

Modeling Human Workload in Unmanned Aerial Systems

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Abstract

Unmanned aerial systems (UASs) often require multiple human operators fulfilling diverse roles for safe correct operation. Although some dispute the utility of minimizing the number of humans needed to administer a UAS (Murphy and Burke 2010), minimization remains a long-standing objective for many designers. This paper presents work toward understanding how workload is distributed between multiple human operators and multiple autonomous system elements in a UAS across time, with an ultimate goal to reduce the number of humans in the system. The approach formally models the *actors* in a UAS as a set of communicating finite state machines, modified to include a simple form of external memory. The interactions among actors are then modeled as a directed graph. The individual machines, one for each actor in the UAS, and the directed graph are augmented with workload metrics derived from a review of the relevant literature. The model is implemented as a Java program, which is analyzed by the Java Pathfinder (JPF) model checker. JPF generates workload profiles showing how workload changes through time. To demonstrate the utility of the approach, this paper presents a case study on a wilderness search and rescue (WiSAR) UAS analyzing two different mission outcomes. The generated workload profiles are shown to be consistent with known features of actual workload events in the WiSAR system.

Introduction

Unmanned aerial systems (UASs), ranging from large military-style Predators to small civilian-use hovercraft, usually require more than one human to operate. It is perhaps ironic that a so-called “unmanned” system requires multiple human operators, but when a UAS is part of a mission that requires more than moving from point A to point B, there are many different tasks that rely on human input including: operating the UAS, managing a payload (i.e., camera), managing mission objectives etc. Some persuasively argue that this is desirable because different aspects of a mission are handled by humans trained for those aspects (Murphy and Burke 2010). As human resources are expensive, others argue that it is desirable to reduce the number of humans involved.

This paper explores the open question of *how* to reduce the number of humans while maintaining a high level of robustness. Some progress has been made by improving autonomy using, for example, automatic path-planning (Wong, Bourgault, and Furukawa 2005; Bortoff 2000; Pettersson and Doherty 2006; Quigley et al. 2006; Nelson et al. 2006), and automated target recognition (Morse, Engh, and Goodrich 2010; Dasgupta 2008; Barber et al. 2006). However, careful human factors suggest that the impact of changes in autonomy are often subtle and difficult to predict, and this decreases confidence that the combined human-machine system will be robust across a wide range of mission parameters (Kaber and Endsley 2004; Chen, Barnes, and Harper-Sciarini 2011; Chen, Haas, and Barnes 2007).

The research in this paper argues that one reason for the limitations of prior work in measuring workload is that the level of resolution is too detailed. For example, although the NASA TLX dimensions include various contributing factors to workload (e.g., physical effort and mental effort), the temporal distribution of workload tends to be “chunked” across a period of time. Secondary task measures can provide a more detailed albeit indirect breakdown of available cognitive resources as a function of time (Kaber and Riley 1999), but with insufficient explanatory power for what in the task causes workload peaks and abatement. Cognitive workload measures, including those that derive from Wickens’ multiple resource theory (Wickens 2002), provide useful information about the causes of workload spikes, but these measures have not been widely adopted; one way to interpret the research in this paper is as a step toward robust implementations of elements of these measures. Finally, measures derived from cognitive models such as ACT-R are providing more low-level descriptions of workload which potentially include a temporal history (Lebiere, Jentsch, and Ososky 2013), but these approaches may require a modeling effort that is too time-consuming to be practical for some systems.

This paper presents a model of four human roles for a UAS-enabled wilderness search and rescue (WiSAR) task, and is based on prior work on designing systems through field work and cognitive task analyses (Adams et al. 2009; Goodrich et al. 2008). The paper first identifies a suite of possible workload measures based on a review of the literature. It then considers seven *actors* in the team: the UAV, the operator and the operator’s GUI, the video analyst and

the analyst’s GUI, the mission manager, and a role called the “parent search” which serves to connect the UAS technical search team to the other components of the search enterprise. The paper then presents the formal model of each of these actors using finite state machines, and then discuss how the connections between these state machines defines what is called a *Directed Team Graph* (DiTG) that describes who communicates with whom and under what conditions. The paper then describes how to augment the model to be able to encode specific metrics based on a subset of the measures identified in the literature. Using the Java PathFinder model checker, a temporal profile is created for each of the workload metrics. These profiles are checked for consistency by associating workload peaks and abatement with likely causes.

Workload Categories

Workload is restricted to three general categories of metrics in this work: cognitive, temporal, and algorithmic.¹

Cognitive workload describes the difficulties associated with managing various signals, decisions, and actions relevant to a particular task or goal (Moray et al. 1991; Lebiere, Jentsch, and Ososky 2013; Goodrich 2004; Chadwick et al. 2004). We adopt a simple form of Wickens’ multiple resource theory (Wickens 2002), and make the simplifying assumption that cognitive workload can be divided into two categories: parallel sensing and sequential decision making. We further restrict the sensing channels to visual and auditory modalities, ignoring haptic. Parallel sensing means that it is possible for a human to perceive complementary stimuli over different channels. An example of this would be an individual hearing their call sign on the radio while analyzing video. However, when multiple signals may occur over the same channel at the same time, this induces attentional workload for the human. Sequential decision making occurs when a decision must be made, where we have adopted the assumption made by Wickens and supported by work in the psychology of attention (Pashler 1998) that a “bottle-neck” occurs when multiple channels either (a) require a decision to be generated or (b) exceed the limits of working memory.

Algorithmic workload results from the difficulty of bringing a task to completion. Adopting a common model from artificial intelligence (Murphy 2000), and consistent with Wickens’ three stage multiple resource model, we assume that this is comprised of three phases: sense, plan, and act. During the sensing phase, the actor takes all active inputs, interprets them, and generates a set of relevant decision-making parameters. In the planning phase the actor reviews the breadth of choices available and selects one. The actor might use search or a more naturalistic decision-making process like recognition-primed decision-making (Zsombok and Klein 1997) or a cognitive heuristic (Todd 1999). In the acting phase the actor carries out the decision. Before concluding, we note that workload is highly dependent on the

experience of the actor (Zsombok and Klein 1997), but we leave a careful treatment of this to future work.

Temporal workload deals with the scheduling of prioritized, infrequent, and/or repetitious tasks (Dessouky, Moray, and Kijowski 1995; Moray et al. 1991). Various measures have been proposed, but we are most interested in those related to so-called “fan-out”, meaning the number of tasks that a single actor can manage (Goodrich 2010; Olsen Jr. and Wood 2004; Crandall et al. 2005; Cummings et al. 2007a). There are two particularly important aspects of temporal workload. First, when a task is constrained by (a) the time by which the task must be completed or (b) the need to complete other tasks before or after the given task then (c) it causes scheduling pressure and workload (Mau and Dolan 2006). The second aspect is operational tempo, which represents how frequently new tasks arrive. From a scheduling or queuing theory perspective, operational tempo impacts workload by causing pressure to manage the rate of arrival and the response time of the decision.

Actor Model

In previous work (Gledhill, Mercer, and Goodrich 2013), we represented each *actor*, human or autonomous component, of the WiSAR search team as a Mealy state machines as has been done in other models (Bolton, Bass, and Siminiceanu 2013). This work uses Moore machines where output is determined only by present state.

Actors represent the human decision-makers and autonomous elements of the WiSAR team. An actor is composed of a set of states S , an initial state s_0 , a set of inputs from the environment Σ_{env} , a set of inputs from other actors on the team Σ_{team} , a set of outputs Λ_{out} , a simple form of memory Ω_{mem} , and a transition function that determines the next state from the inputs and memory δ . Formally, we denote an actor as:

$$Actor = (S, s_0, \Sigma_{env}, \Sigma_{team}, \Lambda_{out}, \Omega_{mem}, \delta) \quad (1)$$

An actor’s output has two components: signals to other actors on a team and a *duration* parameter that represents the time required for the actor to complete its transition to the next state. Thus, $\Lambda_{out} = \Sigma_{team} \times \mathbb{N}^+$. Relative task difficulty is expressed by the duration of the transition. We justify this by assuming that all tasks are performed at a constant rate, thus more difficult tasks take longer.

A transition is a relation on the cross product of inputs with outputs.

$$\delta : [S \times \Sigma_{env} \times \Sigma_{team} \times \Omega_{mem}] \times [S \times \Sigma_{team} \times \Omega_{mem}], \quad (2)$$

where the brackets separate inputs from outputs.

Given an actor’s current state, set of input signals, and memory, it is possible for multiple transitions to be possible. This occurs because we assume that multiple environment signals or inter-actor signals may be occurring at the same time, which are all perceived by the actor since we assume perception is a parallel operation. Thus, it is useful to explicitly note the number of transitions that are possible from a given state. A transition is considered *enabled* when all of its input requirements are met and *disabled* otherwise.

¹A fourth relevant workload category is the cost of maintaining team constructs like shared situation awareness is future work (Elias and Fiore 2011).

When an actor is in a given state, it is useful to explicitly denote the set of enabled and disabled transitions. This information enables an estimate of algorithmic workload, where we assume that algorithmic workload is a function of the number of choices available to the actor. Thus, we allow the current state to give a workload signal

$$s_0^{\text{work sig}} = (T_{\text{enabled}}, T_{\text{disabled}}) : T_{\text{enabled}} \cap T_{\text{disabled}} = \emptyset \quad (3)$$

Internal variables within an actor are comprised of facts stored by an actor and used in decision making. A good example of this can be seen in the mission manager actor of our simulation. As the search begins, the mission manager receives a number of data items from the parent search, e.g. search area and target description. These items of information need to be communicated separately to different actors, so they must be stored internally in the mean time.

Directed Team Graph (DiTG)

A key element of the actors is that inputs to one actor can be outputs from another actor. We can therefore create a directed graph from actor to actor, with an edge from actor A to actor B existing if the output from actor A is a possible input to actor B. We call this graph a *Directed Team Graph* (DiTG); Figure 1 illustrates the DiTG for the WiSAR team used in this paper.

Using the fact that multiple resource theory indicates that visual and auditory channels can be perceived in parallel (Wickens 2002), it is useful to label the edges in the graph with the *channel type* as in Figure 2. These labels allow the model-checker to identify when multiple signals are given to a single actor over the same channel. When this occurs, we expect actor workload to be high.

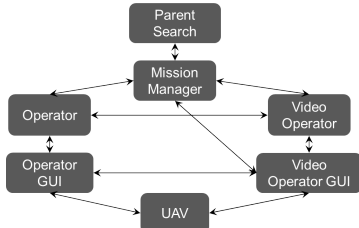


Figure 1: High Level DiTG

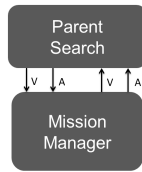


Figure 2: Detail view of DiTG: V is a Visual channel and A is an Audio channel

We represent a system as a DiTG, a collection of actors connected to one another by a set of channels. Whenever the state of the system changes, an actor will petition from its current state, a list of enabled transitions thus defining what

decisions can be made. The actor may then activate one of these transitions.

Since transitions from one state to another take time, as encoded in the *Duration* element of the output, it is useful to label transitions as either *active* or *fired*. Transitions in the actor model are labeled as *enabled* and *disabled*. When we consider the workload of an actor as part of the overall team, workload depends on what is going on with other team members, so we add the active and fired labels in order to determine when an enabled transition (meaning a possible choice available to an actor) is chosen by an actor (making it active) and when the actor completes the work required to enter the next state (the transition fires).

From an implementation perspective, when a transition becomes active it creates temporary output values for declarative memory and channels. These temporary values are then applied to the actual declarative memory and channel values once the transition fires.

For our model we never explicitly define a single task. Instead we define actors, states, and transitions. Each transition defines its own perceptual, cognitive, response, and declarative resources (Salvucci and Taatgen 2008), allowing the model to represent multiple possible tasks. In this way, an actor's state determines what task(s) are being performed, achieving multi-tasking without explicitly defining tasks.

To simplify the modeling process and ensure rigorous model creation we developed a transition language, similar to a Kripke structure,² which allows models to be expressed as a list of Actor transitions. A parser then automatically generates the classes required to run the model simulation. The transition language uses the following structure.

$$(s_{\text{current}}, [\phi_{\text{input}} = \text{value}, \dots], [\omega_{\text{input}} = \text{value}, \dots], \text{duration}) \times (s_{\text{next}}, [\phi_{\text{output}} = \text{value}, \dots], [\omega_{\text{output}} = \text{value}, \dots]) \quad (4)$$

The language is compiled to a Java program suitable to run standalone as a simulation or analyzed by the JPF model checker to create workload profiles.

Workload Metrics

We are now in a position to combine the three categories of workload (cognitive, algorithmic, and temporal) with the formal model of the actors and team to generate a set of workload metrics. Because the categories include many possible measurements that are beyond the scope of this paper, we use labels for the workload metrics that are slightly different from the workload categories. As shown in Figure 3, cognitive workload or resource workload as it is termed in this work, is measured using metrics under the *resource* workload label, algorithmic under *decision*, and temporal workload is labeled the same.

Resource workload is separated into both inter-actor communication and actor memory load. JPF listens to the output

²Since our purpose behind building a model was to allow us to examine workload we decided against using standard model checkers such as Spin since they did not provide the same level of flexibility that we obtained via java and JPF.

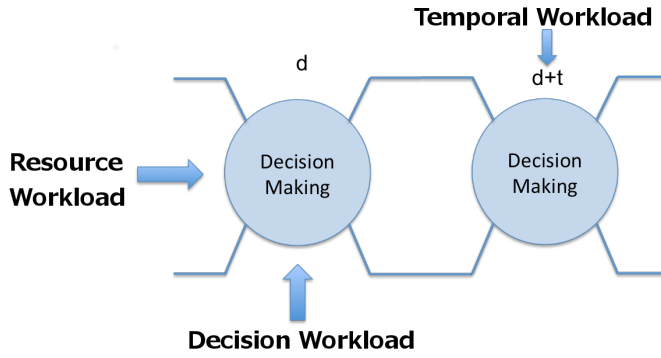


Figure 3: Workload in the model.

of the state transitions and records outputs to Ω_{mem} . JPF also listens to all channel reads, noting how many communications are on the visual and auditory input channel, identified by the labeled edges of the DiTG, of each actor.

Decision workload can be broken down into timing, complexity of the algorithm, and complexity of the solution. JPF is instrumented to measure timing as the time between when a transition becomes active and when it fires. JPF is also instrumented to count the number of enabled transitions in each state as it is visited, giving us an $O(n)$ estimate of how the number of choices affects workload. Finally, JPF is instrumented to count the number of output signals generated (Σ_{team}), yielding an $O(n)$ estimate for the complexity of computing the required outputs of a state given its inputs.

Temporal workload includes three metrics: operations tempo, arrival rate, and response time. JPF measures the average op-tempo counting how many transitions occur over a course of the simulation. JPF measures arrival rate by tracking the rate at which inputs become active. Finally, JPF measures response time by recording the time from when an input goes active to the point when it is read by the actor.

Results

In the interest of consolidating operators it is critical to find an accurate measurement that detects situations that exceed the capacity of a given human. One way to detect this is by building a map of each actor's workload as a function of time. JPF explores all possible paths the model can take and returns the ones that violate the model's criteria. By augmenting our model with the workload metrics we can identify all possible areas of high workload.

We propose three levels of increasing validity for evaluating the approach in the paper. The first level, the one used in this paper, is to check for *consistency*. We say that the approach is *consistent* if the workload peaks, valleys, and trends match what we know about a small set of given situations; in other words, the approach is consistent if it matches our expectations on tasks that we know a lot about.

The second level, which is an area for future work, is to check for *sensitivity*. We say that the approach is sufficiently *sensitive* if we can use JPF to find new scenarios that have

very high or very low workloads, and we can then generate a satisfactory explanation for the levels of workload by evaluating the new scenarios. The third level, another area of future work, is to *substantiate* workload levels using experiments with human participants by comparing the perceived workload of humans with those predicted by the model.

In this paper, we restrict attention to finding areas of high and low workload, and then checking these areas for consistency. We evaluated consistency using two scenarios. The first is when the Video Operator was able to identify the target during a flight without any complications occurring (see Figure 4). As the workload measure currently does not have units, the plots are normalized in each category. For the first 40 time steps everything behaves as expected with low to moderate workload. An initial workload bump occurs as actors exchange information necessary to start a search. At time step forty we see a dramatic deviation from the norm. This deviation is a result of constant information passing between the GUIs and the operators making it only logical that the workload would increase substantially.

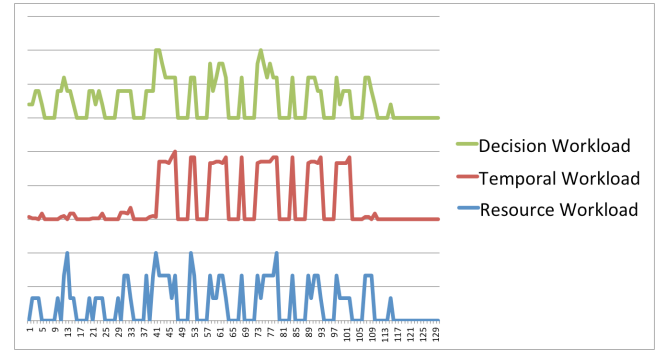


Figure 4: Workload over an uneventful flight.

The second simulation is a scenario where after a short period of flight the battery rapidly fails. In this particular situation, the operator was unable to respond quickly enough to land the UAV before it crashed (see Figure 5). There is an immediate spike in the temporal workload (middle plot), but surprisingly, the workload then decreases back to normal levels in just five time steps. The second spike indicates an unexpected fluctuation in options among one of the actors, which will have to be investigated further to verify if this is an accurate response or if a flaw in the model had slipped past the verification stage of development. Finally, as would be expected, when the UAV crashed there was a small spike in the workload before everything came to a halt.

Related Work

This work is an extension of previous work which focused on modeling human machine systems, specifically WiSAR. This work extends this model to incorporate the measurement of workload (Gledhill, Mercer, and Goodrich 2013).

Multiple resource theory plays a key role in how we are measuring workload (Wickens 2002). The multiple resource model defines four categorical dimensions that account for

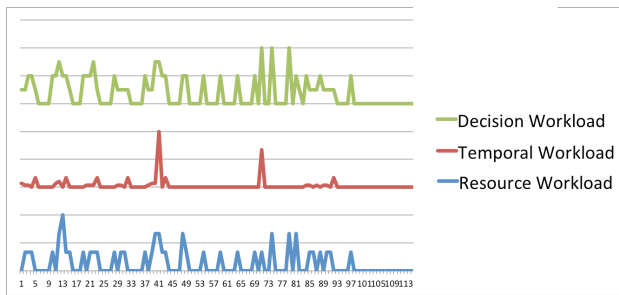


Figure 5: Emergency battery failure simulation

variations in human task performance. A task can be represented as a vector of these dimensions. Tasks interfere when they share resource dimensions. Using these vectors, Wickens defined a basic workload measure consisting of the task difficulty (0,1,2) and the number of shared dimensions. Using this metric it is possible to predict task interference by looking at tasks which use the same resource dimensions. Our model differs in that we do not explicitly define tasks, instead we use Actor state transitions which may imply any number of concurrent tasks. The transition then informs us of which resources are being used and for how long.

Threaded cognition theory states that humans can perform multiple concurrent tasks that do not require executive processes (Salvucci and Taatgen 2008). By making a broad list of resource assumptions about humans, threaded cognition is able to detect the resource conflicts of multiple concurrent tasks. Our model differs from threaded cognition theory in that it does not allow learning nor does our model distinguish between perceptual and motor resources. In almost all other aspects our model behaves in a similar fashion.

Related work on temporal workload has attempted to predict the number of UAVs an operator can control, otherwise known as *fan-out* (Cummings et al. 2007b; Olsen Jr. and Wood 2004; Crandall et al. 2005). This work used queuing theory to model how a human responds in a time sensitive multi-task environment. Queuing theory is helpful in determining the temporal effects of task performance by measuring the difference between when a task was received and when it was executed. Actors can only perform a single transition at a time, similar to queuing theory, but it is possible for each state to take input from multiple concurrent tasks which differs from standard models of queuing theory.

ACT-R is a cognitive architecture which attempts to model human cognition and has been successful in human-computer interaction applications (Anderson et al. 2004; Lebiere, Jentsch, and Ososky 2013). The framework for this architecture consists of modules, buffers, and a pattern-matcher which in many ways are very similar to our own framework. The major difference is that ACT-R includes higher levels of modeling detail, such as memory access time, task learning, and motor vs perceptual resource differences. Our model exists at a higher level of abstraction.

Complementary work has been done using Brahms. Brahms is a powerful language that allows for far more detail than we found our research required. In addition at the

time we started developing our model Brahms lacked some of the tools we needed for extracting workload data from the model. Because of this we found that Java in conjunction with JPF made a better match for our needs.

Grant, Kraus, and Perlis have done exceptional work compiling formal approaches to teamwork. They came up with the following categories: the persistence of joint intentions, the complexity of the roles of each agent, the individual actions required for teamwork, the joint commitment to a goal and cooperation, the collective intonations modeled as a multi-modal logical framework, and the subcontracting between cooperative agents. All of these approaches can be modeled within our simulator. For example, joint intentions would be represented in actors containing complement transitions. While the formalisms are not explicit in our modeling, our informed modelers apply these approaches.

Summary and Future Work

This paper proposes a model-checking approach to analyzing human workload in an UAS. Humans and other autonomous actors are modeled as modified Moore machines, yielding a directed graph representing team communication. Workload categories are distilled from the literature, and the models of the actors and team are augmented so that specific workload metrics can be obtained using model-checking. Preliminary analysis demonstrates a weak level of validity, namely, that the temporal workload profile is consistent with expected behavior for a set of well-understood situations. For these scenarios, inter-actor communication is a primary cause of spikes in workload.

A sensitivity study, followed by an experiment with real human users is needed to understand and justify the workload measures. Once we have verified that our system analyzes workload correctly, it will be useful to design a GUI optimized to managing workload and to formulate a generalized model that will have application to other human-machine systems.

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