions of this thesis.

2.1 Human-Machine Collaboration

Autonomous systems have the potential to augment human performance and enable new operational capabilities in domains ranging from the depths of the ocean to the outer reaches of space [73, 100]. Human-machine collaboration addresses the integration of these systems into applications involving humans to leverage the relative strengths of human and machine [22]. This collaboration may be thought of as being human-centered, in that the machine conforms to human behavior [3, 12, 18], or automation-centered, where the human acts as a supervisor, guide, or safety net to the overall system [10, 23]. Other mixed-initiative approaches require shared responsibility, cooperation, and support between human and autonomous elements for the accomplishment of mutual goals [69, 79].

Significant attention has been paid to defining success in human-machine collaboration. Objective system-derived metrics can detail aspects of mission effectiveness such as task response time, speed of accomplishment, task accuracy, area coverage,
mission makespan (total length), and distance traveled [80, 109]. Subjective metrics may include operator confidence, usability, automation transparency, and trust in the system [59, 117]. There has also been work to formulate metrics specific to human-robot interaction, like *robot attention demand* (i.e. fraction of human’s time spent interacting with a machine), *fan out* (i.e. number of robots that a user can operate at once), and *functional delay* (i.e. time between completion of one agent’s action and beginning of the other’s action) [29, 56, 80]. These measures shed light on how effective human-machine collaboration should operate and point to the challenges of achieving such aims.

Collaboration between humans and autonomous systems is inherently demanding, as it requires the coordination of flexible, dynamic, and often unpredictable human behavior with typically prespecified, rigid algorithmic reasoning. Operator trust should be properly calibrated with sufficient knowledge, training, and system transparency [99]. Situational awareness should be maintained in all system configurations and contexts [37, 54]. Workload should be moderated throughout human-machine missions even as levels of demand on the human may vary; this often requires simplified models or active monitoring of the operator’s state [30, 78, 93]. Autonomous systems should be robust to differences between individuals, such as how they choose to interact with the system or how well they perform on tasks [25]. Finally, suitable interfaces or other mechanisms for collaboration are necessary for seamless cooperation between humans and machines [124].

A strategy for dealing with some these challenges is to create autonomy that has flexible authority within the human-machine system [61]. The work of Parasuraman et al. provides a model for types and levels of human interaction with automation that defines the range of control authorities between human and machine as a discrete set of levels of automation (Figure 2-1) [83]. These levels span from fully manual control to complete autonomy and may differ among the various stages of human information processing (to be discussed in detail in Section 2.3) [91]. Varying a system’s level of automation has generally been the preferred method of achieving flexibility and robustness in human-machine collaboration [82].
these levels of automation throughout mission execution, termed *adaptive autonomy*, leverages human models, realized operator performance, mission events, or real-time physiological assessment to trigger a change in the automation’s role [60, 62, 112]. These adaptations can provide benefits in overall mission performance, trust in the autonomy, moderation of workload, and numerous other factors [35, 48]. An alternative to autonomous adjustment of the human-machine system is to allow the operator himself to adapt the level of automation, coined *adaptable autonomy* [65, 71, 113]. This can enhance the user’s control of the environment, which has been shown to help in terms of change detection, system transparency, and overall user satisfaction within a variety of domains [62, 96].

This research draws upon work in adaptive and adaptable automation strategies for effective human-robot collaboration. Past work has compared autonomous versus human-invoked adjustments for supervisory control of multiple autonomous vehicles [62], aircraft crewmember flight activities [9], process control [96], air traffic management [65], and many other applications [61]. An important commonality among these studies is that they all focus on autonomous versus human authority over dynamic function allocations between human and machine (e.g., whether the human or automation is responsible for certain tasks). Chapters 4 and 5 of this thesis, however, provide a new perspective on adaptive and adaptable systems, experimentally investigating manual versus autonomous adjustments to agent *models* rather than agent...
roles. Function allocations between human and autonomous elements are fixed, and instead human performance models (and thus multi-agent coordination and mission pacing) are dynamically adapted to optimize overall effectiveness. In adaptive conditions, the autonomous system leverages realized human performance to update human modeling parameters, enabling predictive models to better reflect actual agent abilities. In adaptable conditions, human operator input directly shifts underlying performance models, giving the user more authority over future task assignments. Effects on performance, awareness, workload, and satisfaction are compared between these approaches to investigate the use of flexible autonomy in a fresh context.

2.2 Multi-Agent Planning

Autonomous task allocation and planning algorithms must coordinate heterogeneous, networked agents to accomplish complex sets of objectives efficiently and effectively [114]. This requires careful consideration of mission goals, costs, resources, and constraints as well as proper spatial and temporal synchronization of the individual agents [88]. Due to the myriad of possible multi-agent compositions, mission specifications, and network configurations for these problems, many solution strategies have been proposed in recent years.

Major organizational paradigms used to structure multi-agent systems include hierarchies, holarchies, coalitions, teams, congregations, societies, federations, markets, and matrices [57]. Each of these group compositions has their own advantages and drawbacks, but agent teams – in which cooperative agents work together toward common goals [13, 42, 111] – are the focus of this research. Three of the most common autonomy planning frameworks for multi-agent teams are Markov Decision Processes (MDPs), Game Theory, and Integer Programming [88]. MDPs treat multi-agent allocations as stochastic sequential decision making problems, but they often suffer from poor scalability or excessive tuning of algorithm parameters [52, 81]. Game theory addresses the multi-agent planning problem by representing agents as individual decision makers that maximize their own local reward [8, 39]. Therefore, this approach
is typically more well-suited for modeling non-cooperative or very decentralized environments [70]. Integer Programming models task allocations amongst agents as binary decision variables and optimizes in terms of a global reward function while enforcing problem constraints [15, 41]. This planning framework has been considered extensively in the literature and provides representations for most cooperative multi-agent problems of interest [11, 68, 84, 106].

Integer Programming-based algorithmic approaches to mission planning for multi-agent teams can be classified as either exact optimization methods or approximation (i.e. heuristic) strategies [88]. Exact optimization (e.g. Branch and Bound [67], Dynamic Programming [14], and Constraint Satisfaction [122]) yields optimal solutions to planning problems, but the computational complexity involved in these algorithms makes them intractable in many situations [15]. Due to this difficulty, approximations have been developed to decrease computation time. Heuristics such as two-phase methods [66], receding horizon techniques [5], and domain-specific mixed-integer linear programming formulations [4] have been created, but the majority can still be too computationally intensive for real-time planning in highly constrained, complex environments [88]. Despite these challenges, a heuristic approach that has been shown to work well in real applications with multiple autonomous vehicles is sequential planning [27]. Under this strategy, tasks are incrementally assigned to members of the team, thereby drastically simplifying the hurdle of computational complexity. Sequential planning has also been investigated as a useful tool for decentralized task allocation, where market-based strategies are implemented to provide robustness to communication constraints [86], as well as for stochastic planning problems, in which parameters are represented as known probability distributions and planners explicitly hedge against uncertainty [2, 89]. However, the topics of decentralized planning and planning under explicit uncertainty are outside the scope of this thesis.

Integer Programming solution algorithms provide predictive plans for multi-agent teams that maximize global objective functions while adhering to problem constraints. But even the most robust plans can become ineffective in the face of real-world scenarios with dynamic environments, changing mission goals, and unpredictable agent
behavior. Therefore, real-time planning that leverages up-to-date information from actual mission execution is important for many applications [88]. Needing to be responsive to unexpected planning configurations further motivates the use of efficient algorithms embedded in closed-loop frameworks. Autonomous planners that dynamically schedule tasks for multi-agent teams can provide mission flexibility, satisfying timing requirements despite temporal perturbations [46, 76, 101, 118]. Other algorithms are tailored to task allocation for multiple autonomous vehicles in dynamic environments, achieving near-optimal performance with feasible computation times for real-time implementation [5, 7]. Finally, several approaches combine multi-agent planning with reinforcement learning for more intelligent planner responses to dynamic scenarios or modeling errors [94, 110]. These strategies inspire a real-time planning framework, outlined in Chapter 3 of this thesis, with responsive agent modeling that is enabled by fast, sequential assignment Integer Programming algorithms.

2.3 Human Performance Modeling

Effective planning for human-robot teams requires thorough understanding and accurate modeling of human performance. A model for the stages of human information processing (shown in Figure 2-2) provides a representation of various psychological processes which can be applied to human interaction with machines [117]. The framework describes a series of mental operations that generally characterize information flow as tasks are performed. Beginning from the left, the environment is first processed by human senses (e.g. sight, sound, smell, touch, etc.). Attention and memory then derive meaning from the sensory information in the perception stage. The perceived meaning may trigger an immediate selection and execution of a response, or it may be retained in working memory or cognition for subsequent use. Either way, information processing is modeled as a closed-loop architecture in which feedback, memory, and cognition provide important context for future information. This conceptualization of human information processing as a series of distinct stages can be useful for analyzing systems or tasks and for formulating more specific models of human performance.
The time duration from sensory imagery input to successful response execution is an essential metric for human performance. As alluded to previously, experience (i.e. long-term memory) and natural skill may vary significantly between individuals. Still, numerous human factors models use the general principles of information processing to adequately describe human performance (encompassed by speed, accuracy, and attentional demand [117]) for a range of tasks, systems, and environments. Specifically, representations for decision making under time pressure and uncertainty are applicable in the context of imagery comprehension and classification (recall Figure 1-1) [16]. These models can generally be reduced to depictions of trade-offs between speed and accuracy, and the information gathering process can be abstracted to a stochastic diffusion process in which information is noisily accumulated until some probabilistic accuracy threshold is met [21]. One of the most long-standing descriptions of this speed-accuracy operating characteristic is referred to as Pew’s model (Figure 2-3a), where the probability of a correct decision in a binary choice evolves over time according to a sigmoidal function [85]. These functions differ between individuals, and external factors like mission requirements for time versus precision may affect the decision’s probabilistic accuracy threshold. In fact, some human-machine systems attempt to maximize reward functions by optimizing and adapting the speed-accuracy trade-off using task release control in operator task queues [21, 107, 108].

In addition to the speed and accuracy of information processing on individual tasks, time between tasks can be equally important to overall human performance.
This refers to the principles of context-switching [75], in which time between successive responsibilities allows the human’s attentional resources (Figure 2-2) to “reset” for new assignments. Models that present connections between rapid context switching and performance degradations illustrate the notion that allowing breaks between tasks is important for effective mission execution, even in time-pressured environments [74, 95]. This moderation of cognitive demand has also been viewed from the perspective of overall workload thresholds [33]. These models often draw from the empirical relationship between arousal (i.e. level of activity) and performance [121], or they may represent human performance as a function of the relation between cognitive resource supply and demand [117]. Such representations can be utilized to design human-machine interaction schemes which maintain operator activity levels within some beneficial range (i.e. preventing boredom or overwhelming demands) to promote optimal performance, awareness, and satisfaction (Figure 2-3b) [77, 97, 98]. Chapter 3 describes in detail the use of Pew’s model for predicted human task duration, temporal buffers between consecutive operator assignments, and a workload threshold model to mitigate human overload throughout human-robot teaming missions.

2.4 Summary and Applications

Research on human-machine systems has identified both the considerable potential and complex challenges of synergistic collaboration between humans and autonomy. This thesis explores autonomous planning for coordination of coupled human-robot
teams, aiming to achieve high levels of mission effectiveness, team fluency, and operator confidence. Parasuraman’s types and levels of automation can be used to formulate a human-robot team composition (Figure 2-4) that is representative of the conceptual scenario presented in Chapter 1 (Figure 1-1). Under this mission context, information in the form of sensor data is acquired by the fully autonomous vehicles, information analysis (e.g., classification of real-time on-site video imagery) is the sole responsibility of the human, decision selection is handled by the autonomous planner allocating and scheduling tasks amongst the human-robot team, and flying actions in the mission environment are handled by the autonomous UAVs. These agent roles provide grounded mission scenarios which showcase the system’s ability to effectively coordinate teams of highly cooperative humans and autonomous robots.

The roles depicted in Figure 2-4 indicate that the mission planning algorithm must assign joint, synchronized tasks to a tightly coupled human-robot team. Algorithms based on the framework of Integer Programming are developed to sequentially assign these tasks amongst the multi-agent team in an efficient manner. As described at the onset of the next chapter, both the global reward function and the problem...
constraints incorporate human operator considerations into their formulations. The algorithmic efficiency of the approach enables real-time planning to adapt to dynamic agents and environments, which is particularly important due to the unpredictable, heterogeneous nature of humans.

The field of human information processing provides useful human performance models for decision making accuracy and speed, task switching considerations, and workload thresholds. Specific model and heuristic implementations into the algorithmic framework are presented in the following chapter. Instead of adjusting the autonomous machine’s control authority throughout mission execution, agent roles are fixed and the human performance models themselves are adapted within a closed-loop modeling architecture using both adaptive and adaptable strategies. Figure 2-5 illustrates a simplified schematic of this closed-loop framework which provides feedback from the realized state of the system or actual user input in order to update planning parameters in real-time. The remainder of this thesis outlines the models, algorithms, interaction schemes, and experiments that demonstrate the efficacy of this approach towards autonomous mission planning for coupled human-robot teams.
Chapter 3

Mission Planning for Coupled Human-Robot Teams

This chapter presents a new algorithm that has been developed in order to address the challenges of mission planning for highly-coordinated human-robot teams. The Allocation and Scheduling of Supervisor-Involved Surveillance Tasks (ASSIST) algorithm efficiently and effectively allocates and schedules discrete tasks to tightly coupled human-robot pairs (i.e. tasks require synchronized temporal commitment from both the human and autonomous agent for their entire duration) to maximize expected mission performance while adhering to human operator heuristics and constraints (e.g. workload thresholds and context switching). The generalized planning problem, solution approach, and performance over alternative strategies are discussed in detail. Additionally, the ASSIST algorithm is incorporated into a closed-loop time-extended planning framework to adapt human and environment models in real-time. Simulations of complex multi-agent missions demonstrate that this adaptive modeling approach can address the challenges of planning for heterogeneous, dynamic, stochastic agents such as human beings.
3.1 General Problem Statement

This section reviews the general multi-agent task allocation and scheduling planning problem and formalizes the extensions that are addressed in this effort. Given a set of $N_h$ human operators, $N_a$ autonomous agents, and $N_t$ tasks, the planner assigns joint tasks to coupled human-robot pairs such that global reward is maximized without violating constraints on vehicle dynamics or human cognitive effort. The overall mission objective is the sum of all individual agent objective functions. Each of these local rewards are a function of all the tasks assigned to the respective human-robot pair and the times at which the tasks will be executed. This planning problem can be written as the following mixed-integer (possibly nonlinear) program with binary decision variables $x_{ij}$ that indicate whether task $j$ is assigned to autonomous agent $i$ and $y_{kj}$ that indicate whether task $j$ is assigned to operator $k$:

$$
\max_{x,y,\tau} \sum_{k=1}^{N_h} \sum_{i=1}^{N_a} \sum_{j=1}^{N_t} S_{ijk}(x_i, y_k, \tau) x_{ij} y_{kj}
$$

s.t. \hspace{1cm} G(x, y, \tau) \leq b \hspace{1cm} (3.1)

Here $x \in \{0, 1\}^{N_a \times N_t}$ and $y \in \{0, 1\}^{N_h \times N_t}$ are the allocation decision variable matrices, and $\tau \in \{\mathbb{R}^+ \cup \emptyset\}^{N_h \times N_a \times N_t}$ is the three-dimensional set of time durations $\tau_{ijk}$ in which each element consists of a tuple that indicates the start and end times that the agent-operator pair $i$ and $k$ will execute task $j$ ($\tau_{ijk} = \emptyset$ if the agent pair $i$ and $k$ have not been assigned task $j$). $S_{ijk}$ is the score that human $k$ and vehicle $i$ achieve for servicing task $j$, which will be explored in detail in the next section.

The optimization is subject to a set of constraints, $G(x,y,\tau) \leq b$, where $G = [g_1, ..., g_{N_c}]^T$ and $b = [b_1, ..., b_{N_c}]^T$ are $N_c$ possibly nonlinear constraints that capture timing requirements, resource limitations, and vehicle transition dynamics, as well as constraints on the human operator’s attention capabilities and thresholds. Addition-
ally, fundamental constraints inherent in this task allocation problem are that only a single human and vehicle pair can be assigned to a task, and that each task is assigned only once. This problem statement can be used to represent most multi-agent task allocation applications for highly coordinated human-robot teams.

### 3.2 Objective Function

The planner’s objective function, referred to as the score $S_{ijk}$, is a function of the operator’s and autonomous agent’s full assignment as well as the task execution time. This scoring function is a summation of the task completion reward, the autonomous vehicle cost associated with incrementally assigning this task conditional on the existing assignment (e.g. extra fuel required for new tasking), and the operator cost incurred from the supervisory task assignment (e.g. additional workload). For example, a highly valued piece of imagery captured at the opportune time by a compatible autonomous vehicle and synchronously analyzed by an available human operator would be much preferred over a low-priority task executed too late by a vehicle that was required to travel a long distance and a human who was already overworked.

This multi-objective optimization of task, vehicle, and human considerations provides synergistic plans for time-critical missions executed by heterogeneous human-robot teams. By encoding human performance metrics directly into the planning problem, ASSIST is able to generate schedules that conform to human abilities and limitations, ultimately alleviating some potential for degraded operator performance. Additionally, the models that relate the planner’s objective function to actual mission performance can be adjusted in real-time in order to meet the needs of the mission at hand. ASSIST’s objective function is presented as Equation 3.2:

$$S_{ijk}(x_i, y_k, \tau) \equiv \text{VAL}(j, \tau_{ijk}) - \text{FUEL}(i, p_i^a, p_j^t, w_{ijk}) - \text{OP}(k, j, \tau_{ijk} | y_k) \quad (3.2)$$

The algorithmic framework assumes a reliable communication network in which the human operator acts as the centralized component, interacting with unmanned
agents on an individual basis to accomplish cooperative human-robot tasks. Such a team composition can be thought of as a *hub and spoke* framework. This introduces tight agent coupling into the task allocation and scheduling problem that must be accounted for in the planning process.

### 3.2.1 Task Values

The first term in the planner’s objective function, $V_{AL}(j, \tau_{ijk})$, represents the value of successful, timely task completion. This work addresses tightly coupled, discrete human-robot tasks in which every task requires a coordinated effort from one human operator and one unmanned vehicle throughout its duration. One such example of this type of synchronized joint task is the need for immediate operator classification of real-time, on-site video imagery provided by the remote autonomous vehicle [44] discussed in Chapter 1 (Figure 1-1). Indeed, this task description – motivated by current and future demands concerning unmanned systems – influences design considerations throughout this work.

The allocation framework is able to plan over large, heterogeneous, time-varying sets of tasks whose values can take any functional form. The three task value functions utilized in this planning approach are functions of their respective execution times. This allows for time windows of validity and mission objectives that penalize late or early arrivals [90]. Task time windows can be implemented as

$$u(j, t) = \begin{cases} 1, & t_{\text{start}} \leq t \leq t_{\text{end}} \\ 0, & \text{otherwise} \end{cases} \quad (3.3)$$

where $t$ is the execution start time. Time-critical tasks can be subjected to time decay functions such as

$$v(j, t) = v_{0j} e^{-\lambda_j(t-t_{\text{start}})} \quad (3.4)$$

where $v_{0j}$ is the task’s maximum value and $\lambda_j$ is a task-specific decay rate. Notice that a value of zero for the decay rate would represent a task in which time is not
a factor. Alternatively, objectives that do not have a distinct time window or decay rate but rather should be accomplished around a specific time may be modeled with Gaussian distributions:

$$v(j, t) = v_0 e^{-\frac{(t-t^*)^2}{2\sigma^2_j}}$$  \hspace{1cm} (3.5)

where $\sigma_j$ is a task-specific parameter to penalize service times away from the desired time $t^*$. The resulting task value for agent $i$ and operator $k$ servicing task $j$ is then computed as $\text{VAL}(j, \tau_{ijk}) = u(j, \tau_{ijk}) v(j, \tau_{ijk})$. Figure 3-1 illustrates these three temporal value functions. A typical mission may involve tasks with all three functions (and their combinations) with a variety of optimal values.

3.2.2 Autonomous Agents

While the concepts of this effort can be generalized to a wide range of human-robot missions, the current work focuses on unmanned aerial vehicles (UAVs) as robotic teammates. Heterogeneous teams consisting of various UAV types with differing velocities, fuel costs, and capabilities are accounted for in the optimization problem. The planning approach assumes reliable task completion on the part of the UAVs, and vehicle dynamics have been simplified to point masses with constant velocities between locations in a two-dimensional world. As the optimization objective function’s second term, fuel cost is a function of the vehicle’s type, the Euclidean distance between its current location and the proposed task, and the amount of time the UAV must wait for a human operator to become available. Equation 3.6 gives the fuel cost.
for vehicle $i$ at location $p_i^a$ traveling to task $j$ at $p_j^t$ and waiting for time $w_{ijk}$:

$$\text{Fuel}(i, p_i^a, p_j^t, w_{ijk}) = f_i^v ||p_j^t - p_i^a|| + f_i^w w_{ijk}$$  \hfill (3.6)

where $f_i^v$ is the vehicle’s fuel cost rate during travel and $f_i^w$ is the rate while waiting. These coefficients are set $a$ priori according to vehicle and mission specifications. In addition to fuel cost, vehicle velocity is important for the multi-agent planning framework as it determines scheduling constraints and time-based task rewards.

### 3.2.3 Human Agents

As introduced in Section 2.3, two well-established models from the human factors community are used to create predictive mission plans for human-robot teams. They were chosen based on their relevance to the allocation and scheduling of coupled human-robot tasks, as they predict time needed for successful task completion and the rate at which new demands can be presented. Rather than fully relying on the predictive power of these simple models, this work demonstrates that their inclusion as planning priors into an adaptive framework is an effective approach to planning for human-robot teams.

The final term in the planner’s objective function (Equation 3.2), $\text{OP}(k, j, \tau_{ijk} | y_k)$, captures the human operator’s impact on the value of a task assignment. This term draws from a model that relates human workload to actual performance using the metric of operator busy time over total mission time, referred to as $\text{utilization}$ [77]. This relation – derived from an inverted Yerkes-Dodson curve [121] – has been shown to correlate closely with actual human-in-the-loop empirical data in missions involving supervisory control of multiple UAVs [33].

The model is implemented as a cost function which penalizes the allocation and scheduling of tasks that will exceed an operator’s workload threshold according to this model. This cost function’s prior is shown in Figure 3-2a, which leverages previous empirical data that indicates 70% utilization as an appropriate threshold for human interaction with multiple UAVs. The operator cost within the task allocation and
(a) Operator cost function included in multi-objective optimization [77]

(b) Pew's model [85] with deterministic choice on expected accuracy

Figure 3-2: Human supervisory control performance models to be treated as planning priors and updated within the closed-loop planning framework

scheduling framework, then, can be derived from the human’s current assignment set, the proposed task, and the time to schedule the task: $O\!P(k, j, \tau_{ijk} | y_k)$. In other words, ASSIST’s objective function will effectively penalize proposed schedules that exceed the specified temporal workload threshold. This measure of current and proposed operator utilization may be calculated over rolling windows of any time length; for simplicity, this work implements computations over full mission duration windows.

In addition to influencing the planner’s objective function, human-robot cooperation implies coupled scheduling constraints on the mission planning problem. This work draws from past strategies for managing human operators’ schedules which analyze the trade-off between completing tasks quickly and providing ample time for human judgment [108]. As discussed in Chapter 2, prediction of human task duration can be derived from Pew’s model, which states that the correctness of a human operator decision in a binary choice evolves as a sigmoidal function of time allotted to the task [85]. Specifically, the probability of correctness (or success) at time $t$ is

$$P(\text{success}) = \frac{p_0}{1 + e^{-(at-b)}} \quad (3.7)$$

where parameters that depend on the human are $p_0 \in [0, 1]$ and $a, b \in \mathbb{R}$. The probability of correct decisions may be optimized [108] or chosen depending on mission requirements to balance speed versus accuracy. The results contained in this thesis
Algorithm 3.1 ASSIST(ℐ, ℤ, ℋ)

1: \( x \leftarrow \{0\}^{N_a \times N_t} \)
2: \( y \leftarrow \{0\}^{N_h \times N_t} \)
3: \( \tau \leftarrow \{\emptyset\}^{N_h \times N_a \times N_t} \)
4: \( r \leftarrow \{0\}^{N_t} \)
5: \( \mathcal{J}' \leftarrow \mathcal{J} \)
6: \textbf{while} \ \neg \text{isempty}(\mathcal{J}') \ \textbf{do}
7: \quad \tau', w \leftarrow \text{ASSIST-Schedule}(\tau, \mathcal{I}, \mathcal{J}', \mathcal{K})
8: \quad i^*, j^*, k^* \leftarrow \arg \max \ {S_{ij'k}(x_i, y_k, \tau')}_{i \in \mathcal{I}, j' \in \mathcal{J}', k \in \mathcal{K}}
9: \quad r_{j^*} \leftarrow S_{i^*j'^*k^*}(x_{i^*}, y_{k^*}, \tau')
10: \quad \textbf{if} \ r_{j^*} \leq 0 \ \textbf{then}
11: \quad \quad r_{j^*} \leftarrow 0
12: \quad \quad \textbf{break}
13: \quad \textbf{end if}
14: \quad x_{i^*j^*} \leftarrow 1
15: \quad y_{k^*j^*} \leftarrow 1
16: \quad \tau_{i^*j'^*k^*} \leftarrow \tau'_{i^*j'^*k^*}
17: \quad p_{i^*}^* \leftarrow p_{j'^*}^*
18: \quad \mathcal{J}' \leftarrow \mathcal{J}' \setminus \{j^*\}
19: \textbf{end while}
20: \textbf{return} \ \langle x, y, \tau, r \rangle

use a deterministic choice of 95% expected accuracy for all taskings. The duration corresponding to this selected value within each instance of Pew’s model is used to generate predicted agent schedules. These predictions may vary between human operators or task types and can be adapted throughout mission execution to account for dynamic human behavior (discussed in Section 3.6).

3.3 Task Allocation

The (ASSIST) algorithm (Algorithm 3.1) sequentially assigns tasks to a coupled human-robot team. Inputs to the mission planner consist of the set of autonomous agents \( \mathcal{I} \), tasks \( \mathcal{J} \), and operators \( \mathcal{K} \). ASSIST is initialized with empty assignments and zero task reward, where \( r \) is an array of size \( N_t \) which records the score of each task (lines 1-4). A temporary copy of the task set is created (\( \mathcal{J}' \)), and the sequential process of task assignment begins (lines 5-6).
The ASSIST-Schedule algorithm (Algorithm 3.2) fills in a temporary copy of proposed task execution times $\tau'$ and the associated vehicle wait time matrix $w$ (defined in the next section) for every combination of human operator, autonomous vehicle, and mission task (line 7 of Algorithm 3.1). The planner selects the best operator-vehicle-task combination to add to the existing set of assignments in $x$ and $y$ according to the multi-objective optimization function (line 8), and the algorithm checks that the proposed assignment’s reward is positive (i.e. contributing to the mission). If the best available task to be added to the assignment set is detrimental to the overall mission, the process terminates (lines 10-13). Otherwise, the task is assigned to both the human and the autonomous vehicle, the vehicle’s position is updated to the new assignment location, and the task is removed from the temporary copy of the task set (lines 14-18). The sequential process is repeated until all tasks (with positive reward) have been assigned.

3.4 Task Scheduling

The ASSIST-Schedule algorithm (Algorithm 3.2) provides execution times for every operator, vehicle, and task combination given current assignment sets and agent states. The tuple for each element in $\tau$ is of the form $(t^{\ominus}_{ijk}, t^{\oplus}_{ijk})$ which indicates the start and end times of an assignment. For a given human-UAV pair and task, the algorithm first evaluates the time at which the autonomous agent can service the task by adding travel time to the UAV’s available time (lines 4-5). Availability is determined from the agent’s latest assigned task ($j^+$), and travel time is calculated as the Euclidean distance from the last assignment location to the proposed task divided by the vehicle’s constant velocity, set a priori. The proposed task execution time starts at the UAV’s arrival time and ends after the predicted task duration, which is derived from Pew’s model (Figure 3-2b) as a function of the human operator and his existing assignments, the task, and the proposed time of execution (line 6).
Algorithm 3.2 ASSIST-Schedule($\mathcal{I}, \mathcal{J}', \mathcal{K}, \tau$)

1: for all $k \in \mathcal{K}$ do
2:     for all $i \in \mathcal{I}$ do
3:         for all $j \in \mathcal{J}'$ do
4:             $j^+ \leftarrow \text{argmax}_{s \in \tau_i} (t^\oplus_s)$
5:             $t^\ominus_j \leftarrow t^\ominus_j + \text{TRAVELTIME}(i, x^t_j, x^t_j)$
6:             $\tau'_{ijk} \leftarrow \{ t^\ominus_j, t^\ominus_j + \text{DUR}(k, j, t^\ominus_j | y_k) \}$
7:             if $\bigcup \tau^\prime_{k_{\mathcal{M}R\mathcal{V}}} \cap \tau'_{ijk} = \emptyset$ then
8:                 $w_{ijk} \leftarrow 0$
9:             else
10:                 $t_{\text{arrive}} \leftarrow t^\ominus_j$
11:                 $j^+ \leftarrow \text{argmax}_{s \in \tau_k} (t^\ominus_s)$
12:                 $t^\ominus_j \leftarrow t^\ominus_j + \text{BUFF}(k, j^+, j)$
13:                 $\tau'_{ijk} \leftarrow \{ t^\ominus_j, t^\ominus_j + \text{DUR}(k, j, t^\ominus_j | y_k) \}$
14:                 $w_{ijk} \leftarrow t^\ominus_j - t_{\text{arrive}}$
15:             end if
16:         end for
17:     end for
18: end for
19: return $(\tau', w)$

ASSIST-Schedule checks to see if the proposed duration conflicts with any of the operator’s other assigned tasks including short durations before and after each assignment, referred to as buffer constraints that allow for a human to shift his attention to a new task. This design heuristic adheres to the principles of context-switching [75] within the human factors community. By incorporating temporal buffers between tasks for the operator’s schedule, situational awareness is maintained and established workload thresholds for supervisory control are not exceeded. The human is given time to mentally “reset” for new assignments with differing robotic teammates under various circumstances. In ASSIST-Schedule, if the newly proposed task time does not conflict with the tasks (or corresponding buffer constraints) that have already been assigned to the human, the vehicle does not need to wait for the operator to become available (lines 7-8). If, however, there is a conflict with the supervisor’s set of assignments, the proposed execution time starts after the buffer time following the operator’s latest task, and the vehicle’s wait time is recorded (lines 10-14).
The ASSIST algorithm calls ASSIST-Schedule at most $N_t$ times as it sequentially assigns tasks to human-robot pairs. At each iteration, ASSIST-Schedule checks every operator, vehicle, and unassigned task combination (at most $N_hN_aN_t$ combinations) with the updated assignment sets and agent states. The time complexity of the planning framework is then $O(N_hN_aN_t^3)$ (polynomial-time). The algorithms are sound, in that all solutions are guaranteed to be free of assignment conflicts and are viable for the specified mission constraints. The sequential assignment process results in solutions that may be suboptimal, but the polynomial-time planner enables highly responsive real-time planning and execution with dynamic agents.

3.5 Predictive Planning Results

The ASSIST and ASSIST-Schedule algorithms provide predictive mission plans for a human-robot team. One example is shown in Figure 3-3, which gives five autonomous UAVs’ paths throughout the two-dimensional map projected over the course of a mission. Colored lines represent vehicle travel, black vertical lines symbolize a UAV remaining stationary to accomplish a surveillance task in conjunction with a human operator, and gaps in the paths demonstrate that a vehicle may be scheduled to wait for an operator to become available. This diagram illustrates that the inclu-
sion of vehicle cost into ASSIST’s multi-objective optimization can result in tasks being allocated to UAVs that are located nearby. Allocations that resemble space partitioning among the team of vehicles can become a by-product of the optimization as long as task value functions and human operator heuristics and constraints are satisfied.

Using identical mission scenarios between algorithms, Figure 3-4 compares ASSIST to a traditional sequential greedy algorithm (SGA) [43] that ignores the metrics and constraints imposed by human operators, optimizing instead solely over UAV parameters. Here the mission plan is represented as a collection of agent schedules rather than a temporally-projected map. Each task requires a coordinated effort from both a human (red block) and a robot (blue block), and UAVs must travel between task locations (light blue lines).

The naive SGA forces operators to split attention between co-occurring supervisory tasks, while ASSIST generates schedules in which operators have temporal workloads that fall within acceptable ranges for utilization and context switching (the specified utilization heuristic of 70% is shown in Figure 3-5b). Expected overall mission reward, $\mathcal{R}$, is calculated according to Equation 3.8 as the summation of each assigned task’s probability of success (derived from Pew’s model, Equation 3.7) as a coefficient on task value (Figure 3-1):

$$E(\mathcal{R}) = \sum_{j \in J} P_{jk}(\text{success}) \cdot \text{VAL}(j, \tau_{ijk})$$  \hfill (3.8)

Using Equation 3.8, the human-centered ASSIST algorithm generates plans with significantly higher expected mission reward than that of the UAV-centered approach (Figure 3-5a). The advantages of ASSIST often come with little to no detriment to the autonomous teammate metrics (Figures 3-5c and 3-5d), and computation remains fast (less than one second for up to 30 tasks) due to the deterministic assumptions made concerning task duration and accuracy.

A qualitative inspection of the human schedules in the ASSIST plan highlights the notion that optimizations involving operator cost functions and buffer constraints
Figure 3-4: Predictive planning comparison of ASSIST algorithm versus UAV-centered sequential greedy algorithm (SGA). Each task requires a synchronized, joint effort from both a human operator (red block) and a UAV (blue block), and vehicles must travel between task locations (light blue lines). UAV-centered SGA produces plans that have co-occurring (i.e. conflicting) tasks for human operators, while ASSIST generates optimized schedules which adhere to utilization workload thresholds and context switching.
produce conservative solutions for uncertain human performance. The planning problem involving stochastic and dynamic agents is optimized over risk-adjusted expected agent performance [89], where operator cost biases the objective function towards more conservative schedules. Consecutive human tasks without time between them may present issues when humans taking longer to complete tasks than predicted, which can lead to delayed start times for subsequent tasks [89]. By encoding the buffer constraints and operator cost functions directly into the planning problem, conservatism towards the challenges of human variability becomes a by-product of the optimization.

The ASSIST and ASSIST-SCHEDULE algorithms encode operator heuristics and constraints directly into the multi-agent task allocation and scheduling problem in order to produce effective plans for highly coordinated human-robot teams. The planner leverages deterministic assumptions on task durations and accuracies to provide mission plans on a timescale that allows for real-time planning and execution. This efficiency is desirable for responsiveness to stochastic, dynamic agents and environ-
ments. The inclusion of ASSIST and ASSIST-SCHEDULE into a flexible real-time planning and execution framework is discussed in the next section.

3.6 Closed-Loop Time-Extended Planning

The challenges of effectively modeling human performance motivates a planning architecture that is responsive to dynamic, stochastic, heterogeneous agents. A closed-loop framework that provides feedback on the actual state of the system in order to update planning parameters in real-time (such as the one depicted in Figure 3-6) may be utilized to achieve this aim. Using this approach, changes in the environment or agent behavior can be observed during mission execution. Underlying agent models are then updated to reflect the newly acquired information. Reacting to unexpected planning configurations can be addressed by replanning with fast algorithms that update mission requirements and use the models in Figures 3-2b and 3-2a as priors to be updated as time passes. This section describes an adaptive strategy to plan for human operators within the multi-agent framework using closed-loop modeling techniques.

3.6.1 Adaptive Human Performance Models

A promising strategy for closed-loop modeling involves adaptive models that respond to dynamic human agents by adjusting to reflect actual human supervisory performance during mission execution (Figure 3-6). Initially, the planner optimizes over models specified prior to the mission to produce task allocations and agent schedules. An example of the model priors would be to specify a predicted human supervisory task duration of eight seconds and an overall workload threshold of 70% utilization. Once the mission begins, UAVs fly to their specified surveillance task locations and provide imagery to the operator. The operator’s predicted task durations are then updated according to the actual amount of time taken to complete that task type, and workload threshold is shifted according to task accuracy or some other human performance metric.
Overall, the goal is for these models to provide replanned allocations and schedules that optimize over true agent states to maximize overall mission reward. Shorter predicted supervisory task durations may allow the human-robot team to accomplish more tasks within specified time windows, or a lowered workload threshold may allow an overworked operator more time, ideally improving subsequent performance. Intricate model learning strategies, filtering heuristics, or optimization techniques can create ideal plans based on acquired information, but Chapters 4 and 5 of this thesis show that even simple adaptation can provide significant improvements.

### 3.6.2 Simulation Results

As mentioned previously, planning for humans is exceptionally challenging in that they are difficult to model and often exhibit dynamic task performance. Predictive plans created prior to mission execution may be brittle to stochastically changing human behavior, especially when taskings are coordinated among coupled agents within a larger team and the timing of task completion is important. In order to conduct real-time planning with human performance models that can be updated during mis-

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**Figure 3-6**: Adaptive human performance models within a closed-loop system architecture. Realized human performance during mission execution is leveraged to update human models in real-time.
sion execution, a high-fidelity multi-vehicle simulation environment was created using the Robot Operating System (ROS) [92]. The simulation consists of virtual UAVs taking off and flying to the specified task locations as described in Section 3.5. It runs in real-time (on a laptop with a 2 GHz Intel® Core™ i7 processor, 8 GB RAM, and Ubuntu® 14.04 operating system) with realistic quadcopter dynamics and path planners for collision avoidance. Mission execution is illustrated in Figure 3-7 with the ROS 3D robot visualizer (RViz), demonstrating that the system can carry out plans for cooperative multi-agent teams.

Monte Carlo simulations with three virtual UAVs, two simulated human operators, and 30 tasks were conducted to determine the effects of adaptive agent performance modeling with dynamic and stochastic operators. Figure 3-8 shows the generic distributions used to represent variable human supervisory task duration. A central concept of this effort is that the task allocation planner is unaware of these functions: the system samples from the underlying distributions to simulate human task durations throughout the mission (e.g. time to classify imagery). For generality, the motion of simulated human supervisory task duration follows a sine function and stochasticity is incorporated as Gaussian noise with a standard deviation of one second. The human’s time constant, measured as the period of each sine function, provides a representation of agent variability.
Preliminary implementation of adaptive mission planning involves shifting Pew’s model (Figure 3-2b) to reflect information from actual mission execution. Human performance is fed back to the planning phase at the completion of each simulated task, and the operator’s latest task duration becomes the new predicted duration for future plans. In this manner, the closed-loop system adapts to dynamic, heterogeneous human agent performance in real-time.

While replanning does incur costs in terms of computation and communication (and potentially human proficiency [31]), Figure 3-9 gives average rewards from repeated simulations as a function of replanning interval, or time between replans, to illustrate the benefits of adaptive replanning in missions with unpredictably dynamic agents. Replanning intervals shorter than 10 seconds most likely experience a degradation in effectiveness due to churning tendencies [17, 34]. On the other hand, intervals longer than ten seconds become increasingly detrimental when dynamic agents are involved. This degradation in mission reward becomes more and more exaggerated for higher levels of operator variability. Model mismatches are exacerbated when replanning intervals are long. This simple experiment demonstrates that monitoring agent states and replanning at appropriate intervals with a flexible planning framework can alleviate the challenges of dynamic, stochastic agent performance.
3.7 Summary

Task allocation and scheduling for highly cooperative human-robot teams is challenging due to tightly coupled agent constraints and the natural variability of human performance. The ASSIST and ASSIST-SCHEDULE algorithms incorporate human models and constraints into the traditional planning problem to enable efficient mission planning for coupled human-robot teams. A closed-loop replanning framework enhances mission effectiveness by adapting to dynamic, stochastic human agent performance in real-time.

This work assumes that the flexible planning framework described in this chapter is robust to actual human behavior by updating well-established models of human performance on the fly. The next two chapters discuss human-in-the-loop studies involving human coordination with multiple autonomous vehicles to both support the inclusion of the human performance models as planning priors and to further validate the closed-loop replanning process.
Chapter 4

Single-Operator Pilot Study

This chapter describes a human-robot teaming pilot study. The goal of the study is to determine the efficacy of the flexible planning approach discussed in Chapter 3 compared to traditional static modeling strategies. The pilot study also investigates comparisons between adaptive human models, which are adjusted by the autonomous planner according to realized human performance, and adaptable human models, where the human operator is given sole authority over adjustments. This study represents a preliminary investigation into flexible mission planning for coupled human-robot teams, and the findings will be built upon in the subsequent experiment described in Chapter 5.

4.1 User Interface Development

The simulation environment used for real-time planning and execution in Chapter 3 can be applied to human-robot experiments in which actual human subjects interact with autonomous agents. The ROS visualizer was incorporated into realistic user interfaces in order to enable human-robot teaming experiments and demonstrations. The designs of the human-computer displays and control systems were created to increase operator situational awareness and task efficiency, ultimately resulting in more effective human-robot teaming.
4.1.1 Design and Implementation

In order to adhere to appropriate design principles and enable effective human-robot teaming for a wide variety of users, a visual display with standard keyboard and mouse controls was developed for this system. Information presented by the visual display was designed to be immediately distinguishable, legible, and understandable. Predictive aiding for future system states was displayed for increased situational awareness, and pictorial realism of the vehicles and the mission environment provided operators with appropriate mental models. With dynamic, fast-paced multi-agent missions in mind, operator controls were designed for quick, discrete inputs.

The full interface is illustrated in Figure 4-1. The human operator can observe the *overhead mission view* in the top right to anticipate vehicles arriving to their specified survey waypoints. Upon arrival, the top-left *command line interface* prompts the user – using the corresponding UAV color – to alert him to incoming sensor imagery from one of the vehicles. The operator’s attention then shifts to the appropriate *UAV camera view* along the bottom of the screen, which portrays the simulated imagery that must be classified and counted. The user continues this process throughout the duration of the mission, cross-checking the overhead view for increased situational
Figure 4-2: Overhead camera view

awareness and looking to the command line for incoming tasks and feedback on task execution performance.

A detailed image of the overhead camera view is presented in Figure 4-2. This perspective provides the human operator with a full picture of the environment, the current positions of all UAV teammates, and projections for future agent states. The information is analogous to a real-time satellite (or high-altitude aircraft) feed for an operational system. Alternatively, this view could be created artificially using GPS waypoints and vehicle locations overlaid on the map. This piece of the display interface is significant for the overall design, as it provides the operator with necessary situational awareness of team-wide mission execution. Instead of narrowly focusing on and piecing together individual UAV sensor data, this vantage point allows the human to quickly perceive the current status of all UAVs, comprehend their actions, and project their future paths and task allocations.

Enabled by the high-fidelity vehicle simulation, the overhead camera view provides quality pictorial realism to the user. This view adheres to careful consideration of principle of the moving part, having the vehicles move across the stationary map in order to portray a grounded view of the environment and relative motion among the UAVs. This also makes the perspective easily learnable, as a novice operator can look
The individual UAV camera feeds, shown in Figure 4-3, relate to the actual sensor data from the autonomous UAVs. This portion of the interface shows views from each of the vehicles, which are relevant for the human operator’s primary task to classify and count pieces of imagery. Figure 4-3 shows the green vehicle actively presenting simulated imagery to the operator while the other two UAVs travel to their next survey locations. The target objects, which move about randomly in the UAV camera view, must be classified as “circles” or “squares” and the individual objects themselves must be counted. This provides a moderately difficult surveillance task for the operator which allows the interface to be tested under conditions similar to what might be expected in an actual operational setting (e.g. military ISR [1] or scientific environmental research [50]).

Just as in the overhead view, the UAVs are color-coded for distinguishability. This prevents confusion and ambiguity within the human-autonomy system and allows the human to focus on the task at hand. Again there is predictive aiding in terms of
path planning and task assignment, providing the user with predictive aids towards understanding the future states of the system. In contrast to the overhead view, the principle of the moving part for UAV camera views implies that the UAV positions remain stationary while the ground moves below. This gives pictorial realism to this portion of the display because it is similar to what actual sensor data might look like. Finally, these camera views are grouped side-by-side in the single operator interface for efficient task switching between UAV sensor data in fast-paced mission scenarios.

Figure 4-4 shows an interface implemented through the command line that allows the human operator to interact with the system. Color-coded text is displayed announcing a new task arrival, and subsequent prompts are displayed asking the operator to classify ("c" or "s") and count the objects in the imagery feed.

The most significant advantage of this interface is its associated input efficiency. The operator can keep both hands on the keyboard and make all inputs simply by pressing buttons which are discrete, fast, and require small amounts of force. Another advantage incorporated into this input mechanism is the color-coded predictive aiding for incoming imagery classification tasks which allows the user to quickly recognize and distinguish the appropriate UAV with which to coordinate. There is also immediate feedback on task accuracy and speed, helping with error identification and correction when improvement must be made and user satisfaction when the team is functioning properly.
Graphical alternatives to the command line interface are illustrated in Figure 4-5. In the fully graphical interface (Figure 4-5a), the operator accomplishes the imagery classification task by either clicking on the “circles” or “squares” button and then entering the number of images into the text box. The primary advantage of this input approach is its facilitation of intuitive learning and functionality. There is very little training required for novice users, as the various input methods of buttons, text boxes, and sliders fit the users’ mental models for how the interface should work. Grouping principles among the various heterogeneous functions may make this
interface more satisfying and aesthetically pleasing than the command line interface in general. In addition to this fully graphical concept, an integrated interface (Figure 4-5b) was developed to utilize the relative strengths of the command line and graphical interfaces. Efficient primary task input is accomplished using the command line, while various secondary functions are handled graphically.

A developmental user study was conducted to receive feedback concerning the relative advantages and disadvantages between the various user input options. When users were asked to evaluate the command line interface, all subjects gave positive responses, citing efficiency, ease of manipulation, and understandability. Several of the users with technical backgrounds commented that they were familiar with the command line interface which helped them interact with the design efficiently. One user was concerned with reliability and critiqued the typed input which could be prone to input errors. Some subjects responded positively to the graphical interface, but most stated that it would be less efficient than the command line for primary task input. They hypothesized that using both the keyboard and mouse would slow down task completion, which could be crucial during fast-paced missions. Most participants responded positively to the integrated interface, but commented on the notion that the issue of both keyboard and mouse controls still limited the efficiency of this interface. Based on this feedback, the command line module was incorporated into the full single-operator interface design along with the overhead and UAV camera views for use in the pilot study (Figure 4-1). The combination of grouping, pictorial realism, predictive aiding, principle of the moving part, error correction, and highly efficient inputs contributes to human operator satisfaction when working with the interface.

4.1.2 Adaptable Human Performance Models

Chapter 3 introduced adaptive modeling as a way to provide flexibility in terms of planning for dynamic, heterogeneous human agents. An interesting alternative to this approach is to give the human authority over adjustments to future plans, labeled adaptable modeling. On one hand, an adaptive strategy can leverage realized
human performance to update models precisely and optimize over actual behavior for maximizing overall mission reward. However, one could argue that human operators know themselves better than an autonomous system. They could provide input on self-perceived performance and projections of their future state that may be difficult to model or anticipate. Additionally, allowing the human to have a say concerning his own task schedules may be important for satisfaction and acceptance of the system.

The adaptable human performance modeling strategy, pictured in Figure 4-6, relies on user input instead of realized performance to make adjustments to the human models for predicted task duration and workload threshold. This allows the user to influence the task allocation and scheduling to their desired specifications, giving them additional authority within the system that is lacking in the adaptive scenario. Simple, efficient inputs that shift each model right or left in a discrete fashion, similar to the adaptive technique, are incorporated in the user interfaces as additional tasks to be performed throughout mission execution. These model adjustments, described in detail in Section 4.3.1, provide the human with control over time allotted for tasks as well as time between tasks throughout mission execution.
4.2 Aim of the Pilot Study

The quantitative hypotheses tested in this experiment compare static (baseline open-loop approach), adaptive, and adaptable modeling strategies using an overall mission reward metric. This measure can be interpreted as a realized value of the expected mission reward metric in Chapter 3’s predictive planning results. Reward is calculated as the summation of all successfully completed task’s values at their respective execution times, and incorrect imagery classifications result in zero reward for a task. Thus overall reward represents a measure of timely, accurate task completion as well as efficiency in the allocation and scheduling of the tasks among the multi-agent team to optimize execution in terms of specified mission goals. Subjective trends from post-experiment participant questionnaires – in addition to other recorded measures such as classification accuracy, mission makespan (total duration), and total vehicle distance traveled – supplement the evaluation.

1. It is hypothesized that adaptive human performance modeling will result in the most overall mission reward, with adaptable modeling resulting in the second most reward, and static modeling resulting in the least. Autonomous adjustments of the models based on realized performance from actual mission execution in real-time should alleviate mismatches between the planning phase’s models and the humans’ actual ability. For the adaptable mode, the user’s adjustment of these models should also mitigate model mismatches, albeit less efficiently than the autonomous adaptive mode. Additionally, the baseline static modeling case will likely illuminate the issues of rigid, one-size-fits-all open-loop approaches to modeling human agents.

2. It is also hypothesized that the adaptable human performance modeling strategy will be the most preferred by users, with adaptive modeling being the second most preferred, and static modeling being the least preferred. Giving the human operator authority over the models that predict his own performance (and thus drive the allocation and scheduling of his tasks) is believed to result in higher user satisfaction than if the adjustments were made by the autonomous system.
instead. It is further predicted that the adaptive mode will be preferable to the static mode due to multi-agent plans that have flexibility and are more conformed to each participant’s actual ability.

4.3 Experimental Methods

The human-autonomy teaming mission consists of discrete surveillance tasks in distinct locations throughout a map. Points of interest may have differing priorities or time-criticalities which correspond to their respective task values. The ASSIST planner allocates and schedules coupled human-robot pairs to the tasks, optimizing plans for maximum task value while adhering to human operator heuristics and constraints. The architecture uses the Robot Operating System [92] for high-fidelity multi-vehicle simulations. Participants interact with the interface on a standard laptop (2 GHz Intel® Core™ i7 processor, 8 GB RAM) using a keyboard and mouse to accomplish missions.

4.3.1 Conditions

There are three conditions in this experiment which relate to the modeling of human performance. Static modeling is a baseline control condition that uses open-loop modeling of humans with planning parameters set \textit{a priori}. Adaptive modeling leverages actual human performance as feedback throughout each mission to autonomously adjust models. Finally, adaptable modeling uses inputs from the human operator to adapt his performance models during the mission. Replanning is conducted at 15 second intervals for all three conditions (set to correspond with performance benefits from Chapter 3’s simulations, see Figure 3-9).

Static Modeling

The static modeling mode provides a baseline open-loop approach to the representation of human performance. In this mode, humans are considered to be homogeneous agents whose predicted task performance is equivalent among different individuals.
Moreover, they are assumed to be static, modeled by rigid functions throughout the length of the mission. The human performance models used for task duration and workload threshold are specified *a priori*. For this pilot study, predicted task duration was set to 6.4 seconds, derived from the average length of time required for novice operators to complete a task in preliminary testing. Projected workload threshold was set to 70%, consistent with previous studies involving human operators and multiple UAVs [77] and aligning with subjective responses from novice operators interacting with the current system.

**Adaptive Modeling**

The adaptive modeling mode leverages realized human performance throughout mission execution to adjust the planner’s underlying models in real-time. Human operators are treated as heterogeneous, dynamic agents in that the specified models are adapted to fit the skills of each individual and remain flexible to track actual human performance throughout the mission. Predicted task duration is initially set to 6.4 seconds and 70% is specified as the operator workload threshold. These values are then updated in real-time based on actual performance by the operator.

Upon each task’s completion, the two human performance models are autonomously adapted by the closed-loop system. The actual time from the imagery’s appearance to the operator’s task completion becomes the new predicted task duration for future human-robot surveillance tasks. If the operator’s inputs are correct, the utilization workload threshold is increased by 5%, functioning as a heuristic to allow more demand on a successful operator. If the classification or count is incorrect, the utilization threshold is decreased by 15%, decreasing overall workload on the operator in the near future. In this mode, replanning not only alleviates discrepancies between the current system state and past projections, but also leverages up-to-date realized agent performance to generate plans that more closely mirror the actual behavior of the multi-agent system. This closed-loop modeling strategy alleviates model mismatches arising from heterogeneous operators (e.g. a model that is appropriate for one person may be ill-fitting for another) as well as dynamic human performance.
Adaptable Modeling

As an alternative to the autonomous system providing feedback consisting of realized performance to the planner, the adaptable mode allows the human operator to have sole authority over the adjustment of performance models. This strategy shifts responsibility of model updates from the autonomy to the human operator to provide insight into both objective effects on multi-agent teaming as well as subjective user perceptions.

Adaptable adjustments are accomplished through the use of additional operator inputs into the user interface. First, each human-robot surveillance task requires the usual “c” or “s” classification input along with specifying the number of images. Following these two inputs, the command line prompts the subject to “Enter ‘z’ if too busy, ‘r’ if too bored (else, hit enter).” Inputting “z” decreases the operator utilization workload threshold by 10%, while “r” increases it by 10%. The command line then prompts the operator to “Enter ‘l’ for less allotted task time, ‘m’ for more allotted task time (else, hit enter).” Entering ‘l’ decreases predicted task duration by three seconds, whereas “m” increases it by three seconds. (These discrete adjustment values were chosen based on preliminary testing.)

4.3.2 Procedure

Twelve individuals were selected to participate in the pilot study. Each experiment began with the subject reading an instruction document that explained the study’s purpose, the responsibilities of the participant, and the interaction procedures for the user interface as well as signing a consent form. Each subject was then guided through two full mission trials (with three autonomous vehicle teammates and 15 surveillance tasks) for training purposes. The first practice trial was conducted in the adaptive human performance modeling mode to allow the subject to become familiar with his primary task. The second practice trial was performed in the adaptable human performance modeling mode in order for the subject to become familiar with providing feedback to the planner. Upon completion of the two practice missions, the
participant completed a human-robot teaming mission in each of the static, adaptive, and adaptable human performance modeling modes. The ordering of modes was counterbalanced among the twelve participants (using the six possible combinations of mode ordering for two participants each) in order to mitigate potential confounding variables of learning and fatigue. The process required less than an hour of each participant’s time. All testing took place over a two week period.

Objective mission metrics were recorded throughout each trial. Total makespan (or mission duration) and total vehicle distance traveled were noted. The start time, duration, and accuracy of each task was recorded and used to compute overall mission reward, average operator accuracy, and average task duration. All model shifting inputs in the adaptable mode (“too busy,” “too bored,” “less time,” “more time”) and their associated input times were also logged. This level of detail into all relevant aspects of the mission allowed analysis of underlying reasons for human-robot team performance trends, such as temporally overloaded operators, model discrepancies between the planning phase and mission execution, and dynamic human performance.

Upon completing all trials, each participant filled out a questionnaire (included in Appendix B). The survey was used to evaluate situational awareness, team fluency, user interface satisfaction, and human performance modeling mode preference. Specific questions relating to the feedback modes (e.g. which was “most efficient in helping you complete the mission” and which mode “you most enjoyed using”) were included in the survey. In order to garner as much information as possible from the pilot study, all questions and choices were open-ended and prompted the subject to specify why they felt a certain way. Participants’ subjective inputs provided insight into trends in the objective metrics and aided in future system development after pilot study completion.

4.4 Results

After all testing was completed, data were investigated both qualitatively and quantitatively to evaluate the effects of the various human modeling strategies on team
Figure 4-7: Overall mission rewards among human modeling modes with standard error bars

4.4.1 Objective Analysis

Numerical mission reward results of the pilot study are given in Table C.2 in Appendix C. Shapiro-Wilk tests [20] are used to confirm normal distribution assumptions for statistical trends. A one-way balanced ANOVA F-test [58] is used to test whether there exists any statistically significant differences among the three modes’ associated mission rewards (Figure 4-7). Based on the data and using a 95% confidence interval, there is reason to believe that there exists significant variation between the three modes in terms of overall mission reward ($F_{2,33} = 8.645, p < 0.001$). Therefore, direct comparisons between each pair of modes using post-hoc paired t-tests with Bonferroni corrections [115] are appropriate.

Comparing adaptive human performance modeling against the baseline static approach shows that average mission reward for the adaptive mode ($M = \ldots$)
8, 116.25, SD = 933.80) is significantly different than the static mode’s (M = 6, 649.21, SD = 1, 372.39) average reward (t(11) = 4.353, p = 0.0012). With mean overall reward being much higher for the adaptive case, results indicate that adaptive human performance models significantly increase total mission reward over the static modeling framework in the context of this experiment. A second paired t-test comparing adaptable human operator modeling against the baseline static modeling strategy gives no indication that mission reward from adaptable modeling (M = 6, 311.36, SD = 1, 036.45) is significantly distinct from reward with static modeling (M = 6, 649.21, SD = 1, 372.39) in this pilot study (t(11) = 0.631, p > 0.05). A final paired t-test examines adaptive and adaptable human performance modeling, demonstrating that adaptive human performance models (M = 8, 116.25, SD = 933.80) result in statistically significant improvement of overall mission reward in comparison to adaptable models (M = 6, 311.36, SD = 1, 036.45) for this experiment (t(11) = 3.826, p = 0.0028).

The data suggest that adaptive human performance models can promote more effective coordination between humans and autonomous agents than traditional open-loop modeling approaches. Leveraging feedback from actual human performance can alleviate model mismatches at both the system level (e.g. workload thresholds for difficult versus routine missions) and the individual level (e.g. different experience and skill between operators). Assuming humans to be homogeneous agents with one-size-fits-all models can be detrimental to overall team performance. In fact, average task duration varied by as much as 87.5% between participants in this pilot study. A histogram of participants’ average task durations in Figure 4-8 shows a Gaussian-like distribution with substantial variance between subjects.

Figure 4-9 shows mission timelines for a single participant in each of the three modes. This subject generally accomplishes tasks more quickly than the predicted task duration of 6.4 seconds set a priori, which causes a model mismatch for the static open-loop modeling approach. The adaptive human performance modeling mode, on the other hand, is able to adjust to the operator’s realized performance once the mission begins. As an additional advantage for adaptive modeling, the human’s
dynamic behavior during this trial – which takes the form of decreasing durations as the mission progresses – is tracked by the closed-loop system throughout the length of the mission.

Other aspects of human-robot team performance among the feedback modes are analyzed to supplement comparisons of overall mission reward (Figure 4-10). Mission makespan (Figure 4-10b), or total mission duration, indicates that adaptive human performance modeling significantly reduces total mission time ($F_{2,33} = 10.729, p < 0.001$) over both baseline static ($t(11) = 6.710, p < 0.001$) and adaptable modeling approaches ($t(11) = 4.563, p < 0.001$). Additionally, overall vehicle distance (Figure 4-10c) was longer in the adaptable modeling mode than both the static ($t(11) = 1.976, p = 0.0738$) and adaptive ($t(11) = 2.012, p = 0.0594$) strategies ($F_{2,33} = 2.656, p < 0.085$). Comparisons between modes in terms of average operator task accuracy (Figure 4-10a) are not statistically significant, but results are trending toward advantages for adaptive human performance modeling.
Figure 4-9: Predicted human operator task duration from underlying models versus actual task duration over the course of one participant’s trials in each mode.
Figure 4-10: Additional objective metrics for comparison between modeling modes with standard error bars

(a) Average human operator task accuracy

(b) Average mission makespan (total duration)

(c) Average total distance traveled by vehicles per mission
4.4.2 Subjective Measures

Post-experiment questionnaires allowed subjects to provide qualitative feedback on their perceptions of the autonomous system, the user interface, and the various human performance modeling modes. All participants provided positive comments on the general system, specifically citing the efficiency of the interface under temporal pressure. In addition, real-time feedback was said to be especially useful in terms of helping operators stay motivated throughout the mission and allowing them to self-correct after errors. Finally, subjects appreciated having the overhead view available for team-wide situational awareness and projections of incoming surveillance tasks.

Participant responses to questions on mode preference align with objective findings, as 92% of subjects chose adaptive human performance modeling as the “most efficient” mode of the three tested. Additionally, 83% of users stated that they “most enjoyed using” the adaptive scheme, describing it as “stimulating,” “well-tuned,” and “most engaging.” This autonomous closed-loop modeling approach was generally perceived as being more effective than the baseline static case, and its lower workload requirements relative to the adaptable strategy allowed users to focus on the primary classification task without distraction.

4.5 Discussion

Consistent with Hypothesis 1 in Section 4.2, results indicate (within the context of this system) that incorporating real-time autonomous adjustments of human performance models provides quantitative advantages over relying on human input for adjustments. However, using flexible closed-loop models with operator input as the feedback mechanism shows no statistically significant improvement in overall mission reward over the baseline open-loop static case. These findings may be explained as the results of two main causes. First, the adaptable mode required slightly longer time to accomplish tasks than the static and adaptive modes. Figure 4-8 shows the adaptable trials favor the right side of the distribution, and a paired t-test confirms that the adaptable mode’s additional inputs resulted in significantly longer average task dura-
tions \((M = 7.246, \text{SD} = 0.997)\) than the adaptive approach \((M = 5.617, SD = 0.986)\) in this pilot study \((t(11) = 3.745, p = 0.00324)\). Second, the human operator may be worse than the autonomous system at adjusting his model appropriately to minimize model mismatches between the planning phase and actual mission execution. Figure 4-9c illustrates that the subject fails to track actual performance accurately. Even more so, at times throughout the trial his adjustments increase model discrepancies rather than mitigate them.

The increase in overall mission reward for adaptive human performance modeling over both the baseline static case and the adaptable approach may be attributed to the adaptive strategy’s ability to minimize model mismatches between the planning phase and actual human ability. Proper prediction of human operator performance within the human-robot teaming missions is important for effective multi-agent planning towards achieving specified mission goals. The ASSIST algorithm is allocating and scheduling tasks amongst the vehicles with the aim of maximizing mission reward. Again, this reward metric is calculated by totaling all successfully completed tasks’ values at their execution times, and these time-varying task score functions may take various functional forms.

When the planning phase over-predicts operator task duration (Figure 4-9a), ASSIST imposes a longer scheduling constraint on future tasks. This may lead to allocations in which other vehicles travel longer distances in order to reach higher-value tasks around the time the human is expected to become available. However, if the operator finishes the task more quickly than predicted, he may then be forced to wait idly for an undesirable amount of time before the next task arrival. If, on the other hand, the planning phase under-predicts operator task duration (Figure 4-9c), ASSIST may allocate tasks in an overly-optimistic fashion. A vehicle may be required to stay committed to a task longer than expected due to the human operator, thus resulting in the vehicle arriving later-than-expected to subsequent tasks. This can lead to both inefficiencies throughout the multi-agent team (e.g. two vehicles each arriving to their tasks at the same time, requiring one to wait an extended period of time for the human) as well as “missed rendezvous” (e.g. missing a task time window).
In addition to task durations, predicting the human operator’s workload threshold is important for the heuristics of the algorithm. Ideally, an operator would be able to achieve 100% accuracy on imagery classification tasks while remaining as busy as possible in order to reduce scheduling constraints on task execution times and minimize overall mission duration. With this in mind, adaptive workload thresholds were increased following accurate imagery classifications to reflect the fact that the operator was able to succeed at the prescribed workload. Upon task failures, adaptive workload thresholds were decreased to allow the user to gather himself for subsequent demands. Instead of this heuristic approach, future experiments will incorporate secondary tasks to analyze and adjust the operator’s workload threshold in a more direct fashion.

In terms of subjective data, the majority of participants preferring adaptive modeling over the adaptable approach is contrary to Hypothesis 2 in Section 4.2, which assumed that providing the human operator with more control over the system would result in greater user satisfaction. However, these results align with other findings in the literature. Specifically, Gombolay et al. [45] showed that humans generally prefer to work within an efficient team rather than have a heightened role in the planning process if that increased role is detrimental to overall team performance. In the current pilot study, allowing human operators to adjust their own performance models imposes additional workload requirements and generally produces larger model mismatches and thus less efficient multi-agent plans.

4.6 Conclusions

Closed-loop planning approaches in which the autonomous system adapts flexible human models throughout mission execution can improve overall mission performance for tightly coordinated human-robot teams. The challenges of unpredictable, heterogeneous human agents with dynamic, stochastic behavior can be addressed through responsive replanning that leverages realized execution information. Also, while adaptable human modeling failed to demonstrate improved mission performance
over the baseline open-loop approach, future work concerning efficient input methodologies and comprehensive interface feedback – particularly as it relates to model mismatches – may reveal added benefits.

This human-robot teaming pilot study highlights many potential avenues for future work, such as testing longer missions to capture more dynamic human performance and utilizing more comprehensive subjective questionnaires and workload assessments. Additional work could be done to test more complicated feedback modes, such as improving adaptable adjustment mechanisms and incorporating stochastic averaging [55], filtering [17], and learning techniques [19] into the adaptive approach. A hybrid “adaptablelive” mode could be created to investigate whether building on both adaptive and adaptable strengths can be synthesized. This could also distinguish effects of additional workload versus model discrepancies to help explain the adaptive mode’s advantageous performance over the adaptable strategy in this work. Using many of the lessons learned from this pilot study, a multiple-operator experiment is described in the next chapter which explores mission planning for teams of multiple humans and multiple autonomous vehicles.
Chapter 5

Multiple-Operator Experiment

This chapter builds upon Chapter 4’s pilot study to present a follow-on experiment that provides further insight on effective human-robot teaming. The two major extensions of this experiment are the use of secondary tasks to drive thresholds for moderating overall workload as well as the expansion of the team to include multiple human operators. Secondary tasks are incorporated into the experiment for both adaptive and adaptable approaches to closed-loop human modeling of workload thresholds. Additionally, the inclusion of multiple human agents demonstrates the planning framework’s ability to allocate and schedule tasks amongst a larger set of agents in real-time, and it further explores the usefulness of adaptive human performance models. While the pilot study demonstrated that closed-loop adaptive modeling can alleviate model mismatches and produce more efficient schedules for a single operator, this multiple-operator experiment investigates whether flexible modeling strategies can also exploit heterogeneous human teammates to produce more advantageous task allocations.

5.1 Experimental Methods

Missions consist of 30 discrete surveillance tasks scattered throughout a map. Tasks may have different time-varying values, and the ASSIST planner optimizes mission plans for maximum task value while adhering to human operator heuristics and con-
strains. The surveillance tasks are accomplished by a human-robot team consisting of two human operators and three simulated UAVs.

5.1.1 Experiment Platform

ROS is used to network multiple operator interfaces to one coordinated human-robot team. Each pair of participants simultaneously interact with the simulation on identical laptops (2 GHz Intel® Core™ i7 processor, 8 GB RAM) using standard keyboards and mouse devices (Figure 5-1).

5.1.2 User Interface Updates

Figure 5-2 portrays two user displays at the same instance during a mission. As shown in the bottom left portion of the figures, the overhead mission view of the environment is the same for both operators because they are cooperating as individual agents on the same multi-agent mission. This display provides equivalent aiding in situational
Figure 5-2: Display interfaces for two operators at the same instance in a mission. The overhead mission view is the same between the two displays, but vehicle sensor imagery and surveillance classification tasks are allocated between the operators according to the ASSIST algorithm. Secondary tasks are also performed within these interfaces.
awareness of vehicle locations, path plans, and future task assignments. This portion of the user interfaces remains unchanged from that of the previous pilot study. UAVs are color-coded and move throughout the map to their assigned task locations. For the purposes of predictive aiding [91], the colors of task waypoints correspond to the vehicle to which they are assigned, and planned UAV paths are illustrated by colored lines. Overhead mission views on each human operator’s interface are identical throughout the length of mission execution.

The top right portion of each display provides sensor imagery to the human if the surveillance task has been allocated to that operator by the ASSIST planner. UAV camera views are also similar to those found in the pilot study, but the manner in which they are integrated into the overall user interface has changed. For the multiple-operator experiment, these live top-down video feeds only appear in the top right portion of an operator’s interface once a vehicle begins presenting imagery from a task to which both the vehicle and the operator are assigned. When a human operator is not actively engaged in cooperation with a UAV to complete a surveillance task, this portion of his interface is grayed out. In Figure 5-2, the blue vehicle is currently presenting imagery to Operator 1 while the red UAV is cooperating with Operator 2. The small colored objects move throughout the sensor feed, and they flash yellow if the target time allotted to the task by the autonomous planner has been exceeded.

Upon receiving UAV surveillance imagery, classification inputs may then be entered into the primary task interface (top left). This is identical to the command line portion of the pilot study interface in its static and adaptive modes. The command line alerts the operator to incoming imagery, then prompts the user to enter the image classification (‘c’ for circles or ‘s’ for squares) and the number of objects (e.g. in Figure 5-2a there are 11 circle objects). Upon completion of each task, the operator receives feedback on task accuracy and duration. The additional questions from the pilot study’s adaptable mode do not appear in the multiple-operator experiment’s interface for any mode. Instead, secondary tasks in a separate portion of the interface are utilized for various forms of closed-loop human performance modeling.
5.1.3 Secondary Tasks

In addition to primary image classification and counting tasks, this experiment requires human operators to perform secondary tasks. These tasks take the form of two yes/no questions in the secondary task portion (bottom right) of the user interface, which is individually depicted in Figure 5-3. The questions ("Desire more time BETWEEN/FOR tasks?") appear in an alternating fashion at an interval of approximately 7.5 seconds (with slight noise to avoid anticipation of appearances). This rate was chosen based on the fact that replanning occurs at 15 second intervals throughout mission execution. With secondary task appearances every 7.5 seconds, human operators are able to answer both questions during each planning interval (thus providing necessary feedback for flexible modeling modes, to be described in detail in subsequent sections). It should be noted that the timing of secondary task appearances are not connected to the appearances of primary imagery classification tasks. Primary task arrivals depend on UAV arrival times, while secondary task arrivals appear at a fixed rate. Therefore, one secondary task question might appear while the operator is actively coordinating with a vehicle on a primary surveillance task, while another might appear in between primary tasks.

Each secondary task appearance is accompanied by an audible bell tone in order to alert the operator to its arrival. Every participant is told that “these secondary tasks are required and may be utilized within the underlying planning framework to drive mission coordination.” They are also directed to “respond to these secondary task questions as quickly as possible without degrading primary task (imagery classification and counting) performance” (see Appendix A for full script).
For the question concerning time between tasks, participants are instructed to respond “y” for “yes” if the imagery provided to them by the UAVs flashes consistently throughout their various tasks, indicating that the planner’s target times are shorter than the actual time that is required for the operator to complete the tasks accurately. Otherwise they may respond “n” for “no” to indicate a desire to keep target times short, allowing the UAVs to move on to other tasks more quickly. In terms of the question concerning time for tasks, users are instructed to respond “y” for “yes” if tasks between different UAVs are being presented more quickly than their comfort level allows (thus the fast pace is decreasing their classification and counting accuracy or pushing their overall workload to undesirable levels). Alternatively, they may respond “n” for “no” to indicate a desire to keep task switching times short and allow vehicles to present them with sensor imagery quickly.

5.1.4 Conditions

Four conditions concerning human performance modeling are evaluated in this experiment. Static modeling serves as a baseline control condition that models humans with planning parameters set a priori. Adaptive (single) modeling leverages information on primary task performance to autonomously adjust Pew’s model (predicted task duration, Figure 3-2b) throughout mission execution. Adaptive (double) modeling utilizes both primary and secondary task performance information to autonomously update both Pew’s model and workload threshold (Figure 3-2a). The inclusion of both adaptive conditions enables an evaluation on the relative contributions of adapting each of the two models. Finally, adaptable modeling uses responses on secondary tasks to manually adjust Pew’s model and workload threshold.

Summary on Experiment Conditions

The conditions selected for this experiment provide important comparisons for several topics of interest. First, comparing adaptive (single), adaptive (double), and adaptable conditions against the static baseline case evaluates the efficacy of flexible human
Table 5.1: Method upon which model adaptations are based for each experimental condition

<table>
<thead>
<tr>
<th>Model Condition</th>
<th>Static</th>
<th>Adaptive (Single)</th>
<th>Adaptive (Double)</th>
<th>Adaptable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pew’s Model (Predicted Task Duration)</td>
<td>N/A</td>
<td>Average primary task duration</td>
<td>Average primary task duration</td>
<td>User response to “Desire more time for tasks?”</td>
</tr>
<tr>
<td>Workload Threshold (Time Between Tasks)</td>
<td>N/A</td>
<td>N/A</td>
<td>Secondary task response time</td>
<td>User response to “Desire more time between tasks?”</td>
</tr>
</tbody>
</table>

performance models for coupled teams of multiple humans and multiple autonomous vehicles. Comparing adaptive (double) with adaptable conditions gives insight on the relative benefits between autonomous and manual adjustment of human performance models. Finally, measuring adaptive (single) modeling against adaptive (double) modeling provides insights into the relative contributions of adjusting Pew’s model for predicted task duration versus the workload threshold model. Table 5.1 presents the way in which models are adjusted for each of the four experiment conditions.

**Static Modeling**

Static modeling serves as a control condition for investigating the benefits of flexible human performance modeling in coupled human-robot teaming applications. Under this approach, humans are modeled as static agents whose models are fixed throughout mission execution. Furthermore, all human operators are assumed to be homogeneous agents whose predicted performance on tasks is equivalent across individuals. Models are specified *a priori* with similar values as the pilot study (task duration predicted as 6.4 seconds and workload threshold at 70% utilization).

**Adaptive (Single) Modeling**

The adaptive (single) modeling mode fixes workload threshold at 70% utilization but uses realized primary task durations throughout mission execution to adjust each operator’s Pew’s model in real-time. Predicted task duration is initially set to 6.4 seconds, but this model prior is then shifted using the average duration (time from
imagery appearance to operator input completion) on tasks from the past 30 seconds (or two planning intervals). Under this approach, predicted task durations track actual recent operator performance in order to treat humans as heterogeneous, dynamic, hard-to-predict agents.

**Adaptive (Double) Modeling**

The adaptive (double) modeling mode leverages the realized performance of each operator on primary and secondary tasks to adapt both of the planner’s underlying models in real-time throughout mission execution. Model priors are still set to 6.4 seconds predicted task duration and 70% utilization threshold, and Pew’s model is shifted using average duration on recent tasks as in the adaptive (single) modeling condition. In the adaptive (double) condition, workload threshold is adapted as well according to performance on secondary tasks. Since there is no notion of correctness on the secondary task questions, which pertain to subjective desires concerning future mission pace, response times to these questions are used as the metric to adjust workload threshold.

The use of response time to secondary task appearances has been used extensively in human-subject testing as a method for evaluating overall user workload, where short response times correlate to low workload and long times correlate to high workload [32, 91, 117]. Additionally, other studies that use secondary task performance to adapt levels of automation (i.e. human versus machine roles) in human supervisory control applications have identified benefits in terms of workload balancing throughout mission execution [61, 62]. Under these approaches, quick response times indicate that the human is underloaded (i.e. has an undesirably low level of activity) while slow response times point to overloading (i.e. workload is undesirably high). But in contrast to adjusting levels of automation, the adaptive (double) modeling condition of this experiment specifically adjusts the operator’s workload threshold model in real-time. Fast secondary response times cause the planner’s workload threshold to increase, enabling higher-performing human agents to take on more primary task demands. Slow secondary response times alternatively result in a workload threshold
decrease, resulting in the autonomous task allocation and scheduling system reducing the load on overwhelmed operators.

To determine appropriate thresholds for mitigating underloading and overloading, a small pilot study \((n = 4)\) was conducted which investigated effects on secondary task performance under both low and high workload conditions. Primary task pace was used as the study’s independent variable to influence overall workload. The study’s underloading primary task condition had UAVs fly at half their normal speed and operator models were set at 50% workload threshold and 9.4 second predicted task duration. The overloading primary task condition had UAVs fly at double the normal speed with 100% workload threshold and 3.4 second predicted task duration. Secondary tasks, with response time as the study’s dependent variable, remained the same for both conditions (appearing approximately every 7.5 seconds). A histogram of secondary task response times is shown in Figure 5-4. As expected, response times were consistently shorter in the low workload condition \((M = 3.41 \text{ s}, \ SD = 1.90 \text{ s})\),
and they were long and had larger variance in the high workload condition \((M = 14.59 \text{ s}, SD = 5.23 \text{ s})\).

The results of this small pilot study are used to set a target secondary task response time range for the adaptive (double) modeling condition that is indicative of human operator performance under desirable workload conditions (i.e. no underloading or overloading). The range is calculated by moving “in” one standard deviation from the means of both distributions in Figure 5-4, giving a desired range of 5.31 to 9.36 seconds. If an operator’s response time is faster than 5.31 seconds, his workload threshold utilization is increased by 10%. If the response time is slower than 9.36 seconds, the threshold is decreased by 10%. If the time is within the desired range, the threshold remains the same. (Note the answer to the secondary task questions does not matter for this condition, only response times to these questions affect future mission pace.) This adaptive procedure leverages realized performance on secondary tasks to regulate workload for heterogeneous operators, allowing high performers to take on more primary demands and overwhelmed individuals to execute the mission at slower paces.

Adaptable Modeling

As an alternative strategy to adaptive modeling, the adaptable condition allows manual – rather than autonomous – control over adjusting the individual’s performance models. In this mode, the answers to secondary task questions result in model shifts. If the user answers “yes” to the question on desiring more time between tasks, his workload utilization threshold is decreased by 10%. If instead he responds “no,” it is increased by 5% (asymmetry due to the fact that he may actually desire for things to stay the same rather than desire less time between tasks). If the operator answers “yes” to the question on desiring more time for tasks, his predicted task duration is increased by three seconds. If “no,” predicted duration decreases by 1.5 seconds. This provides the human operator with authority over both his performance models, and thus he has greater influence over his future task allocations and schedules.
5.1.5 Metrics

As with the pilot study, \textit{overall mission reward} (i.e. the summation of all successfully accomplished task’s values at their respective execution times) is used as the primary objective metric to compare experiment conditions. As a reminder, this reward represents effective coordination of the multi-agent team by the autonomous planner as well as a measure of timely, accurate task completion. Other objective metrics such as mission makespan (i.e. total duration), vehicle distance, and operator accuracies/durations supplement the evaluation, while subjective tools such as the NASA Task Load Index (TLX) method \cite{53} and post-trial questionnaires provide insights into participant preferences for each modeling strategy.

Objective

Throughout each mission trial, quantitative metrics on individual and team performance were recorded. Primary task start times, accuracies, and durations were separately recorded for each human operator, as well as their secondary task responses with associated input times and response latencies. Objective multi-agent team metrics of total mission makespan and vehicle distance were logged, and overall mission reward was calculated.

Subjective

Upon completion of each mission, participants were asked to answer 20 Likert-scale questions and complete a NASA-TLX assessment in order to assess their experience on the previous trial. The post-trial questions are shown in Table 5.2, adapted from the human-robot teaming experiments of Gombolay et al. \cite{45}. After all mission trials were completed, participants also answered open-ended questionnaires on demographic information, modeling mode preferences, and role of autonomy preferences (see Appendix B).
### Table 5.2: Post-trial Likert-scale questions

<table>
<thead>
<tr>
<th><strong>System Traits</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>The multi-agent system was intelligent.</td>
</tr>
<tr>
<td>2.</td>
<td>The multi-agent system was trustworthy.</td>
</tr>
<tr>
<td>3.</td>
<td>The multi-agent system was committed to the mission.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Team Fluency</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>4.</td>
<td>I feel uncomfortable cooperating with the UAVs. (reverse scale)</td>
</tr>
<tr>
<td>5.</td>
<td>I feel uncomfortable cooperating with my human teammate. (reverse scale)</td>
</tr>
<tr>
<td>6.</td>
<td>The multi-agent system and I understand each other.</td>
</tr>
<tr>
<td>7.</td>
<td>I received adequate feedback on my task performance throughout the mission.</td>
</tr>
<tr>
<td>8.</td>
<td>The system perceives accurately what my abilities are.</td>
</tr>
<tr>
<td>9.</td>
<td>I find what I am doing within the system confusing. (reverse scale)</td>
</tr>
<tr>
<td>10.</td>
<td>I was satisfied by the team's performance.</td>
</tr>
<tr>
<td>11.</td>
<td>I would rely on the system next time the tasks were to be completed.</td>
</tr>
<tr>
<td>12.</td>
<td>The multi-agent system increased the productivity of the team.</td>
</tr>
<tr>
<td>13.</td>
<td>The team collaborated well together.</td>
</tr>
<tr>
<td>14.</td>
<td>The team performed the tasks in the least time possible.</td>
</tr>
<tr>
<td>15.</td>
<td>The multi-agent allocation and scheduling system was necessary for the successful completion of the tasks.</td>
</tr>
<tr>
<td>16.</td>
<td>My human partner was necessary for the successful completion of the tasks.</td>
</tr>
<tr>
<td>17.</td>
<td>I was necessary for the successful completion of the tasks.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Decision Authority</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>18.</td>
<td>I wish I had more say over the scheduling and allocation of tasks among the UAVs. (reverse scale)</td>
</tr>
<tr>
<td>19.</td>
<td>I wish I had more say over the allocation of tasks between me and my human partner. (reverse scale)</td>
</tr>
<tr>
<td>20.</td>
<td>I wish I had more say over the pace of the mission. (reverse scale)</td>
</tr>
</tbody>
</table>

### 5.2 Aim of the Experiment

Based on findings from the pilot study, it is hypothesized that adaptive human performance modeling will demonstrate objective and subjective advantages over both static and adaptable conditions. The adaptive approach’s autonomous model adjustment is predicted to alleviate model mismatches and exploit differences between heterogeneous operators to provide more effective allocations and schedules for the human-robot team, resulting in significantly higher overall mission reward. It is further hypothesized that this efficiency will lead to the majority of participants preferring adaptive modeling and reporting that they experienced better team fluency and felt lower perceived workload in this condition.
5.3 Procedure

Twenty-four individuals were selected to participate in the experiment. Participant ages ranged from 20 to 62 years old with an average of 31 years of age. Six subjects were women (25%), 16 had some form of military experience (67%), 12 had experience operating aerial vehicles of some kind (50%), and 6 played video games for at least one hour per week (25%). The individuals were paired into teams of two for the experiment, and all participants personally knew their assigned partner beforehand.

Each experimental test was carried out according to the script in Appendix A. The participants began by reading and signing a consent form. They were then told the experiment’s purpose, their roles as operators in the coupled human-robot team, and the interaction mechanisms for the user interfaces. A full practice trial with 30 tasks, three UAVs, and the two participants was then conducted in the static modeling mode without secondary tasks in order to allow the users to become acquainted with the interfaces and their primary task roles (i.e. classifying and counting imagery). The participants then accomplished a full practice trial in the static modeling mode with the inclusion of secondary tasks for training on their combined primary and secondary task roles. Following the practice trials, subjects completed a mission in each of the four modeling modes according to a Latin Square design for condition ordering [119]. The full experiment required approximately one hour to complete, and all testing took place over a three week period.

5.4 Results

After completing data collection, results were analyzed to investigate the effects of flexible human modeling on coupled human-robot teaming with multiple human operators and multiple autonomous vehicles. Normal distribution assumptions for statistical trends are confirmed with Shapiro-Wilk tests [20]. Statistical significance is defined at the $\alpha = 0.05$ level, and significant pairwise comparisons are labeled as $^* p < 0.05$, $^{**} p < 0.01$, and $^{***} p < 0.001$ on figures in this section.
5.4.1 Objective Analysis

Numerical rewards for all teams across experiment conditions are given in Table C.7 in Appendix C. Modeling mode was shown to have a statistically significant effect on overall mission reward (Figure 5-5) using a one-way repeated measures ANOVA F-test ($F_{3,33} = 10.65$, $p < 0.001$). Therefore, post-hoc pairwise comparisons were performed using Tukey’s honestly significant difference (HSD) tests [20] to evaluate differences between conditions. Reward for both adaptive (single) modeling ($M = 12,046.81$, $SD = 1,764.65$) and adaptive (double) modeling ($M = 12,841.97$, $SD = 1,666.38$) were significantly higher than that of the baseline static modeling case ($M = 10,740.70$, $SD = 1,637.14$) in this experiment ($p < 0.01$ and $p < 0.001$ respectively). These increases demonstrate that autonomous adaptation of human operators’ predicted task duration based on actual performance during mission execution can result in more effective planning for coupled human-robot teams of multiple humans and multiple autonomous agents. Additionally, adaptive (double) modeling ($M = 12,841.97$, $SD = 1,666.38$) was shown to produce higher overall reward than the adaptable modeling condition ($M = 11,719.95$, $SD = 1,792.05$) with statistical significance ($p < 0.05$).
Additionally, team metrics for mission makespan (Figure 5-6a) and total distance traveled (Figure 5-6b) were significantly affected by the modeling conditions (\(F_{3,33} = 5.99, p < 0.01\) and \(F_{3,33} = 5.87, p < 0.01\)). Makespan with adaptive (double) modeling (\(M = 227.27\) s, \(SD = 42.03\) s) and adaptable modeling (\(M = 234.44\) s, \(SD = 41.69\) s) was shown to be significantly less than that of static modeling (\(M = 264.67\) s, \(SD = 43.19\) s) using Tukey’s HSD tests (\(p < 0.01\) and \(p < 0.05\) respectively). Adaptive (double) modeling (\(M = 923.68\), \(SD = 81.07\)) significantly reduced vehicle travel distance compared to adaptive (single) (\(M = 1,036.92\), \(SD = 54.57\)) and adaptable (\(M = 1,028.61\), \(SD = 76.73\)) conditions (\(p < 0.01\) for both).

As illustrated in Figure 5-7, modeling mode was not shown to have a significant effect on individual operators’ primary task accuracy (\(F_{3,69} = 1.49, p > 0.05\)) or overall means of secondary task response time (\(F_{3,69} = 1.75, p > 0.05\)), but a two-sample F-test demonstrated that the adaptive (double) modeling condition significantly reduced response time variance compared to the baseline condition (\(p < 0.001\)). Primary task duration (Figure 5-8) was significantly influenced by modeling condition (\(F_{3,69} = 4.12, p < 0.01\)). Post-hoc Tukey’s HSD tests confirmed that all three flexible modeling approaches (\(M = 6.93\) s, \(SD = 1.54\) s for adaptive (single); \(M = 7.01\) s, \(SD = 1.58\) s for adaptive (double); \(M = 6.97\) s, \(SD = 1.79\) s for adaptable) significantly decreased average task duration over the static baseline condition (\(M = 7.73\) s, \(SD = 2.55\) s; \(p < 0.05\) for all three pairwise comparisons).

Demographic correlations with overall mission reward were investigated by comparing the 24 participants with two-sample t-tests assuming unequal variances [20]. Participant gender showed a marginally significant effect on reward (\(p < 0.10\)) with males (\(M = 12,121.08\), \(SD = 1,478.38\)) slightly outperforming females (\(M = 10,986.18\), \(SD = 1,247.65\)). Age also marginally correlated with mission reward (\(p < 0.10\)), where subjects under 25 years of age (\(M = 12,306.01\), \(SD = 1,174.05\)) achieved slightly higher rewards than those over 25 years old (\(M = 11,181.25\), \(SD = 1,681.12\)). Neither military nor flying experience had any significant effect (\(p > 0.10\)). However, recent video game experience correlated with increased reward (\(p < 0.05\)), which is consistent with past studies involving simulations [25, 31, 120].
Figure 5-6: Additional team performance metrics

(a) Mission makespan (total duration)

(b) Total vehicle distance traveled
Figure 5-7: Individual operator performance metrics

(a) Average operator accuracy

(b) Average secondary response time

Figure 5-7: Individual operator performance metrics
(a) Average primary task duration

(b) Task duration histogram

Figure 5-8: Individual operator task duration
5.4.2 Subjective Measures

Upon completing all experimental trials, subjects were asked which of the four modeling modes they most preferred. Note that this was not a blind experiment (i.e. users knew when they were in the “static” mode, “adaptable” mode, etc.). Participant responses are presented in Figure 5-9a, showing that adaptive and adaptable human performance modeling can improve operator experience in missions with multiple humans and multiple autonomous vehicles. Those who preferred the static baseline modeling case stated that it was “easiest” and “more predictable” than flexible modeling conditions. Subjects choosing adaptive (double) modeling reported that it had the “most accurate pace,” it was “most balanced,” had the “best workload allocation,” and pushed them to achieve their “potential in terms of speed and accuracy.” Preference for the adaptable mode was generally explained by people who felt it was “easiest” and for those who “felt better control” of their role in the system for this condition. A two-sample t-test assuming unequal variances showed no significant correlation between preferring the adaptive (double) condition and achieving high overall mission reward ($p > 0.10$), and there were no significant correlations of modeling mode preference with any of the demographic characteristics.

Subjects were also asked post-experiment, “if you were going to cooperate with autonomous UAVs throughout an actual surveillance mission, would you prefer you or the autonomous system be responsible for allocating and scheduling tasks? Why?” Responses are shown in Figure 5-9b, indicating that participants valued the autonomous task allocation and scheduling system as it applies to this simulation experiment. Those preferring autonomy stated that it would “reduce mental workload,” help them “focus on the mission,” give them a “broader view of team performance,” and generally be better at real-time mission adjustments. People preferring manual allocation and scheduling of tasks either desired authority over the multi-agent team, stating things like “my mission, my responsibility,” or disliked their experience interacting with the autonomous system, saying “the system annoyed me by changing the pace.” Others preferred a shared responsibility on mission coordination that could
(a) Most preferred modeling mode for all experiment participants

(b) Preference for automated versus manual coordination of multi-agent team

Figure 5-9: Participant responses on post-experiment surveys
Table 5.3: Significant results to post-trial Likert-scale questions (in bold)

<table>
<thead>
<tr>
<th>Question Number</th>
<th>Question Text</th>
<th>Omnibus ( (p &lt; 0.05) )</th>
<th>Adaptive (D) preferred to Static ( (p &lt; 0.0083) )</th>
<th>Adaptable preferred to Static ( (p &lt; 0.0083) )</th>
<th>Adaptive (D) preferred to Adaptive (S) ( (p &lt; 0.0083) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>The multi-agent system increased the productivity of the team.</td>
<td>0.0269</td>
<td>0.0012</td>
<td>0.0068</td>
<td>0.0078</td>
</tr>
<tr>
<td>14</td>
<td>The team performed the tasks in the least time possible.</td>
<td>0.0312</td>
<td>0.0040</td>
<td>0.2633</td>
<td>0.0327</td>
</tr>
<tr>
<td>20</td>
<td>I wish I had more say over the pace of the mission.</td>
<td>0.0416</td>
<td>0.0034</td>
<td>0.0295</td>
<td>0.0079</td>
</tr>
</tbody>
</table>

depend on workload or “other external factors,” or nominally having the autonomy optimize the multi-agent mission plan and giving the human operator the ability to adjust it. Again, a two-sample t-test assuming unequal variances showed no significant correlation between preferring the autonomous system over manual control and achieving high overall mission reward \( (p > 0.10) \), and there were no significant correlations between role preference and demographic characteristics.

An omnibus Friedman test [20] confirmed that modeling mode significantly affected participant answers to Likert-scale questions 12, 14, and 20 (Table 5.2; \( p < 0.05 \) for all three questions). Post-hoc pairwise comparisons between modeling strategies were conducted using Wilcoxon signed-rank tests with Bonferroni corrections [20, 115]. Experiment subjects were shown to prefer adaptive (double) and adaptable modeling over the static baseline case \( (p < 0.01 \) for both comparisons) when asked if the system increased the productivity of the multi-agent team, highlighting the notion that operators recognized the advantages of flexible performance modeling. Subjects also preferred the adaptive (double) condition over adaptive (single) in terms of team productivity \( (p < 0.01) \), showing that autonomous adjustment of workload threshold can improve user perception of overall team performance. When asked about whether the team performed the mission in the least time possible, subjects preferred adaptive (double) over the baseline condition \( (p < 0.01) \), which correlates to objective mission metrics (Figure 5-6a). Finally, participants generally wished they had more say over the pace of the mission in the static and adaptive (single) modeling cases than in the adaptive (double) modeling condition \( (p < 0.01 \) for both comparisons).
Modeling mode was demonstrated to have a significant effect on NASA-TLX workload evaluations using an omnibus Friedman test ($p < 0.05$). Post-hoc Wilcoxon signed-rank tests showed that adaptive (double) modeling increased subjective workload over both the static and adaptive (single) conditions ($p < 0.01$), showing that flexibility in terms of workload threshold can add subjective experiences of increasing workload demands on human operators. An analysis of all specific categories involved in the NASA-TLX assessment (mental demand, physical demand, temporal demand, performance, effort, and frustration) revealed that temporal demand (i.e. time pressure) is the only aspect with even marginal significance between modeling modes ($p < 0.10$), pointing to adjustments on operator utilization thresholds – rather than more adverse effects like frustration or performance degradations – as the major contributor to heightened perceived workload.

5.5 Discussion

The increase in mission reward for the two adaptive human modeling conditions confirms the objective hypothesis in Section 5.2. As in the previous pilot study, this
trend may be attributed to the autonomous system’s ability to closely track actual human performance throughout mission execution. Figure 5-11 presents predicted versus actual task durations for two human operators throughout three mission trials (adaptive (single) and adaptive (double) are the same in terms of modeling predicted task duration). Figure 5-11b illustrates that leveraging up-to-date execution information with simple averaging techniques alleviates much of the mismatch between the planning phase’s predictive models and actual dynamic, stochastic human behavior. Rigid models whose parameters are specified \textit{a priori} suffer from differences between human individuals and dynamic performance (Figure 5-11a), and manual control over adjustments leaves the system open to misjudgment, bias, and error (Figure 5-11c). Inconsistencies between planning and execution result in plans that are overly conservative – with bloated, unnecessary constraints – or plans that are too optimistic, causing inefficiencies and conflicts amongst the multi-agent team.

In addition to mitigating model mismatches, adaptive human performance modeling is able to exploit the heterogeneity of the two cooperating human operators in this experiment. Figure 5-8b highlights the wide range of skill levels among subjects in terms of average primary task duration. Furthermore, workload threshold flexibility in the adaptive (double) condition meant that operators could carry out the mission at whatever pace suited their personal skill level. The adaptive model adjustment strategy allowed the autonomous multi-agent planner to produce more effective plans based on these differences. In general, higher-performing operators were allocated more tasks throughout the mission at a more rapid pace than their human teammates (see Operator 1 in Figure 5-11b). Thus proper representation of heterogeneous agents through responsive closed-loop modeling strategies can result in higher effectiveness in terms of achieving mission goals (Figure 5-5) and more efficiency in the coordination of the multi-agent team (Figures 5-6a and 5-6b).

These benefits come without detriment to individual human performance, as the flexible models are matched to each operator’s actual abilities (Figure 5-7a). Workload is appropriately regulated throughout missions for all skill levels, as exemplified by the adaptive (double) modeling condition containing average secondary task response
Figure 5-11: Predicted human operator task duration (from Pew’s model) versus actual task duration over the course of one pair of participants’ trials in each mode.
times near the middle of the desired range with low variance among participants (Figure 5-7b). Flexible modeling was even shown to enhance human performance concerning primary task duration (Figure 5-8a), adjusting mission pace to allow both high and low performers to be more comfortable on their primary taskings (and thus shortening the right tail of the distribution in Figure 5-8b).

Subjective metrics showed additional benefits for adaptive human performance modeling strategies, again supporting the hypotheses of Section 5.2. Comparisons of participant modeling mode preferences are assumed to be more fair for this multiple operator experiment than for the previous pilot study, as all modes required equivalent interaction mechanisms in this work. Figure 5-9a and the associated participant comments illustrate that adaptive modeling can improve general user satisfaction with the autonomous system in addition to producing objective advantages. Likert-scale question responses and NASA-TLX workload assessments reinforce the advantages of user experience under adaptive human performance modeling approaches. Though participants may have been biased by the experimental trials, the majority of subjects’ preference for autonomous control of the task allocation and scheduling system shows that humans can be willing to delegate authority to autonomy in certain contexts. The variety of statements on subjects’ reasoning point to the usefulness of mixed-initiative [69] and flexible level-of-automation approaches [61] to ensure the appropriate application of autonomous support for human-centered systems.

5.6 Conclusions

Adaptive human modeling in which the autonomous system leverages realized information from mission execution can lead to more effective overall performance for coupled human-robot teams consisting of multiple humans and multiple autonomous agents. The difficulties of planning for the stochastic, dynamic, heterogeneous nature of humans can be handled – and even exploited – by closed-loop modeling strategies and appropriate planning techniques. Human-robot teams utilizing adaptive models can be more apt at achieving overall mission goals, are generally able to accomplish
tasks in more efficient fashion, and give human operators more satisfaction during cooperation with autonomous systems.

Further work could be done to investigate even more beneficial strategies for mission planning with coupled human-robot teams. More intricate feedback modes such as a hybrid approach that nominally uses adaptive modeling with the additional ability of operator adjustment could give added advantages to flexible modeling techniques. Furthermore, more sophisticated averaging, filtering, or machine learning techniques continue to be interesting extensions to this work as methods for increasing robustness and dealing with the dynamic, stochastic, and heterogeneous nature of humans.
Chapter 6

Conclusions

6.1 Contributions

This thesis addresses the problem of multi-agent task allocation and scheduling for coupled human-robot teams. Human operator heuristics and constraints are included in the mission planning problem, and humans are treated as dynamic, heterogeneous agents using adaptive performance models. The specific contributions of this thesis are summarized in this section.

Formulations for extending the traditional autonomous task allocation and scheduling problem to include highly coordinated human-robot teams are presented in Chapter 3. Models and strategies from human factors literature are used to design a multi-objective optimization function that includes human operator considerations in addition to traditional mission goals. Well-established heuristics are utilized to establish hard and soft human constraints within multi-agent plans. The resulting planning problem represents efficient execution of task sets which require joint effort and coordination between humans and robots, effectively accomplishing mission goals while adhering to human and vehicle constraints.

Polynomial-time planning algorithms are developed to generate mission plans quickly for these heterogeneous, coupled human-robot teams. A sequential assignment strategy is used in order to make the highly constrained problem more tractable, producing solutions efficiently even for large teams and task sets. Resulting mission plans
show substantial quantitative and qualitative benefits over alternative algorithms in terms of goal achievement and human operator heuristics.

Additionally, adaptive human performance models are integrated into the closed-loop planning framework to respond to dynamic, stochastic, and heterogeneous human agent parameters in real-time. Realized human task performance is leveraged to adjust planning parameters to more accurately reflect actual mission execution. Multi-vehicle simulations with generic distributions representing dynamic, stochastic human operator behavior demonstrate the benefits of replanning at appropriate intervals with flexible agent models based on feedback from true mission performance.

Chapter 4 describes a pilot study that investigates the efficacy of the adaptive modeling approach for actual human-robot teams. Findings show that autonomous model adjustment can alleviate model mismatches between planning and execution phases, resulting in more effective multi-agent plans and improved user experience. Subjects generally preferred to function within the more automated, higher-performing team than to have more control themselves over adjustments to mission pacing and future task allocations.

Chapter 5's experiment demonstrates that flexible models can both mitigate model mismatches and exploit heterogeneity between multiple human operators to improve overall mission performance and human satisfaction. The use of secondary tasks to drive operator models – rather than levels of automation – for both adaptive and adaptable modeling strategies represents a new technique for effective human-machine collaboration.

### 6.2 Future Work

There are several avenues for future research related to this thesis. This section mentions some of these topics along with their associated challenges and potential benefits.

This work addresses mission planning for strictly coupled human-robot teams that cooperate on synchronized, joint tasks. It would be interesting to broaden the
planning problem to account for task sets that require asynchronous human and robot coordination [45], humans as supervisors of robotic agents [105], or decentralized approaches to human-robot teaming [64]. Including separated human and robot tasks along with coupled objectives may provide more realism for mission scenarios as well as intriguing complexities in planning problem formulations. Synthesizing this thesis’s contributions with existing adaptive and adaptable strategies for level-of-automation adjustments [61] could allow humans to act in supervisory roles with enhanced layers of flexibility and robustness. Finally, these new team roles could make decentralized planning strategies more applicable (due to less required coordination), supporting algorithms that are robust to communication constraints and failures [27].

It could also be worthwhile to investigate the integration of more complex human models into this planning framework. This thesis demonstrates that treating relatively simple human performance models as priors within a closed-loop modeling system can result in effective mission plans for coupled human-robot teams. Including other models that take into account considerations of attentional resources [72], learning characteristics [91], fatigue effects [117], and multi-tasking ability [32] could give more informative planning priors at the onset of human-robot teaming missions.

In addition to supplementing human models, more sophisticated planning algorithms could further enhance multi-agent coordination and team performance. Efficient alternatives to sequential algorithms could be considered (such as hierarchical mixed-integer linear programming formulations [47]), and robust planning strategies could explicitly hedge against the stochastic nature of human task execution [86]. Although accounting for parameter uncertainty in tightly coupled human-robot plans would be quite challenging, the advantages of representing and accounting for stochastic behavior could result in more robust multi-agent assignments and could provide mission planners with better understanding of the plans’ possible outcomes. Notably, the experiments from this thesis give stochastic probability distributions on human performance (in terms of task durations) for simple imagery classification and counting tasks, which are important prerequisites for approaches to planning under uncertainty.
Furthermore, it would be interesting to continue progress in terms of feedback strategies for adaptive and adaptable human performance modeling. The incorporation of stochastic averaging techniques [55] could result in more intelligent adaptations for human models. Filtering approaches to both human model updates and overall plan adjustments [6, 17] could remove performance outliers and take operator proficiency into consideration in terms of changing assignments [31]. Learning strategies [19] for adaptive human performance modeling could provide greater predictive power to time-extended planning algorithms by recognizing dynamic agent behaviors such as learning or fatigue. Finally, flexible human performance modeling that synthesizes both adaptive and adaptable mechanisms could be explored in order to enable the highest levels of both mission performance and operator satisfaction.
Appendix A

Experiment Instructions

This appendix provides the script used to guide the multiple operator experiment discussed in Chapter 5:

Please begin by reading and signing the consent form for this experiment...

Thank you for participating in our study on human-machine collaboration! In this experiment, you will be working with a system that simulates three autonomous unmanned aerial vehicles (UAVs). You and your partner must cooperate with these vehicles in order to successfully complete a distributed surveillance mission. You two will first accomplish a full training mission to become familiar with the interface and your primary task responsibilities. You will then accomplish a full training mission with the inclusion of secondary tasks. Finally, you will conduct four mission trials under various planning modes. In between trials, we will ask you questions relating to your perceived workload and your perception of the system in general. We expect the entire process to take approximately one hour.
We will begin the experiment by initializing your user interface. You will see something similar to the layout in Figure A-1. We will go over the various sections of the interface now.

The top-left portion of the interface is represented in the form of a command line. This is where you will conduct your primary tasks concerning imagery classification throughout the mission.
The bottom-left section of the user interface provides a top-down view of the mission environment. In this view you will see three white quadrotor UAVs, each with a corresponding circular background color. UAV 1 is depicted with a red circular background, UAV 2 with a green circular background, and UAV 3 with a blue circular background. Additionally, all surveillance task waypoints are shown as yellow squares on the mission map.

The top-right portion of the user interface is reserved to provide incoming sensor data from the simulated UAVs. These perspectives can be thought of as live, top-down video feeds from on-board UAV cameras. The color-coded circular backgrounds of each UAV are illuminated in the center of each of these frames in order to distinguish the three vehicles. These colors correspond to those illustrated in the full mission map view. Further instruction will be given on when you can expect incoming sensor imagery to show up on your interface. If none of the autonomous UAVs are currently
providing you with surveillance imagery, this view in the full user interface will be grayed out.

To set up a trial, I will enter the appropriate pre-mission information in the command line then give you control of the system. You will be prompted by the command line to enter “b” when ready to begin the mission. Note that all command line inputs require you to perform a keystroke and then press “Enter” on the keyboard.

![Figure A-5: User interface with mission in progress](image)

The mission will begin with the three UAVs autonomously flying out to their first assigned waypoints. Understand that the system is being automated at both the UAV flight control and the multi-agent task allocation and scheduling levels in order to optimize the overall mission. Therefore, your role in the multi-agent team does not involve flying the vehicles or even telling them where to go. Your responsibilities cover the imagery classification portion of the mission.

The automatic traveling of the vehicles will be apparent from the quadrotors moving across the map in the overhead view. In addition to these movements, the interface incorporates predictive aiding in both the flight path of the UAVs to their next waypoints (shown by color-coded lines) as well as the planned allocation of surveillance tasks amongst the vehicles. This planned allocation is shown by color-coding the surveillance task waypoints either red, green, or blue in order to distinguish that either UAV 1, 2, or 3 is assigned to the task. Be advised that these allocations may change throughout the mission.
In Figure A-5, the UAVs have begun flying from their start locations to their first assigned waypoints. Their flight paths are illustrated by the color-coded lines, and all tasks have been allocated amongst the three vehicles. Upon reaching a task location, the UAV will scan the area and present real-time imagery data to either you or your partner through the user interface, similar to what is shown in Figure A-6.

Figure A-6: Imagery provided by the simulated UAV to be classified by the human operator

This imagery will take the form of either little moving circles or little moving squares (all images are either one shape or the other for a given task waypoint). These little pieces of moving imagery are not to be confused with the larger circular backgrounds of UAV positions or the larger color-coded squares of the task waypoint locations. In Figure A-6, UAV 2 has provided imagery consisting of 12 little moving squares. Notice that you must not count the small and large concentric circles that are unmoving in the center of the screen. These are connected to UAV position and should not be counted as pieces of imagery. Additionally, you should ignore the big squares which correspond to current and future surveillance task waypoints.

Figure A-7: Human operator’s primary task input
Once the vehicle has arrived at the surveillance task location and scanned the area, the command line portion of the user interface will prompt you with an indication of arriving imagery. It is now your responsibility to classify the small moving pieces of imagery as either circles or squares by inputting “c” for circles or “s” for squares then pressing “Enter.” In this case (as shown in Figure A-7), the user has inputted “s” for square images. Second, the command line will prompt you for the number of pieces of moving images. Since there are 12 small moving squares for this surveillance task, the user types “12” and presses “Enter.” Once you press “Enter” in the command line to submit the information, there is no way to correct it. The command line will then notify you of your accuracy and task duration. You must get both the shape classification and count correct in order to successfully complete the task. If you are incorrect on either input, you will receive zero reward for the task. Accuracy on this primary imagery classification task is your main priority. Additionally, you want to be as fast on these tasks as possible while maintaining accuracy. This will allow UAVs to fly to new waypoints earlier, and will result in a shorter overall mission time. Task rewards generally decay over time throughout the mission, so accomplishing tasks accurately and quickly will result in high overall mission reward.

![Figure A-8: Overlapping imagery from two UAVs](image)

Sometimes when two UAVs are close together, your provided sensor data from one UAV may also contain some of the squares or circles from a different UAV who is currently cooperating on a surveillance task with your partner. You must not count the moving objects of the other UAV, like the green circles in Figure A-8. Only count the objects whose color corresponds with that of your UAV.
Each task also has a target time allotted for execution, provided by the automated task allocation and scheduling system. When that target time has been exceeded, the moving objects will flash yellow as shown in Figure A-9. Exceeding the target task times may result in suboptimal planning, and could lead to missed task time windows or poor coordination amongst the vehicles.

You and your partner will continue to cooperate with the UAVs on the image classification and counting tasks until all surveillance tasks within the mission have been completed.

We will now conduct the first practice trial to get you acquainted with the interface and your primary task roles. If you have any questions, please do not hesitate to ask me at this time and/or during the practice trial.

***First practice trial (Static mode WITHOUT secondary tasks)***

We will now have you answer an assessment of your perceived workload and thoughts on the system...

In addition to your primary image classification and counting tasks, you will be asked to perform secondary tasks in order to provide the system with updates on how the mission is progressing. These tasks will appear in the form of questions in the bottom right section of your user interface.
We will now go over the questions that you may be asked to answer.

*Desire more time FOR tasks (y/n)?*

You may respond “y” for “yes” if the imagery provided to you by the UAVs flashes consistently throughout your various tasks, indicating that the planner’s target times are shorter than the actual time that is required for you to complete the tasks accurately. Otherwise, you may respond “n” for “no” to indicate a desire to keep target times short, allowing the UAVs to move on to other tasks more quickly.

*Desire more time BETWEEN tasks (y/n)?*

You may respond “y” for “yes” if tasks between different UAVs are being presented more quickly than your comfort level allows, and thus decreasing your classification and counting accuracy or pushing your overall workload to undesirable levels. Alternatively, you may respond “n” for “no” to indicate a desire to keep task switching times short and allow UAVs to present you with imagery more quickly. Â– You should respond to these secondary task questions as quickly as possible without degrading your primary task (imagery classification and counting) performance. These
secondary tasks are required and may be utilized within the underlying planning framework to drive mission coordination.

We will now conduct the second practice trial for training on your combined primary and secondary task roles. If you have any questions, please do not hesitate to ask me at this time and/or during the practice trial.

***Second practice trial (Static mode WITH secondary tasks)***

We will now have you answer an assessment of your perceived workload and thoughts on the system...
If you are ready, we will now begin the experimental trials.

***Experimental trials with balanced ordering of modes and questionnaires after each trial***

Thank you for your time! We will conclude the study by recording demographic information and open response questions...
Appendix B

Pilot Study & Experiment

Questionnaires

This appendix presents the participant questionnaires included in Chapter 4’s pilot study and Chapter 5’s multiple operator experiment.

B.1 Single-Operator Pilot Study

Situational Awareness Measures

What colors were the UAVs in the simulation?

How many tasks did you complete during each trial?

Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future.

Rate your situational awareness during this study from 1-10:
User Interface Analysis

The command line interface you used for the study is shown in the figure above. Do you think this interface was an efficient way to interact with the simulation? What did you like about the interface? What could be improved to make it a more efficient interface?

We designed a graphical user interface to be used in future experiments. It is shown in the figure above. Would you have preferred to use this interface? Please explain why you prefer this interface or the command line interface.
An interface that integrates the command line into a graphical user interface is shown in the figure above. Please comment on the utility of the interface shown and indicate whether you would prefer this interface to the other two presented.

**Modeling Mode Evaluation**

Which modeling mode was most efficient in helping you complete the mission?

Which modeling mode did you most enjoyed using?

Do you have any other comments on the experiment?
# B.2 Multiple-Operator Experiment

## NASA-TLX Workload Analysis (after each trial)

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mental Demand</td>
<td>How mentally demanding were your tasks throughout the mission?</td>
<td>Very Low (1) - Very High (10)</td>
</tr>
<tr>
<td>Physical Demand</td>
<td>How physically demanding were the tasks?</td>
<td>Very Low (1) - Very High (10)</td>
</tr>
<tr>
<td>Temporal Demand</td>
<td>How hurried or rushed was the pace of the overall mission?</td>
<td>Very Low (1) - Very High (10)</td>
</tr>
<tr>
<td>Performance</td>
<td>How successful were you in accomplishing what you were asked to do?</td>
<td>Perfect (1) - Failure (10)</td>
</tr>
<tr>
<td>Effort</td>
<td>How hard did you have to work to accomplish your level of performance?</td>
<td>Very Low (1) - Very High (10)</td>
</tr>
<tr>
<td>Frustration</td>
<td>How insecure, discouraged, irritated, stressed, and annoyed were you?</td>
<td>Very Low (1) - Very High (10)</td>
</tr>
</tbody>
</table>

Next, please select the item that in your opinion contributes the most to workload in this experiment:

*Evaluate 15 pairwise comparisons between the six demand categories*
   (e.g. Mental Demand versus Physical Demand)
System Perception (after each trial)

<table>
<thead>
<tr>
<th>System Traits</th>
<th>Strongly Disagree</th>
<th>Disagree</th>
<th>Disagree Somewhat</th>
<th>Undecided</th>
<th>Agree Somewhat</th>
<th>Agree</th>
<th>Strongly Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>The multi-agent system was intelligent.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The multi-agent system was trustworthy.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The multi-agent system was committed to the mission.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Team Fluency</strong></td>
<td>Strongly Disagree</td>
<td>Disagree</td>
<td>Disagree Somewhat</td>
<td>Undecided</td>
<td>Agree Somewhat</td>
<td>Agree</td>
<td>Strongly Agree</td>
</tr>
<tr>
<td>I feel uncomfortable cooperating with the UAVs within this framework.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I feel uncomfortable cooperating with my human teammate within this framework.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The multi-agent system and I understand each other.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I received adequate feedback on my task performance throughout the mission.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The system perceives accurately what my abilities are.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I find what I am doing within the system confusing</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I was satisfied by the team's performance.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I would rely on the system next time the tasks were to be completed.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The multi-agent system increased the productivity of the team.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The team collaborated well together.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The team performed the tasks in the least time possible.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The multi-agent allocation and scheduling system was necessary for the successful completion of the tasks.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>My human partner was necessary for the successful completion of the tasks.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I was necessary for the successful completion of the tasks.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decision Authority</th>
<th>Strongly Disagree</th>
<th>Disagree</th>
<th>Disagree Somewhat</th>
<th>Undecided</th>
<th>Agree Somewhat</th>
<th>Agree</th>
<th>Strongly Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>I wish I had more say over the scheduling and allocation of tasks among the UAVs.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I wish I had more say over the allocation of tasks between me and my human partner.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I wish I had more say over the pace of the mission.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Open Response Questions and Demographic Information (upon completion)

Gender (circle one): M/F Age: _____ Military experience (circle one)? Yes/No

Approximately how many hours per week do you spend playing video games (circle one)?

- Less than 1 hour
- 1-5 hours
- 5-10 hours
- Greater than 10 hours

Do you have experience operating aerial vehicles (real or simulated)? If yes, please describe your experience.

Do you know your experiment partner? If so, please briefly describe how you know them.

Which of the four modeling modes did you most prefer (check one)?

- Static
- Adaptive – Single
- Adaptive – Double
- Adaptable

Why?

If you were going to cooperate with autonomous UAVs throughout an actual surveillance mission, would you prefer you or the system be responsible for allocating and scheduling tasks? Why?

Do you have any further comments about the system or the experiment?
Appendix C

Pilot Study & Experiment Data

This appendix presents in-depth data from Chapter 4’s pilot study and Chapter 5’s multiple-operator experiment.

C.1 Single-Operator Pilot Study

<table>
<thead>
<tr>
<th>Metric</th>
<th>Condition</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>Static</td>
<td>12</td>
<td>6,649.21</td>
<td>1,372.39</td>
<td>396.18</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>12</td>
<td>8,116.25</td>
<td>933.80</td>
<td>269.56</td>
</tr>
<tr>
<td>Mission</td>
<td>Static</td>
<td>12</td>
<td>6,311.36</td>
<td>1,036.45</td>
<td>299.20</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>12</td>
<td>189.83</td>
<td>37.39</td>
<td>10.79</td>
</tr>
<tr>
<td>Makespan (s)</td>
<td>Static</td>
<td>12</td>
<td>140.44</td>
<td>22.26</td>
<td>6.43</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>12</td>
<td>190.62</td>
<td>29.66</td>
<td>8.56</td>
</tr>
<tr>
<td>Vehicle</td>
<td>Static</td>
<td>12</td>
<td>809.44</td>
<td>66.49</td>
<td>19.20</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>12</td>
<td>788.33</td>
<td>82.64</td>
<td>23.86</td>
</tr>
<tr>
<td>Distance Traveled</td>
<td>Static</td>
<td>12</td>
<td>902.10</td>
<td>152.12</td>
<td>43.91</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>12</td>
<td>938.9</td>
<td>7.76</td>
<td>2.24</td>
</tr>
<tr>
<td>Operator Accuracy (%)</td>
<td>Static</td>
<td>12</td>
<td>95.00</td>
<td>9.48</td>
<td>2.74</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>12</td>
<td>98.89</td>
<td>2.59</td>
<td>0.75</td>
</tr>
<tr>
<td>Avg. Task Duration (s)</td>
<td>Static</td>
<td>12</td>
<td>5.00</td>
<td>1.01</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>12</td>
<td>5.62</td>
<td>0.99</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>12</td>
<td>7.25</td>
<td>1.00</td>
<td>0.29</td>
</tr>
</tbody>
</table>
Table C.2: Overall mission rewards achieved by the team for each pilot study trial

<table>
<thead>
<tr>
<th>Participant</th>
<th>Static</th>
<th>Adaptive</th>
<th>Adaptable</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6,214.48</td>
<td>7,899.87</td>
<td>6,362.49</td>
</tr>
<tr>
<td>2</td>
<td>5,794.95</td>
<td>8,556.89</td>
<td>6,599.01</td>
</tr>
<tr>
<td>3</td>
<td>8,426.59</td>
<td>9,828.13</td>
<td>3,645.39</td>
</tr>
<tr>
<td>4</td>
<td>7,446.97</td>
<td>8,027.88</td>
<td>7,070.91</td>
</tr>
<tr>
<td>5</td>
<td>5,848.94</td>
<td>6,612.97</td>
<td>5,656.46</td>
</tr>
<tr>
<td>6</td>
<td>5,958.89</td>
<td>7,830.10</td>
<td>5,885.81</td>
</tr>
<tr>
<td>7</td>
<td>7,496.40</td>
<td>9,019.74</td>
<td>6,112.21</td>
</tr>
<tr>
<td>8</td>
<td>8,869.99</td>
<td>8,071.02</td>
<td>6,483.82</td>
</tr>
<tr>
<td>9</td>
<td>3,721.73</td>
<td>7,165.91</td>
<td>6,364.52</td>
</tr>
<tr>
<td>10</td>
<td>6,489.96</td>
<td>9,294.12</td>
<td>6,705.65</td>
</tr>
<tr>
<td>11</td>
<td>6,205.47</td>
<td>7,152.18</td>
<td>6,821.50</td>
</tr>
<tr>
<td>12</td>
<td>7,316.12</td>
<td>7,936.14</td>
<td>8,028.59</td>
</tr>
<tr>
<td>Mean</td>
<td>6,649.21</td>
<td>8,116.25</td>
<td>6,311.36</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1,372.39</td>
<td>933.80</td>
<td>1,036.45</td>
</tr>
<tr>
<td>Std. Error</td>
<td>396.18</td>
<td>269.56</td>
<td>299.20</td>
</tr>
</tbody>
</table>

Table C.3: Pilot study's subjective poll results

<table>
<thead>
<tr>
<th>Poll</th>
<th>Condition</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Most efficient mode”</td>
<td>Static</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>1</td>
</tr>
<tr>
<td>“Most enjoyable mode”</td>
<td>Static</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Adaptive</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>2</td>
</tr>
</tbody>
</table>
## C.2 Multiple-Operator Experiment

### Table C.4: Participant demographics

<table>
<thead>
<tr>
<th>Demographic Characteristic</th>
<th>Percentage of Experiment Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>25%</td>
</tr>
<tr>
<td>Military</td>
<td>67%</td>
</tr>
<tr>
<td>Flier</td>
<td>50%</td>
</tr>
<tr>
<td>Video gamer</td>
<td>25%</td>
</tr>
</tbody>
</table>

### Table C.5: Age statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>31.13</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>13.30</td>
</tr>
<tr>
<td>Std. Error</td>
<td>2.71</td>
</tr>
<tr>
<td>Median</td>
<td>23.5</td>
</tr>
<tr>
<td>Mode</td>
<td>23</td>
</tr>
<tr>
<td>Minimum</td>
<td>20</td>
</tr>
<tr>
<td>Maximum</td>
<td>62</td>
</tr>
<tr>
<td>Count</td>
<td>24</td>
</tr>
</tbody>
</table>

### Table C.6: Descriptive statistics for experiment performance metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Condition</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mission Reward</td>
<td>Static</td>
<td>12</td>
<td>10,740.70</td>
<td>1,637.14</td>
<td>472.60</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>12</td>
<td>12,046.81</td>
<td>1,764.65</td>
<td>509.41</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>12</td>
<td>12,841.97</td>
<td>1,666.38</td>
<td>481.04</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>12</td>
<td>11,719.95</td>
<td>1,792.05</td>
<td>517.32</td>
</tr>
<tr>
<td>Total Mission Makespan (s)</td>
<td>Static</td>
<td>12</td>
<td>264.67</td>
<td>43.19</td>
<td>12.47</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>12</td>
<td>241.74</td>
<td>40.13</td>
<td>11.58</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>12</td>
<td>227.27</td>
<td>42.03</td>
<td>12.13</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>12</td>
<td>234.44</td>
<td>41.69</td>
<td>12.03</td>
</tr>
<tr>
<td>Total Vehicle Distance</td>
<td>Static</td>
<td>12</td>
<td>1,001.38</td>
<td>77.10</td>
<td>22.26</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>12</td>
<td>1,036.92</td>
<td>54.57</td>
<td>15.75</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>12</td>
<td>923.68</td>
<td>81.07</td>
<td>23.40</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>12</td>
<td>1,028.61</td>
<td>76.73</td>
<td>22.15</td>
</tr>
<tr>
<td>Average Operator Accuracy (%)</td>
<td>Static</td>
<td>24</td>
<td>92.73</td>
<td>7.91</td>
<td>1.62</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>24</td>
<td>94.71</td>
<td>7.54</td>
<td>1.54</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>24</td>
<td>94.78</td>
<td>5.53</td>
<td>1.13</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>24</td>
<td>91.62</td>
<td>8.88</td>
<td>1.81</td>
</tr>
<tr>
<td>Primary Task Duration (s)</td>
<td>Static</td>
<td>24</td>
<td>7.73</td>
<td>2.55</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>24</td>
<td>6.93</td>
<td>1.54</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>24</td>
<td>7.01</td>
<td>1.58</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>24</td>
<td>6.97</td>
<td>1.79</td>
<td>0.37</td>
</tr>
<tr>
<td>Secondary Task Response Time (s)</td>
<td>Static</td>
<td>24</td>
<td>7.08</td>
<td>5.34</td>
<td>1.09</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>24</td>
<td>5.29</td>
<td>1.66</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>24</td>
<td>6.50</td>
<td>2.21</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>24</td>
<td>6.09</td>
<td>3.27</td>
<td>0.67</td>
</tr>
</tbody>
</table>
Table C.7: Overall mission rewards achieved by the human-robot team for each trial

<table>
<thead>
<tr>
<th>Participants</th>
<th>Static</th>
<th>Adaptive (Single)</th>
<th>Adaptive (Double)</th>
<th>Adaptable</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 &amp; 2</td>
<td>8,184.53</td>
<td>10,658.60</td>
<td>10,421.33</td>
<td>10,713.18</td>
</tr>
<tr>
<td>3 &amp; 4</td>
<td>11,014.05</td>
<td>9,858.32</td>
<td>10,997.36</td>
<td>11,428.38</td>
</tr>
<tr>
<td>5 &amp; 6</td>
<td>12,670.15</td>
<td>13,206.31</td>
<td>14,151.83</td>
<td>11,599.89</td>
</tr>
<tr>
<td>7 &amp; 8</td>
<td>12,116.94</td>
<td>12,960.72</td>
<td>12,788.97</td>
<td>14,288.53</td>
</tr>
<tr>
<td>9 &amp; 10</td>
<td>13,256.38</td>
<td>14,461.21</td>
<td>15,549.95</td>
<td>14,320.27</td>
</tr>
<tr>
<td>11 &amp; 12</td>
<td>10,622.87</td>
<td>11,464.87</td>
<td>11,979.85</td>
<td>11,219.60</td>
</tr>
<tr>
<td>13 &amp; 14</td>
<td>11,636.94</td>
<td>15,082.69</td>
<td>15,581.78</td>
<td>14,051.20</td>
</tr>
<tr>
<td>15 &amp; 16</td>
<td>9,947.78</td>
<td>10,456.89</td>
<td>11,223.23</td>
<td>9,512.76</td>
</tr>
<tr>
<td>17 &amp; 18</td>
<td>10,020.52</td>
<td>12,606.05</td>
<td>12,968.44</td>
<td>12,002.32</td>
</tr>
<tr>
<td>19 &amp; 20</td>
<td>11,238.99</td>
<td>10,862.93</td>
<td>13,731.94</td>
<td>9,813.19</td>
</tr>
<tr>
<td>21 &amp; 22</td>
<td>10,367.04</td>
<td>13,063.53</td>
<td>12,157.23</td>
<td>12,434.16</td>
</tr>
<tr>
<td>23 &amp; 24</td>
<td>7,812.25</td>
<td>9,879.56</td>
<td>12,551.79</td>
<td>9,255.95</td>
</tr>
<tr>
<td>Mean</td>
<td>10,740.70</td>
<td>12,046.81</td>
<td>12,841.97</td>
<td>11,719.95</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1,637.14</td>
<td>1,764.65</td>
<td>1,666.38</td>
<td>1,792.05</td>
</tr>
<tr>
<td>Std. Error</td>
<td>472.60</td>
<td>509.41</td>
<td>481.04</td>
<td>517.32</td>
</tr>
</tbody>
</table>

Table C.8: Demographic/preference correlations with average overall mission reward (two-tailed t-test with unequal variances and sample sizes)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>t-stat</th>
<th>d.f.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>1.82</td>
<td>15</td>
<td>0.088</td>
</tr>
<tr>
<td>Gender</td>
<td>1.84</td>
<td>10</td>
<td>0.096</td>
</tr>
<tr>
<td>Military</td>
<td>1.08</td>
<td>16</td>
<td>0.298</td>
</tr>
<tr>
<td>Flier</td>
<td>0.89</td>
<td>20</td>
<td>0.383</td>
</tr>
<tr>
<td>Video gamer</td>
<td><strong>2.29</strong></td>
<td><strong>13</strong></td>
<td><strong>0.039</strong></td>
</tr>
<tr>
<td>Prefer Adaptive (D)</td>
<td>1.29</td>
<td>22</td>
<td>0.212</td>
</tr>
<tr>
<td>Prefer Autonomy</td>
<td>1.29</td>
<td>17</td>
<td>0.213</td>
</tr>
</tbody>
</table>
Table C.9: Results for post-trial Likert-scale questions (Friedman’s omnibus test evaluating significance of modeling mode condition on subject responses with α ≤ 0.05)

<table>
<thead>
<tr>
<th>Number</th>
<th>Question Text</th>
<th>H-stat</th>
<th>d.f.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The multi-agent system was intelligent.</td>
<td>2.44</td>
<td>3</td>
<td>0.487</td>
</tr>
<tr>
<td>2</td>
<td>The multi-agent system was trustworthy.</td>
<td>2.76</td>
<td>3</td>
<td>0.430</td>
</tr>
<tr>
<td>3</td>
<td>The multi-agent system was committed to the mission.</td>
<td>0.84</td>
<td>3</td>
<td>0.840</td>
</tr>
<tr>
<td>4</td>
<td>I feel uncomfortable cooperating with the UAVs within this framework.</td>
<td>1.21</td>
<td>3</td>
<td>0.750</td>
</tr>
<tr>
<td>5</td>
<td>I feel uncomfortable cooperating with my human teammate within this framework.</td>
<td>0.41</td>
<td>3</td>
<td>0.938</td>
</tr>
<tr>
<td>6</td>
<td>The multi-agent system and I understand each other.</td>
<td>1.21</td>
<td>3</td>
<td>0.750</td>
</tr>
<tr>
<td>7</td>
<td>I received adequate feedback on my task performance throughout the mission.</td>
<td>0.45</td>
<td>3</td>
<td>0.929</td>
</tr>
<tr>
<td>8</td>
<td>The system perceives accurately what my abilities are.</td>
<td>2.70</td>
<td>3</td>
<td>0.440</td>
</tr>
<tr>
<td>9</td>
<td>I find what I am doing within the system confusing.</td>
<td>0.39</td>
<td>3</td>
<td>0.943</td>
</tr>
<tr>
<td>10</td>
<td>I was satisfied by the team’s performance.</td>
<td>1.51</td>
<td>3</td>
<td>0.679</td>
</tr>
<tr>
<td>11</td>
<td>I would rely on the system next time the tasks were to be completed.</td>
<td>0.91</td>
<td>3</td>
<td>0.822</td>
</tr>
<tr>
<td>12</td>
<td>The multi-agent system increased the productivity of the team.</td>
<td>9.19</td>
<td>3</td>
<td>0.027</td>
</tr>
<tr>
<td>13</td>
<td>The team collaborated well together.</td>
<td>2.59</td>
<td>3</td>
<td>0.460</td>
</tr>
<tr>
<td>14</td>
<td>The team performed the tasks in the least time possible.</td>
<td>8.86</td>
<td>3</td>
<td>0.031</td>
</tr>
<tr>
<td>15</td>
<td>The multi-agent allocation and scheduling system was necessary for the successful completion of the tasks.</td>
<td>1.64</td>
<td>3</td>
<td>0.651</td>
</tr>
<tr>
<td>16</td>
<td>My human partner was necessary for the successful completion of the tasks.</td>
<td>1.39</td>
<td>3</td>
<td>0.709</td>
</tr>
<tr>
<td>17</td>
<td>I was necessary for the successful completion of the tasks.</td>
<td>0.71</td>
<td>3</td>
<td>0.870</td>
</tr>
<tr>
<td>18</td>
<td>I wish I had more say over the scheduling and allocation of tasks among the UAVs.</td>
<td>4.74</td>
<td>3</td>
<td>0.192</td>
</tr>
<tr>
<td>19</td>
<td>I wish I had more say over the allocation of tasks between me and my human partner.</td>
<td>2.73</td>
<td>3</td>
<td>0.436</td>
</tr>
<tr>
<td>20</td>
<td>I wish I had more say over the pace of the mission.</td>
<td>8.23</td>
<td>3</td>
<td>0.042</td>
</tr>
</tbody>
</table>
Table C.10: Significant p-values for post-trial Likert-scale questions (Friedman’s paired two-tail tests evaluating preference between modeling modes with $\alpha \leq 0.0083$)

<table>
<thead>
<tr>
<th>Question Number</th>
<th>Question Text</th>
<th>Adaptive (S) preferred to Static</th>
<th>Adaptive (D) preferred to Static</th>
<th>Adaptable preferred to Static</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>The multi-agent system increased the productivity of the team. The team performed the tasks in the least time possible. I wish I had more say over the pace of the mission.</td>
<td>0.2061</td>
<td><strong>0.0012</strong></td>
<td><strong>0.0068</strong></td>
</tr>
<tr>
<td>14</td>
<td>The multi-agent system increased the productivity of the team. The team performed the tasks in the least time possible. I wish I had more say over the pace of the mission.</td>
<td>0.1514</td>
<td><strong>0.0040</strong></td>
<td>0.2633</td>
</tr>
<tr>
<td>20</td>
<td>The multi-agent system increased the productivity of the team. The team performed the tasks in the least time possible. I wish I had more say over the pace of the mission.</td>
<td>0.5171</td>
<td><strong>0.0034</strong></td>
<td>0.0295</td>
</tr>
</tbody>
</table>

Table C.11: Experiment’s subjective poll results

<table>
<thead>
<tr>
<th>Poll</th>
<th>Condition</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Most preferred modeling mode”</td>
<td>Static</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>9</td>
</tr>
<tr>
<td>“Preferred Authority for MRTA”</td>
<td>Autonomy</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>User</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Mixed</td>
<td>6</td>
</tr>
</tbody>
</table>
Table C.12: Post-trial NASA-TLX (subjective workload analysis) results

<table>
<thead>
<tr>
<th>Scale</th>
<th>Condition</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Workload</td>
<td>Static</td>
<td>24</td>
<td>53.33</td>
<td>14.07</td>
<td>2.87</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>24</td>
<td>56.12</td>
<td>16.49</td>
<td>3.37</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>24</td>
<td>61.89</td>
<td>15.21</td>
<td>3.11</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
<td>24</td>
<td>57.86</td>
<td>14.07</td>
<td>2.87</td>
</tr>
<tr>
<td>Mental Demand</td>
<td>Static</td>
<td>24</td>
<td>62.08</td>
<td>20.74</td>
<td>4.23</td>
</tr>
<tr>
<td></td>
<td>Adaptive (S)</td>
<td>24</td>
<td>64.58</td>
<td>21.72</td>
<td>4.43</td>
</tr>
<tr>
<td></td>
<td>Adaptive (D)</td>
<td>24</td>
<td>66.25</td>
<td>21.83</td>
<td>4.46</td>
</tr>
<tr>
<td></td>
<td>Adaptable</td>
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Bibliography


[50] Kate Groetzinger. Researchers are Asking for the Public’s Help Counting All of the Penguins in these Photos, 2016.


