Human Supervisory Control of Robotic Teams

Integrating Cognitive Modeling with Engineering Design

Jeffrey R. Peters[1], Vaibhav Srivastava[2], Grant S. Taylor[3], Amit Surana[4], Francesco Bullo[1], and Miguel P. Eckstein[5]

[1]Center for Control, Dynamical Systems, and Computation, UCSB
[2]Department of Mechanical and Aerospace Engineering, Princeton University
[3]US Army Aeroflightdynamics Directorate, Moffett Field
[4]United Technologies Research Center, Hartford
[5]Department of Psychology and Brain Sciences, UCSB

The emergence of sensor networks operating at different modalities, mobility, and coverage has opened the door to systems involving diverse data sources and analysis tools. These complex systems often contain both human and robotic elements, and in many cases it is the job of humans to process information generated by autonomous agents [1], [2]. The incredible amount of data generated by modern sensors makes these human operators susceptible to *information overload*, which can have detrimental effects on performance and may lead to dire consequences [3]. To alleviate this loss in performance, programs like the recent National Robotic Initiative [4] emphasize collaboration between humans and their robotic partners, and envision symbiotic mechanisms to facilitate interactions between diverse system components.

In what follows, we focus on the design of systems in which a human operator is responsible for overseeing autonomous agents and providing feedback based on sensor data. In the control systems community, the term *human supervisory control* (or simply *supervisory control*) is often used to describe such systems and the unique set of challenges that they bring about [5], [6], [7]. In a typical human supervisory control application, the operator does not directly manipulate autonomous agents, but rather indirectly interacts with these components via a central data processing station (see Figure 1). As such, system designers have the opportunity to easily incorporate automated functionalities to control how information is presented to the operator, and how the input provided by the operator is utilized by automated systems. The goal of these functionalities is to take advantage of the inherent robustness and adaptability of human operators, while mitigating adverse effects such as unpredictability and high variability in performance. In some contexts, in order to meet future goals of single operator supervision of multiple automated sensor systems, such facilitating mechanisms are not only useful, but necessary for practical use [8], [9].

A successful system design must carefully consider the goals of each part of the system as a whole, and seamlessly stitch components together using facilitating functionalities.

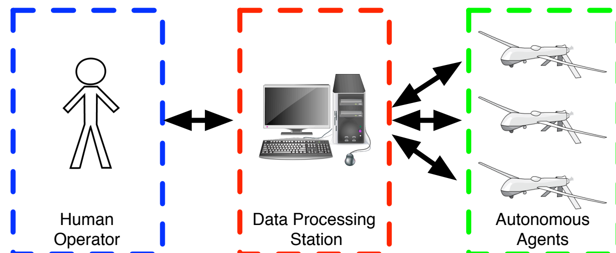


Figure 1. A typical human supervisory control setup consisting of 3 main components: the human operator(s), the data processing station, and the autonomous agents. Human operator(s) interact with the autonomous agents through the data processing station. The degree to which human performance and input affects automation, as well as the method by which sensor data is presented to the operators is determined by the data processing station and its internal functionalities.

Design Considerations

The design of any effective supervisory control system starts with a model of human cognitive processing [10]. This model, which forms the "backbone" of the human-centered system, must capture the operator's underlying decision making mechanisms, while still taking into account the variability that is inherent to human processing. Other factors, such as mental workload, memory, fatigue, etc., can significantly affect these driving mechanisms as well, and may also need to be incorporated into the model to achieve design goals.

Once an appropriate model has been constructed, the question becomes how to use the information that the model provides to manage data presentation and automated control schemes. For example, data collected by autonomous agents in supervisory control applications is often visual in nature, i.e., photos or video. Given such visual imagery, can we use operator performance, imagery characteristics, and system parameters to decide which region of the image the operator should focus on? If multiple images are waiting to be processed, can we determine how much time the operator should spend on each image? Can we detect non-optimal user behavior and adjust system parameters to mitigate negative effects? How should the autonomous agents take human responses into account?

It is apparent that an effective system design incorporates a broad range of theoretical and practical tools from varying scientific disciplines, including control systems, human factors, and psychology. As such, system designers face a series of diverse and complex choices when deriving models and strategies to govern system behavior. Our goal for this article is to provide insight into some of these choices through examination of common theoretical tools relevant to each of the main components making up a supervisory control system; namely, the human operator, the autonomous agents, and the interface between them. In particular, we focus our discussion on those tools which have close ties to control and dynamical systems. We also seek to highlight key challenges that arise in practical implementation and in combining these tools for use in the overall system. In some sense, this article can be thought of as a brief survey of work relevant to the design of human supervisory control systems; however, we also seek to provide a proof of concept, by illustrating how basic, well-studied theory from various disciplines can work together for use in a broader, human-centered systems perspective.

State of the Art

Automation can be formally defined as the "execution by a machine agent of a function that was previously carried out by a human" [11]. In this broad context, the use of human operators to monitor the functionality of automated systems has arisen in widespread domains. Examples of current applications which incorporate human-centered automation systems include dynamic positioning systems in maritime applications [12], command and control systems for monitoring satellites and space assets [13], automated vehicle operation aids [14], aviation accident and emergency response systems [15], numerous military operations [16], [17], medical imaging systems [18], advanced traffic management and intelligent transportation systems [19], and many more.

As a consequence of this growing interest in human supervisory control, a large body of research has focused on the direct incorporation of human performance models into autonomous system design. Significant research efforts have gone into finding systematic ways of distributing operator cognitive resources. In some approaches, the human decision-making process is unregulated, but the automated system is catered to the human operator's cognitive requirements. The fundamental research questions under this approach include (i) optimal scheduling of the tasks to be processed by the operator [20], [21], [22], [23], [24], [25], [26]; (ii) enabling shorter operator reaction times by controlling the fraction of the total time during which the operator is busy [27], [28]; and (iii) efficient work-shift design to counter fatigue or interruption effects [29]. In other approaches, both the operator's decision making process and the autonomous agents are controlled. For example, the human operator is told the duration they should spend on each task, and their decision is utilized to adaptively adjust automation schemes. The fundamental research questions under this approach include (i) determining optimal operator attention allocation both within and across tasks [30], [31], [32]; (ii) controlling operator utilization to enable better performance [33]; and (iii) controlling autonomous agents to collect relevant information [34], [35], [33].

Many researchers have also studied adaptive strategies to human centered system design, in which both physiological and performance measures are used to infer the operator cognitive state (i.e., mental workload, operator intentions, etc.), and automated functionalities are only triggered when a non-optimal or undesirable state is detected [36], [37]. However, the majority of such adaptive systems to date have been experimental rather than practical due to difficulties in constructing accurate indicators of user cognitive state [38]. Despite such difficulties, continually improving accuracy and affordability of physiological sensors, such as eye-tracking and electroencephalography (EEG), have led to a better understanding of objective measures that can give insight into operator cognitive behavior [39].

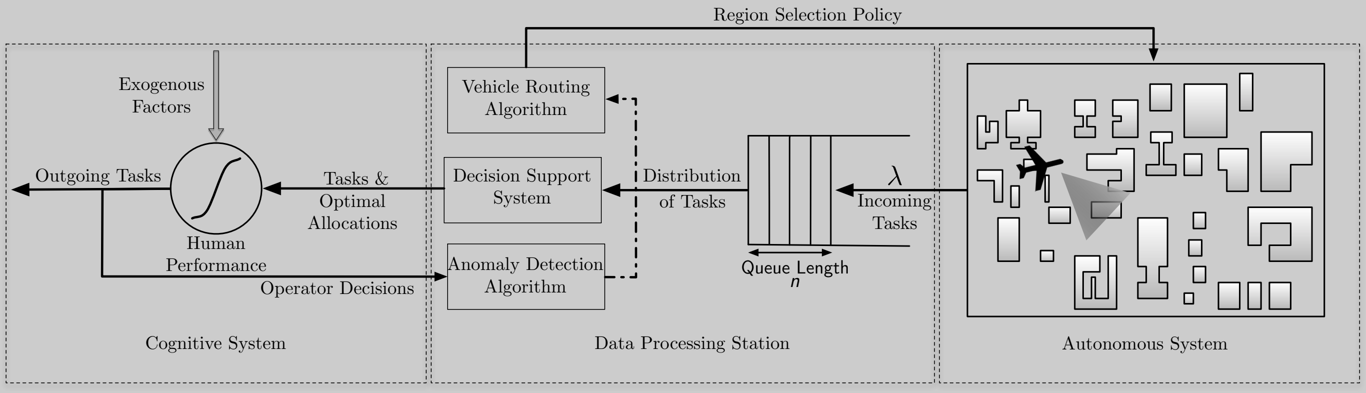
For the remainder of this exposition, we discuss the three main components of a human supervisory control system as defined in Figure 1. Due to the vast amount of literature and theory that is available on each of these topics, an exhaustive survey is infeasible. Therefore, we accomplish our goal of providing insight into system design considerations and challenges by focusing our discussion on a subset of available literature which is particularly relevant to control and dynamical systems theory, and illustrates key system design issues. We note that most of our discussion will be motivated by the control of mobile sensors which collect visual data (e.g., unmanned vehicles taking photos or video), although many of the concepts discussed readily extend to other related domains.

Human Modeling

We start by providing an overview of a few common models used to capture human cognitive behavior in tasks where a person must choose between a set of alternative choices. Although many such models exist in psychology, information theory, and computer science, we choose to focus our discussion on *accumulator models*, a class of dynamical models which capture the evidence accumulation process in visual perception. We select this class since (i) they have close ties to dynamical systems, (ii) are widely used in cognitive psychology, (iii) are relevant to visual perception which is a commonly encountered task in supervisory control, (iv) have been proven to capture a large amount of relevant behavioral phenomena [40], [41], [42], and (v) appropriately illustrate key challenges involved in modeling human behavior.

EXAMPLE: PERSISTENT SURVEILLANCE MISSION

Problem Overview and Setup



Overview

To further illustrate the design principles discussed, in this and the subsequent sidebars we present an example human supervisory control problem, which involves continuous search of target regions by a mobile sensor. This type of persistent surveillance using mobile sensors is applicable to a variety of real scenarios, including military applications, such as area reconnaissance and battlefield damage assessment, search and rescue operations such as disaster assistance and target extraction, and environmental monitoring tasks, such as the control of forest fires and wildlife regulation.

An efficient persistent surveillance policy can have multiple objectives, including minimization of the time between subsequent visits to a region and minimization of the delay in detecting anomalous events. The fundamental trade-off in persistent surveillance is between the amount of evidence collected from the visited region and the resulting delay in evidence collection from other regions. In this example, we aim to address this trade-off by designing an efficient surveillance policy that takes into account human responses to image analysis tasks, and subsequently collects evidence from regions that are highly likely to be anomalous. We utilize cognitive models for human decision-making to ascertain the accuracy of human decisions and thus, determine the likelihood of a region being anomalous using operator's decisions. Finally, we illustrate how these tools can be brought together by designing a simple decision support which uses user models to determine how the operator should allocate their time to the multiple image processing tasks.

Setup

We assume that the primary objective of our example surveillance mission is to detect, within a prescribed accuracy, any anomaly in a set of discrete regions.

Our setup for the mission is shown in the diagram above. The setup is comprised of three main components, consistent with the abstraction in Figure 1: (i) the autonomous system, (ii) the cognitive system, and (iii) the data processing station.

The autonomous system consists of a single unmanned aerial vehicle (UAV) that surveys a set of regions according to a routing policy. We assume the UAV is equipped with a camera, and during each visit to a region, the UAV generates an image to send to the data processing station, which eventually sends it to the cognitive component (human operator).

The cognitive component is comprised of a single human operator who examines the evidence and decides on the absence/presence of an anomaly at the associated region.

In this example, the data processing station is comprised of three elements: (i) the decision support system, (ii) the anomaly detection algorithm, and (iii) the vehicle routing algorithm. The purpose of the decision support system is to use performance of the operator to suggest the optimal amount of time that the operator should allocate to each perceptual task, i.e., image generated by the UAV. Decisions made by the human operator may be erroneous, and thus the anomaly detection algorithm is a sequential statistical algorithm that treats the operator's decision as a binary random variable and ascertains the desired accuracy of the anomaly detection. The anomaly detection algorithm also provides the likelihood of an anomaly at each region. The vehicle routing algorithm uses the likelihood of each region being anomalous to determine an efficient vehicle routing policy.

The goal of the overall system is to detect anomalies in the quickest amount of time possible, subject to a false-alarm constraint. In subsequent sidebars, we examine each problem component in detail.

Two-alternative Choice Tasks

A *two-alternative choice task* is one in which an operator must decide between two possible hypotheses. Models for two-alternative choice tasks within continuous sensory information acquisition scenarios rely on three assumptions: (i) evidence is collected over time in favor of each alternative; (ii) the evidence collection process has an element of randomness; and (iii) a decision is made once a stopping criterion is met. Several models for two-alternative choice tasks have been proposed [40], however, almost all accumulator models are based

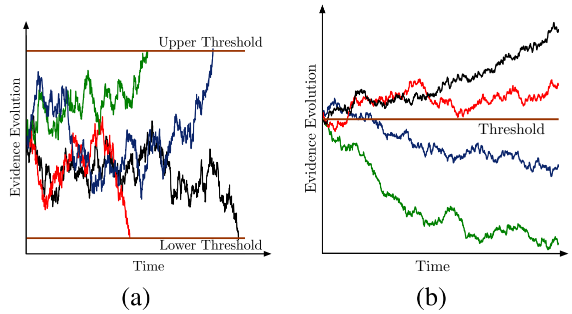


Figure 2. (a) Free response paradigm for decision-making. Evidence evolves according to (1) and the operator makes a decision once a threshold is crossed. (b) Interrogation paradigm of decision-making. Evidence evolves according to (1) and the operator's decision depends on whether the evidence is above or below a threshold after a given amount of time.

on the drift diffusion model (DDM) [43], [44], [45]. The DDM is popular because: (i) it is simple and well characterized; (ii) it captures a significant amount of behavioral and neuroscientific data; and (iii) the optimal choice of parameters in many other models for two-alternative choice tasks reduces them to the DDM [40].

In the most basic version of the DDM, evidence toward an alternative is modeled as a variable $x \in \mathbb{R}$, which evolves according to a stochastic differential equation of the form:

$$dx(t) = \mu dt + \sigma dW(t), \quad x(0) = x_0, \tag{1}$$

where $\mu \in \mathbb{R}$ is the *drift rate*, $\sigma \in \mathbb{R}_{>0}$ is the *diffusion rate*, $W(\cdot)$ is the standard Wiener process, and $x_0 \in \mathbb{R}$ is the initial evidence. For an unbiased operator, the initial evidence $x_0 = 0$, while for a biased operator x_0 captures the odds or the prior probability of each hypothesis being true.

For the information aggregation model (1), human decision-making is studied in two paradigms, namely, *free response* and *interrogation* [40] (see Figure 2). In the free response paradigm, the operator takes their own time to decide on an alternative, while in the interrogation paradigm, the operator needs to decide within a given time window. The free response paradigm is modeled via two thresholds (positive and negative) and the operator decides in favor of the first (second) alternative if the positive (negative) threshold is crossed from below (above). In contrast, the interrogation paradigm makes use of a single threshold, and the operator decides in favor of the first (second) alternative if the amount of accumulated evidence is above (below) the threshold at the end of the allotted time.

Free Response Paradigm

A typical evolution of the DDM under free response paradigm is shown in Figure 2(a). For equally likely alternatives, the two decision thresholds are chosen symmetrically. If $\pm\eta \in \mathbb{R}$ represents symmetrically chosen thresholds, the expected decision time (T_{Decision}) under the free response paradigm is

$$T_{\text{Decision}} = \frac{\eta}{\mu}\tanh\frac{\mu\eta}{\sigma^2} + \frac{2\eta(1-e^{-2x_0\mu/\sigma^2})}{\mu(e^{2\eta\mu/\sigma^2}-e^{-2\eta\mu/\sigma^2})} - \frac{x_0}{\mu}.$$

Reaction time on a task is $T_{\text{Decision}} + T_{\text{Motor}}$, where $T_{\text{Motor}} \in \mathbb{R}_{>0}$ is the time taken by motor processes unrelated to the decision process. With proper choice of parameters, the DDM (1) can predict reaction times with some success (see Figure 3).

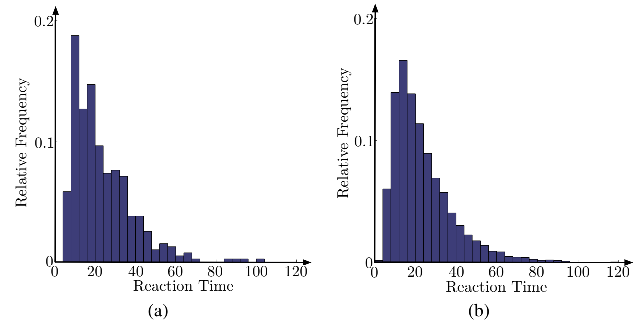


Figure 3. (a) Empirical reaction time data taken from [23]; (b) Decision times under the free-response paradigm, as predicted by an appropriately chosen DDM (1).

The choice of the threshold is dictated by a trade-off between speed and accuracy. The two most common criteria to capture the speed-accuracy trade-off are: (i) Bayes' risk (BR) and (ii) reward rate (RR) [40]. Bayes' risk is defined by $\text{BR} = \xi_1 T_{\text{Decision}} + \xi_2 \mathbb{P}_{\text{Error}}$, where $\xi_1, \xi_2 \in \mathbb{R}$ are the cost per unit delay in decision and the cost of error, respectively, and $\mathbb{P}_{\text{error}}$ is the error rate. For the DDM, minimization of BR yields the following transcendental equation for the threshold [40]:

$$\frac{\xi_2}{\xi_1}\frac{2\mu^2}{\sigma^2} - \frac{4\mu\eta}{\sigma^2} + e^{-(2\mu\eta/\sigma^2)} - e^{(2\mu\eta/\sigma^2)} = 0.$$

Reward rate is generally defined by the proportion of correct trials divided by the average duration between decisions [46]:

$$\begin{aligned}\text{RR} &= \frac{1-\mathbb{P}_{\text{Error}}}{D_p\mathbb{P}_{\text{Error}} + T_{\text{Reaction}} + D} \\ &= \frac{1-\mathbb{P}_{\text{error}}}{D_p\mathbb{P}_{\text{Error}} + T_{\text{Decision}} + T_{\text{motor}} + D},\end{aligned}$$

where $D \in \mathbb{R}_{\geq 0}$ is the delay between a correct response and the next stimulus and $D_p \in \mathbb{R}_{\geq 0}$ is a penalty delay introduced by an incorrect decision. Similar to the Bayes' risk, the optimal threshold for RR can be found by minimizing the equation:

$$\frac{\eta}{\mu} + D + T_{\text{Motor}} + (D + T_{\text{Motor}} + D_p - \frac{\eta}{\mu})e^{-(2\mu\eta/\sigma^2)} = \frac{1}{\text{RR}}.$$

These transcendental threshold equations can be solved numerically, and ξ_1 and ξ_2 can be estimated from empirical data [40].

Interrogation Paradigm

A typical evolution of the DDM under the interrogation paradigm is shown in Figure 2(b). The interrogation paradigm relies upon a single threshold: for a given deadline $T \in \mathbb{R}_{>0}$, the operator decides in favor of the first (second) alternative if the evidence collected until time T, (i.e., $x(T)$) is greater (smaller) than a threshold $\nu \in \mathbb{R}$. For equally likely alternatives, the threshold ν is chosen to be zero. From equation (1), the evidence collected until time T is a Gaussian random variable with mean $\mu T + x_0$ and variance $\sigma^2 T$. Thus, the probability to decide in favor of the first alternative under the interrogation paradigm can be written in closed-form as

$$\mathbb{P}(x(T) > \nu) = 1 - \mathbb{P}(x(T) < \nu) = 1 - \Phi\Big(\frac{\nu - \mu T - x_0}{\sigma\sqrt{T}}\Big), \tag{2}$$

where $\Phi(\cdot)$ is the Gaussian cumulative distribution function.

Variations of the DDM

A myriad of other accumulator models consider variations on the basic DDM. These variants often serve to capture additional behavioral characteristics which are not captured by the general DDM. For example, the Ornstein-Uhlenbeck model [47], [48] incorporates an additional linear term into the evidence accumulation equation:

$$dx(t) = (\lambda x(t) + \mu)dt + \sigma dW(t), \quad x(0) = x_0, \tag{3}$$

where $\lambda \in \mathbb{R}$. The sign of λ determines whether evidence aggregation accelerates or decelerates with increasing evidence. In the case where $\lambda < 0$, the dynamics in (3) reduce to what some call the *leaky accumulator model* [49]. In this case, the point $x = -\mu/\lambda$ is a fixed point of (3). Thus, this model can represent situations where evidence accumulation asymptotes over time, i.e., the human is never perfectly accurate. This is a feature that the DDM (1) does not have, as the DDM assumes that in the absence of noise a person will always make a correct decision, given enough time. Other variants, such as the *extended DDM* [44], [50] and the *full DDM* [51], incorporate additional parameters, including a noise parameter associated with the drift rate, a parameter characterizing initial latency, and a parameter capturing bias in the initial accumulation process. These variants have been shown to more accurately model the user response time distributions than the standard DDM [45], [52]. Further variants introduce the use of *collapsing thresholds*, where the decision-making threshold $\eta > 0$ is a function of the form $\eta(t) = ce^{-rt}$, where c, r are constants representing the initial threshold and the rate of convergence, respectively. These collapsing thresholds can be thought of as an "urgency signal" that prevents subjects from taking an excessive amount of time when drift rates are close to zero [51] Such models can more accurately capture higher reaction times which often occur in incorrect trials [53].

Discrete-Time Decision Making

The DDM is also related to classical hypothesis tests from probability theory. In the free response paradigm, the DDM (1) is the continuum limit of the *Sequential Probability Ratio Test* (SPRT) [54], a test that can be used when evidence is acquired sequentially at time-steps $\ell \in \mathbb{Z}_{\geq 0}$. That is, the SPRT is equivalent to the DDM in the limit as the time between samples tends to zero [55]. Indeed, SPRTs utilize a statistic Λ_ℓ which is incremented with each new observation y_ℓ. A decision is made in favor of one of the alternatives once a threshold is reached. With symmetric thresholds $\pm\Lambda_{\text{Thresh}}$, unbiased initial evidence, and independent observations, a standard SPRT for deciding between hypotheses H^0, H^1 is:

1: initialize $\Lambda_0 := 0$;
2: at time $\ell \in \mathbb{N}$, collect observation y_ℓ;
3: integrate evidence $\Lambda_\ell := \Lambda_{\ell-1} + \log \frac{\mathbb{P}(y_\ell|H^1)}{\mathbb{P}(y_\ell|H^0)}$;
   % decide only if the threshold Λ_{Thresh} is crossed
4: **if** $\Lambda_\ell < -\Lambda_{\text{Thresh}}$, **then** Alternative 0 is true
5: **else if** $\Lambda_\ell > \Lambda_{\text{Thresh}}$, **then** Alternative 1 is true
6: **else** continue sampling (step 2:)

The statistic Λ_ℓ plays the role of evidence in favor each alternative. For sequentially accumulating data with known sampling likelihoods under each hypothesis, the SPRT is the optimal statistical test for two-alternative choice tasks, in the sense that it achieves a given error rate in minimum time [54], [56]. Despite this, some researchers argue that the standard SPRT does not capture reaction times observed in empirical data [50], and have turned to a variety of other variations in attempt to increase accuracy. In the interrogation paradigm, the DDM (1) is the continuum limit of the Neyman-Pearson hypothesis test [57], a test designed to decide among two hypotheses when the number of discrete data samples is fixed *a priori*. Given a set of observations $\{y_1, y_2, \ldots, y_n\}$, the Neyman-Pearson test calculates the likelihood ratio

$$\Lambda(y_1, y_2, \ldots, y_n) = \frac{\mathbb{P}(H^0 \mid y_1, y_2, \ldots, y_n)}{\mathbb{P}(H^1 \mid y_1, y_2, \ldots, y_n)},$$

and rejects the hypothesis H^0 in favor of the hypothesis H^1 if Λ is less than a threshold. Once again, the statistic Λ plays the role of evidence accumulated in favor of each alternative after a fixed amount of sampling. For a fixed number of data samples with known likelihoods, the Neyman-Pearson test is optimal in that it has the highest statistical power [58].

Multi-alternative Choice Tasks

A *multi-alternative choice task* is one in which an operator or observer must choose among multiple disjoint hypotheses. Broadly speaking, researchers have attempted to extend many of the same strategies for modeling two-alternative choice tasks for use with multiple alternatives through the use of *race models* [59], [60]. Race models can be thought of as another variant of the standard DDM in which each alternative is assigned its own separate accumulator. That is, in a race model for an m-alternative choice task, there are m evidence accumulation variables $x_1, x_2, \ldots x_m$, representing evidence accumulated in favor of each respective alternative. Each of these variables then evolves according to a random process (such as the DDM), and a decision is made in favor of the alternative whose corresponding evidence x_i is the first to cross its respective evidence accumulation threshold (or has the largest value at the deadline in the case of the interrogation paradigm). The degree to which the accumulators interact varies depending on the problem setup.

Classical race models have exhibited some success in capturing behavioral phenomena. However, the multi-alternative scenario is inherently much more difficult to model than the two-alternative case, as one often encounters phenomena that cannot be explained in the context of the two-choice paradigm [58]. For example, in discrete time the SPRT is the optimal test for achieving a given error rate in minimum time with sequentially accumulating data, but it has been shown that it is difficult to create an analogous multi-hypothesis sequential probability ratio test that is optimal in the same sense [61]. Despite this fact, some commonalities are generally accepted such as *Hick's Law* [62], which states that in choosing between m alternatives, if accuracy is fixed at a high rate then the mean reaction time increases at a rate proportional to $\log(m)$ (although the exact form of this relation remains an open question). These commonalities are often used in attempt to validate models. For example, studies have shown that variations on the leaky accumulator model for multiple hypotheses [49], [58] outperform classic race models in some respects and capture the dynamics predicted by Hick's law.

More recent models have incorporated the use of modern technology. For visual stimuli, physiological sensing tools, namely eye-tracking, have been used in the context of race models as well. In this context, it is assumed that the relevant parameters which govern the dynamics of each accumulator are dependent upon the position of the observer's gaze. For example, in [63], the authors assume that the drift rate for a given accumulator is higher when the observer is focusing their attention on the alternative in question. Other works, such as [64], have begun to utilize eye-tracking to explore the connection between visual characteristics such as saliency to the evidence accumulation process modeled via race model.

Exogenous Factors

Human performance models discussed thus far only capture dynamics of evidence aggregation in decision-making. Exogenous factors, such as workload, fatigue, situational awareness, information retention, among others, also affect the decision-making process. For brevity, we do not include an in-depth discussion about the incorporation of exogenous factors into evidence accumulation models. However, to give the reader a flavor for the types of models that exists, we briefly mention a few key factors here. We note that these factors are closely linked with those discussed in the "Key Challenges" section.

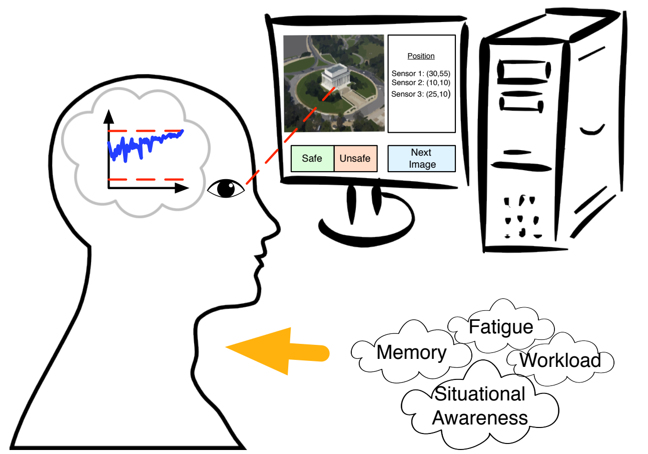


Figure 4. Many factors can affect the decision making process.

Mental Workload, Arousal, and the Yerkes-Dodson Law

Mental workload is the extent to which a task places demands on the operator's cognitive resources [67], with a variety of models further reducing the construct into various subcomponents [68], [69], [70]. Although operator mental workload is generally a subjective experience, many researchers attempt to capture this phenomena through more objective, quantifiable measures. For instance, operator workload is sometimes modeled as the utilization ratio (the fraction of recent history during which the operator was busy), with the utilization ratio u following the dynamics

$$\dot{u}(t) = \frac{b(t) - u(t)}{\tau}, \quad u(0) = u_0, \tag{4}$$

where $b : \mathbb{R}_{>0} \to \{0, 1\}$ represents if the operator is idle or busy, $\tau \in \mathbb{R}_{>0}$ is the sensitivity of the operator, and $u_0 \in [0, 1]$ is the initial utilization ratio [28]. Typically, system design focuses on methods of reducing workload to decrease the strain on the operator, but when taken too far this approach can result in performance degradation as well.

Closely related to mental workload is *operator arousal* or *stress*. The Yerkes-Dodson law [71], [72] is a classical model that captures the performance of an operator as a unimodal function of arousal level (stress). A typical representation of this relationship is shown in Figure 5(a). The law demonstrates that there is a moderate level of arousal, dependent on the task that optimizes operator performance, while excessive arousal (hyperstress) overwhelms the operator and too little arousal (hypostress) leads to boredom and vigilance decrement [73]. Recent work by Hancock and Warm has expanded on this concept through more detailed models which differentiate between regions of psychological and physiological adaptability [74].

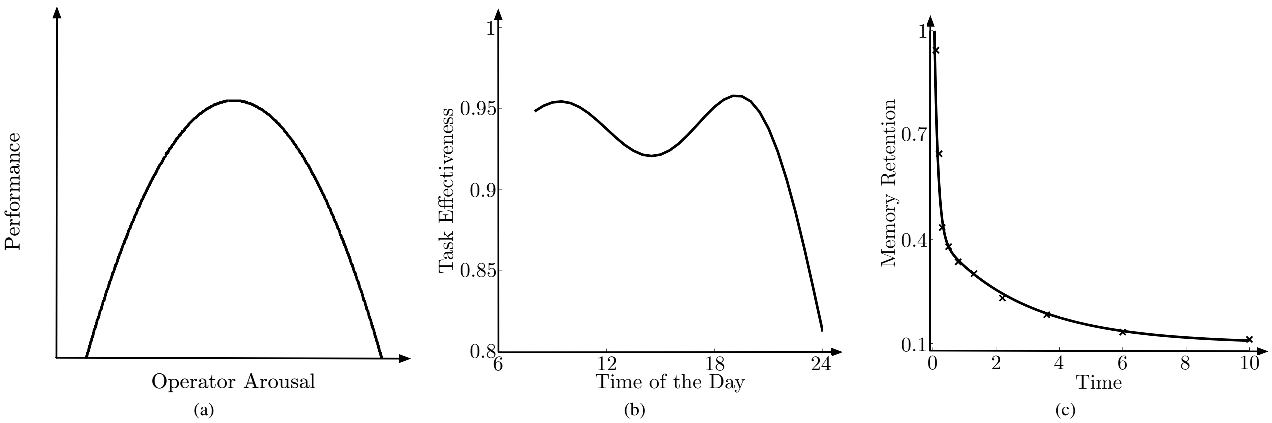


Figure 5. Curves illustrating some key exogenous factors: (a) Performance as a function of operator arousal, as described by the Yerkes-Dodson law; (b) Task effectiveness of a operator who wakes up at 6am after 6 hours of sleep, as predicted by the SAFTE model (5) using the default parameters in [65]; (c) Empirical memory retention data taken from [66], fitted with a curve that is the sum of two exponentials and a constant function.

Fatigue, Sleep Cycle, and the SAFTE model

Fatigue is defined as the feeling of bodily discomfort after prolonged activity, and is known to have detrimental effects on operator performance [75]. Several models have been proposed which seek to capture cognitive performance as a function of sleep deprivation [76]. One example is the Sleep Activity Fatigue Task Efficiency (SAFTE) model [65], which assumes that a fully rested operator has a finite reservoir capacity R_c which depletes over time while the operator is awake, and replenishes when the operator sleeps. The SAFTE model determines the task effectiveness as

$$\mathrm{TE} = 100\frac{R_c - 60KT_a}{R_c} + \Big(a_1 + a_2\frac{60KT_a}{R_c}\Big) \Big[\cos\Big(\frac{2\pi}{24}(T_d - p)\Big) + \beta\cos\Big(\frac{4\pi}{24}(T_d - p - p')\Big)\Big], \quad (5)$$

where T_a is the number of hours the operator has been awake, T_d is the time of the day in hours, K is reservoir drain rate due to wakefulness, $a_1, a_2, \beta \in \mathbb{R}$ are constants, p is the time of the peak in the 24h circadian rhythm and p' is the relative time of the 12h peak. Under this model, if the reaction time of a fully rested operator is T_{Reaction}, then the reaction time of the fatigued operator is $T_{\text{Reaction}}/\mathrm{TE}$. An example TE curve generated using the SAFTE model is shown in Figure 5(b).

Information Retention and Situational Awareness

Information retention refers to the fraction of newly acquired information the operator remembers over time. Traditionally, the curve has been modeled as an exponential decay [77]. Some researchers [78] argue that the information retention curve should be modeled by a power law function, while others [66] model the curve as a sum of two exponential functions and a constant function. An example of such a curve fitted to empirical data from [66] is shown in Figure 5(c).

In many tasks, including supervisory tasks, the operator must not only perceive, process, and retain information, but also apply that knowledge in order to formulate an accurate mental image of their current situation. This leads to the notion of *situational awareness*, which can be defined as the sum of operator perception and comprehension of process information, and the subsequent ability to make projections of system states on this basis [79]. It has been argued that a lack of situational awareness results in poor performance by creating large waiting times, i.e., the operator takes more time to start working on a task [80]. Situational awareness is critical as the operator is incapable of making timely and effective decisions without an accurate mental representation of the current and predicted future state of their operational environment.

COORDINATION OF AUTONOMOUS AGENTS

We now shift our focus to the design of coordination strategies for systems of autonomous agents. The design of such strategies is an issue that is at the heart of control theory and has generated a vast amount of research (see e.g., [81], [82], [83], [84], [85]). Here, we choose to focus our discussion on *coverage problems* in the context of wireless sensor networks with a fixed number of nodes (agents), as this class of problem is applicable in many human supervisory control scenarios. Loosely speaking, the coverage problem can be described as follows: Given a compact area of interest $\mathcal{Q} \subset \mathbb{R}^2$ and a team of agents equipped with sensors capable of gathering information about their surroundings, determine a strategy to deploy and control the autonomous agents such that some coverage metric is maximized. In supervisory control, the agents generally can transmit data to a central location either by direct or multi-hop communication. In what follows, we briefly discuss a few of the most common coverage problems, and highlight theoretical tools that can aid in solving them.

EXAMPLE: PERSISTENT SURVEILLANCE MISSION
Human Performance Modeling

In the design of a human supervisory control system, the choice of human model forms the basis for the cognitive system and supports virtually all other operations in the design strategy. In this section, we focus on the design of a performance function, which will drive our strategy the rest of our system design.

In this example, we will use the classic DDM (1) as the basis for constructing our human performance model. In general, human decision making will hinge upon a variety of factors not captured by the basic DDM. For our purposes, we do not explicitly incorporate these factors into our model, however, we note that other models of decision making which do incorporate these factors can also be used to construct a performance function in a similar manner.

We use the accuracy of the decisions made by the operator as a measure of their performance. Accordingly, we pick the probability of making the correct decision as the performance metric. We assume the drift rates to be symmetric, i.e., the drift rates are $+\mu$ and $-\mu$ when alternatives 0 and 1 are true, respectively. Recalling Equation (2), the performance function when alternative 0 is true is $f^0 : \mathbb{R}_{\geq 0} \times [0, 1] \to [0, 1)$ defined

$$f^0(t, \pi) = 1 - \Phi\Big(\frac{\nu - \mu t - x_0}{\sigma\sqrt{t}}\Big).$$

Similarly, the performance function when alternative 1 is true is $f^1 : \mathbb{R}_{\geq 0} \times [0, 1] \to [0, 1)$ defined

$$f^1(t, \pi) = \Phi\Big(\frac{\nu + \mu t - x_0}{\sigma\sqrt{t}}\Big).$$

Given a prior probability π of the first alternative being true, we define overall performance $f : \mathbb{R}_{\geq 0} \times [0, 1] \to [0, 1)$ by

$$f(t, \pi) = \pi f^0(t, \pi) + (1 - \pi) f^1(t, \pi). \tag{6}$$

This performance function is a sigmoid function of time.

We denote the k-th region by $\mathcal{R}_k, k \in \{1, \dots, m\}$. We model the surveillance mission as a sequence of two-alternative choice tasks and accordingly, model the operator performance as in equation (6). The two alternatives H^0, H^1 in this setting are (i) the presence of an anomaly and (ii) the absence of an anomaly, respectively. We denote the performance of the operator at region $\mathcal{R}_k$ by $f_k : \mathbb{R}_{\geq 0} \times [0, 1] \to [0, 1)$. We make the assumption that the evidence accumulated in the different regions is mutually independent from one another

Static Coverage

The most basic coverage problem is that of *static coverage*, i.e., determining *a priori* a location where each of the agents will remain for some time. When the area $\mathcal{Q}$ is relatively small, this often reduces to the problem of finding a location that maximizes the sensing footprint of the agents. The well-known Art Gallery Problem [86] is an example of this type of coverage. The classic Art Gallery Problem involves simple polygonal environments and visibility constraints, however, various extensions have been proposed to incorporate issues like holes in the environment [87], additional coverage requirements [88], and sensor placement specifications [89].

In many cases, the environment of interest involves an element of stochasticity, i.e., there is a probability density function $\phi : \mathcal{Q} \to \mathbb{R}_{\geq 0}$ which encodes the likelihood of some event of interest occurring in any subregion. In this scenario, the goal is generally to place the sensors in a way that maximizes their ability react to events which may occur, proportional to the function ϕ. Existing approaches for achieving this goal include the use of potential fields [90], spectral methods [91], and many other heuristics [92]. Often the static sensor placement issue reduces to one of load-balancing. That is, each point in $\mathcal{Q}$ is assigned to one agent, and the goal is to minimize a *multicenter function* $\mathcal{H} : \mathcal{Q}^m \times (2^{\mathcal{Q}})^m \to \mathbb{R}_{\geq 0}$ defined by

$$\mathcal{H}\left((c_1, \dots, c_m), (P_1, \dots, P_m)\right) = \sum_{i=1}^{m} \int_{P_i} d(k, c_i)\phi(k) dk,$$

where $m \in \mathbb{N}$ is the number of sensors, $(c_1, \dots, c_m)$ represents the location of the sensors, $(P_1, \dots, P_m)$ is a partition of $\mathcal{Q}$ (i.e., satisfies $\bigcup_{i=1}^m P_i = \mathcal{Q}$ and $P_i \cap P_j = \emptyset$ for any $i \neq j$), and $d : \mathcal{Q} \times \mathcal{Q} \to \mathbb{R}_{\geq 0}$ is a distance metric. Finding global minimizers of the function $\mathcal{H}$ is difficult in general, however, algorithms exist for finding high-quality approximate solutions in most typical cases. For example, if d is taken to be the square of the Euclidean distance, then the optimal sensor placement $(c_1, \dots, c_m)$ and assignment $(P_1, \dots, P_m)$ forms a centroidal Voronoi partition. Finding a (not necessarily globally optimal) centroidal Voronoi partition can easily be achieved through the well-known the Lloyd algorithm [93] and its variations. Additional partitioning schemes have also been proposed to incorporate constraints on coverage assignments [94], other cost functions [95], and varying communication protocols [96].

Dynamic Coverage

Dynamic coverage typically refers to those problems in which a set of autonomous agents do not remain at a single position, but rather continually move throughout the environment in order to accomplish some task. Dynamic coverage is often used to accommodate certain performance goals or environmental characteristics that are not well-suited to static coverage schemes. For instance, large and time varying environments, i.e., those in which importance weights may change or the likelihood of events of interest is time-varying, may be better suited to dynamic coverage. One particularly relevant class of dynamic coverage problems consists of persistent coverage

EXAMPLE: PERSISTENT SURVEILLANCE MISSION
Vehicle Routing and Anomaly Detection Algorithms

In this sidebar, we focus on the construction of a vehicle routing policy to govern motion of the UAV (autonomous agent). To this end, we adopt a simple routing policy that directs the UAV to a randomly chosen region during each visit. Recall that our goal is to detect anomalies in each of the regions of interest in the quickest amount of time, subject to a false-alarm constraint. To be consistent with this goal, we wish to define the probability of the UAV traveling to a given region as being proportional to the likelihood of that region being anomalous. However, since the decisions made by the human operator may be erroneous we cannot accept their raw input as a reliable indicator of the presence of an anomaly. Therefore, to employ our routing strategy, we need a tool to accurately determine the likelihood of an anomaly at each region.

The tool we choose to use is a statistical quickest change detection algorithm called the *ensemble CUSUM algorithm* [34], a variation of the standard Cumulative Sum (CUSUM) [97] algorithm which consists of a set of m parallel CUSUM algorithms [97] (one for each region). Accordingly, we treat the binary decisions by the operator as Bernoulli random variables whose distribution is dictated by the performance function, and subsequently run the ensemble CUSUM algorithm on these decisions to decide reliably on a region being anomalous. The standard CUSUM algorithm [97] requires the observations from each region to be independent and identically distributed. However, the decisions made by the operator do not satisfy these requirements. Therefore, instead of the standard CUSUM algorithm, we resort to the CUSUM-like algorithm for dependent observations proposed in [98]. The ensemble CUSUM algorithm maintains a statistic Λ_k^ℓ for each region $\mathcal{R}_k$, $k \in \{1,\dots,m\}$ and time step ℓ. The statistic at region $\mathcal{R}_k$ is updated using the binary decision of the operator whenever a task from region $\mathcal{R}_k$ is processed. If the statistic associated with a region crosses a threshold Λ_{thresh}, then the region is declared to be anomalous. The choice of this threshold dictates the accuracy of the detection [97]. We assume that once an anomaly has been detected, it is removed, and consequently, the operator's belief about the region being anomalous resets to the default value. Letting k_ℓ represent the region index of the ℓ-th task, and let π_k^ℓ represent the prior probability of an anomaly at region k after processing the ℓ-th task. The ensemble CUSUM algorithm is:

1: initialize $\ell := 1$, $\Lambda_k^0 := 0$, for each $k \in \{1,\dots,m\}$
2: **if** $\texttt{dec}_\ell == 1$ and $t_\ell > 0$, **then**

$$\Lambda_{k_\ell}^\ell = \max\Big\{0, \Lambda_{k_\ell}^{\ell-1} + \log\frac{f_{k_\ell}^1(t_\ell,\pi_{k_\ell}^{\ell-1})}{1-f_{k_\ell}^0(t_\ell,\pi_{k_\ell}^{\ell-1})}\Big\},$$

3: **else if** $\texttt{dec}_\ell == 0$ and $t_\ell > 0$, **then**

$$\Lambda_{k_\ell}^\ell = \max\Big\{0, \Lambda_{k_\ell}^{\ell-1} + \log\frac{1-f_{k_\ell}^1(t_\ell,\pi_{k_\ell}^{\ell-1})}{f_{k_\ell}^0(t_\ell,\pi_{k_\ell}^{\ell-1})}\Big\},$$

% detect an anomaly if a threshold is crossed
4: **if** $\Lambda_{k_\ell}^\ell \geq \Lambda_{\text{thresh}}$, **then**
5: declare an anomaly at region k_ℓ;
6: $\Lambda_{k_\ell}^\ell = 0$;
7: set $\ell = \ell + 1$; go to 2 :

Having established this anomaly detection tool, we employ a simple routing policy that sends the UAV to each region with a probability proportional to the likelihood of that region being anomalous. In particular, the probability to visit region $\mathcal{R}_k$ is initialized to $q_k^0 = 1/m$ and after processing each task, the probability to visit region $\mathcal{R}_k$ is chosen proportional to $e^{\Lambda_k^\ell}/(1+e^{\Lambda_k^\ell})$. This simple strategy ensures that a region with a high likelihood of being anomalous is visited with a high probability. Moreover, it ensures that each region is visited with a non-zero probability at all times and consequently, an anomalous region is detected in finite time.

Such a simple vehicle routing algorithm does not take into account the geographic location or the difficulty of detection at each region. We note that these factors could be incorporated into the vehicle routing algorithm [34]; however, for simplicity of the presentation, we do not consider such factors here.

or patrolling, where a set of multiple vehicles are required to endlessly survey an environment. This type of coverage arises for applications such as the monitoring of oil spills [99], the detection of forest fires [100], the tracking of border changes [101], and general environmental monitoring [102]. In persistent coverage schemes, vehicles continuously visit regions in the environment according to some policy that is deterministic or stochastic. We briefly discuss each of these cases in what follows.

Deterministic Policies

In continuous regions of interest (i.e., a 2D area), deterministic policies for persistent coverage usually rely on the construction of pre-set motion routines (e.g., lawnmower patterns), while in discretized regions (i.e., the region of interest is represented as a graph), deterministic policies usually rely on (i) computing a shortest tour through the regions and (ii) requiring the vehicles to endlessly move along the tour. The discrete case is closely related to network location, multiple traveling salesperson (TSP), graph exploration, or other classic vehicle routing problems (see e.g., [103], [104], [105], [106]). Indeed, almost all traditional approaches to solving the discrete, deterministic, persistent coverage problem rely on state space decomposition, and TSP tour computation [107].

Deterministic policies are often simple to implement, but are mostly periodic and predictable which may be undesirable. If, for example, we wish to detect the existence of an intruder, then the intruder may hide at instants when a vehicle is nearby and thus, most deterministic policies will fail [108] (although there do exist a few deterministic strategies which partially address this issue, such as those in [109], [110] which use ergodic theory to produce vehicle trajectories that are largely unpredictable to an outside observer).

Stochastic Coverage Policies

In contrast to deterministic policies, stochastic coverage policies are often much less predictable. Although a few researchers have adopted elements of stochasticity into surveillance of continuous regions (e.g., [111], [112], [113]), the majority of existing policies assume discretized areas or discrete regions of interest (e.g., [114], [115], [116]). In light of this fact, we focus the remainder of our discussion on this domain.

Stochastic coverage policies typically involve an ergodic Markov chain in which each region represents a state. Transition probabilities and stationary distributions are then designed according to an appropriate surveillance criterion. In general, the coverage criterion depends on the mission objective. For example, if the mission objective is the detection of anomalous regions, then the surveillance criterion may be chosen to minimize the average detection delay [34]. The minimization of the average detection delay inherently considers the difficulty of detection at each region, the travel times between the regions, and the likelihood of each region being anomalous.

For a single vehicle, there are two popular schemes to construct a Markov chain with a desired stationary distribution (surveillance criterion), namely, the Metropolis-Hastings algorithm and the fastest mixing Markov chain (FMMC) method. The two schemes can be briefly described as follows. Consider a set of regions modeled by the graph $\mathcal{G} = (V, \mathcal{E})$, where V is the set of m nodes (each node corresponds to a region) and $\mathcal{E}$ is the set of edges representing the connectivity of the regions. Let the surveillance criterion be $\boldsymbol{q} = (q_1, \dots, q_m) \in \Delta_m$. The Metropolis-Hastings algorithm [117] picks the transition matrix A, i.e., the matrix of transition probabilities from each state to every other state of the Markov chain, according to:

$$A_{ij} = \begin{cases} 0, & \text{if } (i,j) \notin \mathcal{E}, \\ \min\left\{\frac{1}{d_i}, \frac{q_j}{q_i d_j}\right\}, & \text{if } (i,j) \in \mathcal{E} \text{ and } i \neq j, \\ 1 - \sum_{k=1, k\neq i}^{m} A_{ik}, & \text{if } (i,j) \in \mathcal{E} \text{ and } i = j, \end{cases}$$

where d_i is the number of regions that can be visited from region $\mathcal{R}_i$. For the FMMC method, the transition matrix $A \in \mathbb{R}^{m\times m}$ with a desired stationary distribution $\boldsymbol{q} \in \Delta_m$ is determined by solving the semi-definite program [118]:

$$\begin{aligned} \text{minimize} \quad & \|\sqrt{Q}A\sqrt{Q} - \boldsymbol{q}_{\text{root}}\boldsymbol{q}_{\text{root}}^\top\|_2 \\ \text{subject to} \quad & A\mathbf{1}_m = \mathbf{1}_m \\ & QA = A^\top Q \\ & A_{ij} \geq 0, \text{ for each } (i,j) \in \mathcal{E} \\ & A_{ij} = 0, \text{ for each } (i,j) \notin \mathcal{E}, \end{aligned}$$

where Q is a diagonal matrix with diagonal $\boldsymbol{q}$, $\boldsymbol{q}_{\text{root}} = (\sqrt{q_1}, \dots, \sqrt{q_m})$, and $\mathbf{1}_m$ is the vector of all ones. In order to achieve the coverage criterion at an accelerated rate, a time-varying Markov chain can also be constructed in the spirit of [115]. Variants on these algorithms exist which also seek to minimize additional heuristics related to the chain, such as the mean first-passage time (also known as the hitting time or Kemeney constant) [119].

For multiple vehicles, remarkably little is known about the design of cooperative surveillance based on "multiple Markov chains." A naive stochastic policy that achieves the coverage criterion is to let each vehicle follow the single vehicle policy. A drawback of such a naive policy is that two or more vehicles may survey the same region simultaneously, which may introduce a risk of collisions and non-optimal coverage strategies. This drawback can be partially mitigated by constructing a Markov chain on a lifted space from which the undesired states are removed. Decentralized strategies, such as the message passing-based auction algorithm in [108], exist for constructing such policies.

Interfacing Humans and Autonomous Agents

Once a model of human behavior has been established and the appropriate vehicle routing policy has been selected, the last step in the design of a human supervisory control system is the construction of the interface which links the two components. In this step, we essentially "close the loop" by linking the autonomous agents with the human operator. As discussed, efficient designs must incorporate automated mechanisms to facilitate interactions between system components. Such mechanisms can take numerous forms, many of which can benefit directly from the incorporation of control theoretic tools. In this section, we illustrate this fact by providing examples of facilitating mechanisms known as *decision supports*, focusing on those which can be derived using control theory. We then conclude with a discussion of key challenges to effectively coupling humans and automated agents.

Decision Supports

Previous researchers have established a simplified four-stage model of human cognition consisting of (i) information acquisition, (ii) information analysis, (iii) decision and action

Example: Persistent Surveillance Mission

Decision Support System

We now consider the design of a decision support system for our example surveillance problem. Specifically, we consider a support which uses operator performance to suggest the optimal amount of time that they should spend on each task. We choose to utilize tools from queueing theory, which has emerged as a popular paradigm to model supervisory control systems [20], [23], [24], [28], [27], [29], [30]. Hence, we assume that the images collected by the UAV at the various regions over time are stacked in a queue, while they await operator analysis. The images arrive to the queue via a stochastic process. We impose a stability requirement on the queue length, namely, the queue length should remain finite for all time. We assume the operator receives a reward for a correct decision on each task, and the performance function is a measure of the expected reward they obtain for allocating a given amount of time to a given task. We seek to suggest time allocations to tasks such that the operator's overall reward per unit task is maximized. We design the system under the following assumptions: (i) operator performance functions for a task originating from region $\mathcal{R}_k$ in absence and presence of an anomaly are $f_k^0 : \mathbb{R}_{\geq 0} \times [0,1] \to \mathbb{R}_{\geq 0}$ and $f_k^1 : \mathbb{R}_{\geq 0} \times [0,1] \to \mathbb{R}_{\geq 0}$, respectively; (ii) based on the importance of the region, a weight $w_k \in \mathbb{R}_{>0}$ is assigned to each task collected from region $\mathcal{R}_k$; (iii) tasks arriving to the queue while the ℓ-th task is served are sampled from a probability distribution that assigns a probability $q_k^\ell \in [0,1]$ to region $\mathcal{R}_k$. Similar to (6), the average performance function $f_k : \mathbb{R}_{\geq 0} \times [0,1] \to \mathbb{R}_{\geq 0}$ at region $\mathcal{R}_k$ is defined by $f_k(t,\pi) = (1-\pi) f_k^0(t,\pi) + \pi f_k^1(t,\pi)$. Under the aforementioned assumptions, each task from region $\mathcal{R}_k$ is characterized by the pair (f_k, w_k).

For simplicity, we assume that tasks in the queue are processed by the operator in a first-come-first-serve basis. Let the ℓ-th task in the queue be from region $\mathcal{R}_{k_\ell}$, and let the belief of the operator about region $\mathcal{R}_k$ being anomalous before processing the ℓ-th task be $\pi_k^{\ell-1}$. We assume that initially the operator is unbiased about each region being anomalous, i.e., $\pi_k^0 = 0.5$, for each $k \in \{1,\dots,m\}$. Given a time allocation $t_\ell \in \mathbb{R}_{>0}$ to the ℓ-th task in the queue, the operator's belief after processing the ℓ-th task can be estimated using the Bayes rule as follows:

$$\bar{\pi}_j^\ell = \begin{cases} \frac{\pi_j^{\ell-1}\mathbb{P}(\mathtt{dec}_\ell | H^1_{k_\ell}, t_\ell)}{(1-\pi_j^{\ell-1})\mathbb{P}(\mathtt{dec}_\ell | H^0_{k_\ell}, t_\ell) + \pi_j^{\ell-1}\mathbb{P}(\mathtt{dec}_\ell | H^1_{k_\ell}, t_\ell)}, & \text{if } j = k_\ell, \\ \pi_j^{\ell-1}, & \text{otherwise,} \end{cases}$$

where H_k^0 and H_k^1 denote the hypothesis that region $\mathcal{R}_k$ is non-anomalous and anomalous, respectively, $\mathtt{dec}_\ell \in \{0,1\}$ is the operator's decision, and $\mathbb{P}(\mathtt{dec}_\ell | \cdot, t_\ell)$ is determined from the performance function of the operator, i.e.,

$$\mathbb{P}(\mathtt{dec}_\ell = 1 | H^1_{k_\ell}, t_\ell) = f^1_{k_\ell}(t_\ell, \pi_{k_\ell}^{\ell-1}).$$

The event that a region becomes anomalous corresponds to a change in the characteristic environment, which may happen at an arbitrary time. In a sequential change detection task, if the belief of the operator about a region being anomalous is below a threshold, then the operator resets their belief to the threshold value [120]. We choose this threshold as 0.5. Consequently, the belief of the operator at region $\mathcal{R}_k$ after processing the ℓ-th task is $\pi_k^\ell = \max\{0.5, \bar{\pi}_k^\ell\}$.

We wish to suggest to the operator the amount of time to spend on each task. To this end, we design the support system to maximize the infinite-horizon average reward, under the finite queue length constraint. We define the reward $r : \mathbb{N} \times \mathbb{R}_{\geq 0} \to \mathbb{R}$ obtained by allocating time t to the ℓ-th task by

$$r(\ell, t) = w_{k_\ell} f_{k_\ell}(t, \pi_{k_\ell}^{\ell-1}),$$

where k_ℓ is the index of the region which generated the ℓ-th task. The objective of the decision support system is to maximize the infinite-horizon average reward defined by

$$V_{\text{avg}} = \liminf_{n \to +\infty} \frac{1}{n} \sum_{\ell=1}^{n} r(\ell, t_\ell),$$

while enforcing stability of the queue length. Since the system evolves according to an uncertain decision process, we cannot solve this problem exactly. However, we can approximate a dynamic solution under a certainty equivalent assumption [121], [122], [123]. Under the certainty-equivalent approximation, future uncertainties of the system are approximated by their expected values [121]. Accordingly, the expected rate of arrival of tasks into the queue using current system parameters is $\lambda_\ell = 1/(\boldsymbol{q}^{\ell\top} D \boldsymbol{q}^\ell + \boldsymbol{q}^{\ell\top}\boldsymbol{T})$, where $\boldsymbol{D}$ is a $k \times k$ matrix whose i,j-th entry represents the travel time between regions $\mathcal{R}_i$ and $\mathcal{R}_j$, and $\boldsymbol{T}$ is a vector whose entries represent image generation times in the respective regions. Further, by the strong law of large numbers, the expected value of the function V_{avg} while the ℓ-th task is processed is simply the expected average reward, calculated using current system parameters, i.e., $\bar{V}_{\text{avg}} = \sum_{k=1}^m q_k^\ell w_k f_k(t_k^{\text{reg}}, \pi_k^{\ell-1})$, for some t_k^{reg} representing a stationary amount of time to be allotted to tasks originating from region $\mathcal{R}_k$. Therefore, under the certainty-equivalent assumption, we can approximate the optimal time allocation to the ℓ-th task by solving the following optimization problem at each time step:

$$\begin{aligned} \underset{\hat{t}_1^{\text{reg}}, \hat{t}_1^{\text{reg}}, \dots, \hat{t}_m^{\text{reg}}}{\text{maximize}} \quad & \sum_{k=1}^m q_k^\ell w_k f_k(\hat{t}_k^{\text{reg}}, \pi_k^{\ell-1}) \\ \text{subject to} \quad & \sum_{k=1}^m q_k^\ell \hat{t}_k^{\text{reg}} \leq \frac{1}{\lambda_\ell} \\ & \hat{t}_k^{\text{reg}} \geq 0, \ \text{for each } k \in \{1,\dots,m\}, \end{aligned} \tag{7}$$

subsequently choosing $t_\ell = \hat{t}_{k_\ell}^{\text{reg}}$. Note that the first constraint enforces queue length stability [30], and Note that optimization problem (7) is a knapsack problem with sigmoid utilities, whose solution can be approximated [30].

selection, and (iv) action implementation [124]. These abstract functions operate at various levels of granularity within a given task, and generally interact with each other in a continuous and complex fashion. As such, there is potential to improve system performance through incorporation of automated tools which focus specifically on aiding decision making, and consequently sharing the total cognitive load across system resources.

In this spirit, we define a *decision support* as any automated function that supports the *decision and action selection* stage of the cognitive process. In human supervisory control, this can mean directing operator attention, providing timing suggestions to the operator, preprocessing of tasks, adjusting automation parameters, among many other possibilities. The specific form and potential for success of a given decision support system varies by application and system constraints. However, to illustrate how decision supports can be integrated at various levels of system operation, we discuss some examples which operate on different decision making tasks and have the potential to drastically improve system performance.

Attention Allocation as an Optimization Problem

In supervisory tasks in which the operator has multiple simultaneous responsibilities, the question of where and how the operator should direct their attention becomes an important component to task success. In visual perception tasks, low level decisions focus on where the operator should direct their attention within a given image or video.

It is well known in psychology literature that evidence accumulation in visual perception is highly dependent upon *radial eccentricity*, i.e., the angular distance of a stimulus from the *foveal region*, the point in the visual field of highest resolution. The foveal region corresponds to the point on the stimulus at which the operator is directly looking. Indeed, due to the high density of foveal receptors when compared to the visual periphery (see Figure 6), evidence accumulation is generally much faster when a person is looking directly at a stimulus [125].

Suppose now that we have a model for a human operator's accuracy in making a decision about a particular target as a function of time and radial eccentricity, and that we have access to a person's fixation locations in real time (an assumption that is not unrealistic, given the increased availability and affordability of eye-tracking hardware [127]). Assume also that we have discretized a given image into m disjoint, equally sized regions. In a static image, the amount of evidence about some target of interest is finite. Therefore, we can associate to each region k, a differential equation of the form

$$\dot{x}_k = g(x_k, e)$$

where x_k is the amount of evidence accumulated about the properties of some target in region k, e is radial eccentricity,

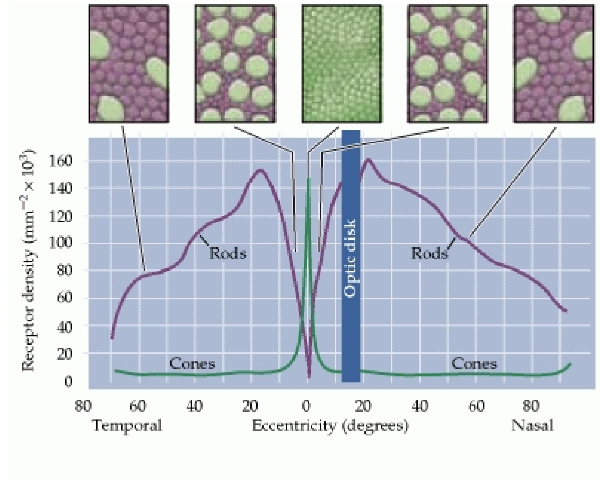


Figure 6. Distribution of foveal receptors as a function of radial eccentricity, taken with permission from [126].

and g is a function which relates these two variables to the speed at which the operator accumulates evidence. Under this construction, the question of directing operator attention within a search task reduces to an optimization problem of the form

$$\begin{aligned} \underset{\{\mathrm{Fix}_1,\ldots,\mathrm{Fix}_n,n\}}{\text{minimize}} \quad & \mathrm{Dur}_{\mathrm{Total}} \\ \text{subject to} \quad & \sum_{k=1}^{m} x_k = \sum_{k=1}^{m} \mathrm{Evid}_{\mathrm{k}}, \end{aligned}$$

where $\mathrm{Fix}_i = (\mathrm{Loc}_i, \mathrm{Dur}_i)$ is a tuple encoding the location and duration of the i-th fixation, $n \in \mathbb{N}$ is the number of fixations, $\mathrm{Evid}_{\mathrm{k}}$ is the total available information about the target in region k, and $\mathrm{Dur}_{\mathrm{Total}} := \sum_{i=1}^{n} \mathrm{Dur}_{\mathrm{i}}$. In other words, we can estimate a sequence of fixations and fixation durations such that the operator accumulates the maximum amount of information about a particular image in the shortest amount of time. With this information, it may be possible to direct operator attention within image searches (assuming that it is possible to construct visual cues that the operator will respond to, an issue that will be discussed later).

In application, the function g could depend on many factors, such as visual clutter of the image [128] and task difficulty [129]. In addition, when the visual stimulus is a video, then the amount of evidence present evolves over time, and thus may not be finite. Further, a changing stimulus may alter the evidence accumulation process, and thus the model may need to be altered to take into account motion characteristics.

Timing as a Resource Allocation Problem

The goal for many supervisory control applications is to have a single operator who is capable of processing multiple tasks or data streams simultaneously [130]. In such tasks, the operator must not only decide how to allocate their attention within each task, but at a higher level must also decide how to allocate attentional resources across tasks. Assuming tasks to be processed are stacked in a queue, then the problem of deciding how much time that the operator should spend on each task in the queue becomes a resource allocation problem. Indeed, we think of time as a resource that needs to be distributed among the necessary tasks. The inherent dynamics in persistent task analysis missions make these resource allocation problems a dynamic optimization. The solution to such optimization problems can be computed for small horizon lengths, however, for large horizons such computations are often not amenable. Despite these difficulties, we can still compute high-quality suboptimal solutions using tools from control theory.

In a general sense, the infinite horizon optimization for a persistent task analysis mission can be formulated as follows: Consider a time-varying dynamical system of the form $x_{\ell+1} = \texttt{evol}_\ell(x_\ell, t_\ell, d_\ell)$, where $\ell \in \mathbb{N}$ denotes the task index, $x_\ell \in \mathcal{X}$ is the state variable, $t_\ell \in \mathbb{R}_{\geq 0}$ is the time to be devoted to the ℓ-th task, $d_\ell \in \mathcal{D}$ is a disturbance, and $\texttt{evol}_\ell : \mathcal{X} \times \mathbb{R}_{\geq 0} \times \mathcal{D} \to \mathcal{X}$ denotes the evolution map of the system. Given a stochastic model for $\{d_\ell\}_{\ell \in \mathbb{N}}$, the control objective is to solve the optimization:

$$\begin{aligned} \underset{\boldsymbol{t}:=\{t_\ell\}_{\ell\in\mathbb{N}}}{\text{maximize}} \quad & \liminf_{n\to+\infty} \frac{1}{n}\sum_{\ell=1}^{n} g(x_\ell, t_\ell, d_\ell), \\ \text{subject to} \quad & \boldsymbol{t} \in \mathcal{C} \\ & t_\ell \geq 0, \text{ for each } \ell \in \mathbb{N}, \end{aligned} \tag{8}$$

where x_1 is the initial state, $\boldsymbol{t}$ is the sequence of times devoted to each task, $g : \mathcal{X} \times \mathbb{R}_{\geq 0} \times \mathcal{D} \to \mathbb{R}$ is the stage reward, and $\mathcal{C}$ is a constraint set.

In general, the optimization (8) is hard, however, solutions can often be approximated in a tractable way using receding-horizon control [123]. *Receding-horizon control* approximates the solution to the infinite-horizon optimization (8) by solving a finite horizon optimization problem at each iteration to sequentially determine the control input. In the presence of uncertainty, however, future parameters required for this finite horizon optimization may not be known. A common strategy for addressing this issue is to adopt a *certainty-equivalent* assumption, which replaces future uncertainties of the system by their expected values [121], [122], [123]. Specifically, the certainty-equivalent receding-horizon control scheme solves the following optimization problem to determine the control to apply at iteration ℓ:

$$\begin{aligned} \underset{\hat{t}_0,\hat{t}_1\ldots,\hat{t}_{n-1}}{\text{maximize}} \quad & \frac{1}{n}\sum_{j=0}^{n-1} g(\bar{x}_{\ell+j}, \hat{t}_j, \bar{d}_{\ell+j}), \\ \text{subject to} \quad & (\hat{t}_0, \hat{t}_1 \ldots, \hat{t}_{n-1}) \in \bar{\mathcal{C}}_\ell \\ & \hat{t}_j \geq 0, \text{ for each } j \in \{0, \ldots, n-1\}, \end{aligned} \tag{9}$$

where $\{\hat{t}_0, \ldots, \hat{t}_{n-1}\}$ is time allocated to each task over the horizon, $\bar{\mathcal{C}}_\ell$ is a modified constraint set, and $\bar{x}_{\ell+j}$ is the certainty-equivalent evolution of the system, i.e., the evolution of the system obtained by replacing the uncertainty in the evolution at each stage by its expected value, $\bar{x}_\ell = x_\ell$, and $\bar{d}_{\ell+j}$ is the expected value of the uncertainty at stage $\ell+j$. The certainty-equivalent receding-horizon control scheme at iteration ℓ solves optimization problem (9) and picks $t_\ell = \hat{t}_0$. If the deterministic dynamic program (9) can be solved efficiently, then certainty-equivalent receding-horizon control offers a computationally tractable sub-optimal solution to problem (8).

In some cases, it may be tractable to solve the optimization (9) over very large or even infinite time horizons without resorting to additional approximations. For example, suppose that tasks are generated from $k \in \{1, \ldots, m\}$ different sources and stacked in the queue for analysis, and suppose that $q_k^\ell \in [0, 1]$ represents the probability that the next task arriving into the queue is generated by the k-th source at time step ℓ. Further, suppose that for each k, $f_k : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$ is a continuous, monotonically increasing function representing the utility obtained by spending time t on a task generated by the k-th source, and that we wish to maximize the infinite horizon reward while requiring a finite queue at all times. Invoking the strong law of large numbers makes solving (9) in the limit as $n \to \infty$ reduce to solving a *knapsack problem*:

$$\begin{aligned} \underset{\hat{t}_1^{\text{reg}},\hat{t}_1^{\text{reg}},\ldots,\hat{t}_m^{\text{reg}}}{\text{maximize}} \quad & \sum_{k=1}^{m} q_k^\ell f_k(\hat{t}_k^{\text{reg}}) \\ \text{subject to} \quad & \sum_{k=1}^{m} q_k^\ell \hat{t}_k^{\text{reg}} \leq \frac{1}{\lambda} \\ & \hat{t}_k^{\text{reg}} \geq 0, \text{ for each } k \in \{1, \ldots, m\}, \end{aligned} \tag{10}$$

where $\lambda \geq 0$ is the arrival rate of tasks into the queue (the constraint function will ensure that the queue remains finite [30]). The control scheme would then choose $t_\ell = \hat{t}_{k_\ell}^{\text{reg}}$, where k_ℓ is the region index of the ℓ-th task. Although the problem (10) is simpler at first glance, it may still be difficult to solve exactly. For example, when the utility (reward) functions associated with knapsack problems are based on accumulator models of human decision making, they may take the form of sigmoid functions, i.e., the utility functions f_k are sigmoid functions of time. The knapsack problem with sigmoid utilities is an NP-hard problem (although computationally tractable 2-factor solutions have been proposed [31]). If the problem (10) can be solved efficiently, we can approximate the solution to (8) by solving an infinite horizon optimization under the certainty-equivalent assumption at each time step.

We remark that one must use caution in using simplifications such as that in (10), since small modifications to the problem structure may cause such a formulation to lose validity. For instance, the addition of deadlines on tasks or latency penalties (penalties due to delay in processing a task) break this structure. In such scenarios, we once again may resort solving the problem (9) over a short time horizon at each time step using standard dynamic programming techniques.

Adaptive Automation as a Feedback Control Problem

In addition to attention allocation issues, at a higher level of granularity there is the issue of deciding what system functions should be left to the human operator and what functions should be automated. According to the 4 stage model in [124], each of the stages of the cognitive process may be automated to differing degrees within a single system. The choice of what aspects to automate is a decision in itself and may vary based on application, or based on the state of the operator.

In a supervisory role, most tasks in the action implementation category (such as vehicle motion control) are automated at a high level; however, even in this case the system must make a decision about how the operator issues commands to automated systems [131]. For example, the authors of [132] show that a task-based control scheme in which the operator is only allowed to issue high-level commands, in many aspects outperformed a vehicle-based scheme, where the operator can control the motion of each automated agent individually.

Studies have shown that great care must be taken in choosing the right level of automation for a given system, as increased automation does not always lead to better performance. Indeed, increased automation can lead to increased operator complacency and bias [133]. As a result, researchers have begun to study an adaptive approach, in which the operator state is monitored, and level of automation is altered in an attempt to maintain the operator state in some desired regime. In this simplified sense, the issue of adaptive autonomy reduces to a control problem. Indeed, if it can be verified that the level of autonomy of a given system has some effect on operator performance, then level of autonomy can be thought of as a control input which can be used to guide user performance.

For example, suppose we choose to model operator workload via the utilization ratio presented in Equation (4). Then, operator workload is inversely related to the level of autonomy of a given system. The Yerkes-Dodson law suggests that moderate levels of operator workload (arousal) lead to the highest levels of performance. It is a natural step, therefore, to design a feedback control law which adjusts automated functionalities to keep the utilization ratio and thus the operator workload within a moderate regime.

Of course, this type of control approach hinges on a myriad of assumptions about operator behavior and its relationship to performance, as well as the ability to accurately measure the complexities of human cognition and performance in real-time. We discuss some of these considerations in subsequent sections, however, the underlying concept of relating automation parameters to performance and using this easily adjustable parameter as a means of control is one that has received recent researcher attention and will remain an important topic.

Key Challenges

In many of the formulations discussed, we have assumed simplified models and optimization strategies which are loosely coupled across system components. Although this framework may suffice in some circumstances, in reality a human supervisory control system and an associated decision support system operate through a combination of driving factors that work together simultaneously. We conclude our discussion by highlighting a few key challenges to improving design strategies and effectively implementing them in practice.

Tightly Coupling System Components

In human supervisory control, the design of a decision support system and the design of coordination strategies for automated agents are often treated as completely decoupled problems. However, in many instances there could be a tighter coupling in how the performance of decision supports and autonomous agents influence each other through the user. For example, in some operational contexts, autonomous agents may have to loiter until the operator can attend to them. Such operator induced delays could lead to degradation in coverage performance. From a mathematical perspective, one could pose a joint optimization problem of scheduling both the user and autonomous agents to achieve overall system objectives. Hence, one could consider jointly the design of the decision support and the autonomous agents. Further research is needed to develop appropriate formulations of such problems, incorporating different dynamic and performance characteristics, and developing tractable computational methods.

Assessing the Operator State

The creation of effective decision supports often hinges upon the ability to accurately assess the operator's cognitive state, e.g, situational awareness, perceived workload, fatigue, etc. However, it difficult to assess such a state with any degree of accuracy using current technology. Recent technological advances have made the use of physiological sensors, such as eye-trackers, electroencephalogram (EEG, measuring cortical electrical activity), and electrocardiogram (ECG, measuring heart beats), a viable option for providing real-time data in many applications [127]. As such, a large body of recent research has gone into finding correlations between cognitive activity and objective measures, such as pupil diameter [39], [134], blink rates [135], heart rate [136], [137] , and EEG activity [138], [139].

Even though these studies have successfully found correlations in certain scenarios, it remains difficult to utilize such findings in practice. One reason is that it is difficult to control exogenous factors in real applications. For example, researchers

EXAMPLE: PERSISTENT SURVEILLANCE MISSION

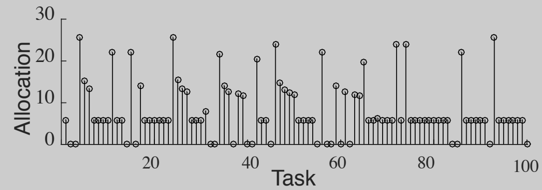
Numerical Simulations

We now illustrate the decision support system designed in the previous sidebars through a numerical example. We consider a surveillance mission involving four regions. The matrix of travel times between the regions is

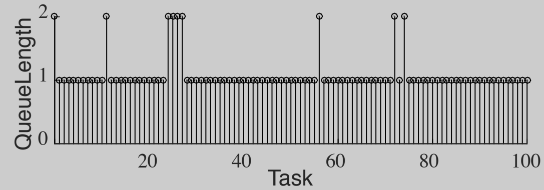
$$D = \begin{bmatrix} 0 & 22.1422 & 34.4786 & 8.9541 \\ 22.1422 & 0 & 19.3171 & 14.6245 \\ 34.4786 & 19.3171 & 0 & 25.5756 \\ 8.9541 & 14.6245 & 25.5756 & 0 \end{bmatrix}.$$

The time to collect information at each region is 10 units. We assume the performance of the operator is the same at each region, and that the importance of each region be equal to that of all other regions. Let the drift rate in the DDM associated with the operator be $\mu = \mp 0.3$ for a non-anomalous and an anomalous region, respectively. Let the diffusion rate for the DDM associated with the operator be $\sigma = 1$. Suppose regions $\mathcal{R}_1, \mathcal{R}_2, \mathcal{R}_3$, and $\mathcal{R}_4$ become anomalous at time instants $20, 80, 140$, and 200 units, respectively.

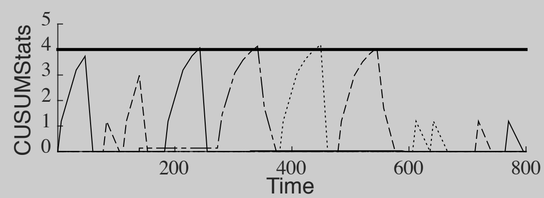
The optimization problem (7) is solved before processing each task to determine the optimal allocations for the human operator. A sample evolution of the system is shown in the figures in the right column. Note that the algorithm keeps the queue length close to unity. The queue length increases only if there is a high likelihood of anomaly at some region. Once an anomaly is detected, the allocation policy drops pending tasks in the queue until only one task remains. The threshold for the CUSUM algorithm is chosen equal to 4 and once an anomaly is detected the CUSUM statistic in (c) resets to zero. Two false alarms happen before time equal to 200. The region selection policy in (a) sends the UAV with a high probability to a region with a high likelihood of being anomalous.



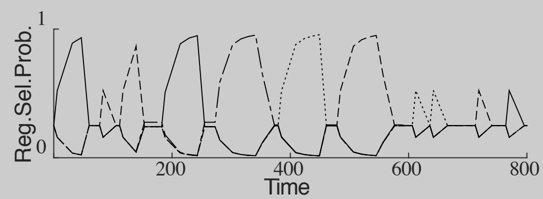
(a) Duration allocation



(b) Queue length



(c) CUSUM statistics



(d) Region selection probabilities

have found correlations between pupil diameter variations and cognitive processing, but Tryon [140] cites at least 23 factors that can affect pupil size. Thus, it is hard to rely on pupil diameter alone as a reliable indicator of workload in a scenario where outside factors are not carefully controlled. Further complicating the issue, many physiological responses are highly task dependent or dependent upon the individual characteristics of the user. A more rigorous understanding of these physiological correlations and user cognitive states, as well as their sources of variation, are necessary.

Graphical User Interface Design

Graphical User Interfaces (GUIs) can have a drastic impact on operator performance and the overall functionality of a system [141]. As such, the issue of designing effective user interfaces has been studied in a variety of contexts including computer science, marketing [142], human factors [143], psychology [144], and engineering [145]. Researchers have studied a wide range of aspects of the interface design problem and its impact on operator performance, including luminosity [146], stimulus specifications [147], interactive window characteristics [148], and many many others.

The standard means of evaluating GUIs is through usability surveys. Some surveys, such as the *System Usability Scale* survey [149], [150], have been studied extensively, and provide benchmark statistics. Other researchers, e.g. [151], have turned to objective measures of usability that are more directly catered to the particular application under consideration. In the context of supervisory control, GUIs play a key role in the success of any system design, and must be carefully tested before being employed in application.

Automation Bias and Operator Trust

Many automated systems which are designed to aid operator performance rely on the use of opportunistic cues or suggestions in attempt to guide operator behavior. Such forms of indirect control are of no use unless the operator responds to them in a meaningful way. Indeed, if the operator never takes into account any of the automated suggestions, then the whole purpose of providing them is defeated. On the other end of the spectrum, if the operator always heeds the automated suggestions without question, the operator can become complacent and lose situational awareness, resulting in performance degradation. This phenomena, sometimes referred to as *automation bias*, has been studied extensively in attempt to understand its effects and the conditions under which it occurs [133], [152], [153].

Both of the issues discussed in the preceding paragraph are related to the issue of operator trust in automation. This complex phenomena is hard to model, due to its dynamic nature, and its inherent situational and interpersonal dependencies [154], [155]. However, a successful human supervisory control system must employ tactics to maintain adequate operator trust, while mitigating automation bias.

Individual Differences

For the sake of simplicity, most system designers create a single, general-purpose model of human cognitive processing, with the intention of using this model with all potential operators. However, different operators may have varying responses to a given system design, and ignoring the vast differences between individuals can greatly reduce accuracy in predicting behavior. Indeed, factors such as personality traits [155], past experiences [154], and even the operator's current mood [156] can all effect performance. Studies of individual differences seek to resolve these shortcomings by identifying the ways in which people with distinct attributes react to the same situations in unique ways [157]. For example, research has shown that the personality trait *extraversion* moderates the relationship between arousal and performance - those with lower extraversion are more resilient to periods of hypostress, and those with higher extraversion are more capable of handing hyperstress [158].

Recent research has been somewhat successful in identifying specific traits that make a significant difference in operator interactions with autonomous systems [155]. For instance, in the context of supervisory control, the authors of [159] show that high spatial ability, attentional control, and video gaming experience can all lead to better performance in some aspects of a multiple agent supervisory control mission. Despite these results, the relationship between individual operator differences and performance remain complex due to task dependencies and environmental sensitivity. It is clear that a more thorough understanding of system robustness to individual differences is needed before successful implementation.

CONCLUSIONS

Human supervisory control of robotic teams is an area that has attracted a significant amount of research attention in recent years, and will only continue to grow as sensor and robotic technology becomes more advanced. The unique set of challenges that this application brings about spans many disciplines, including control systems, human factors, and psychology. In a broad sense the human supervisory control problem can be broken down into three components: the human, the autonomous agents, and the interface between them. In surveying each of these components and discussing examples of relevant theory for each, it becomes apparent that well-studied tools from different scientific disciplines can work in conjunction with one another to create efficient overall systems which have the potential to drastically increase productivity and efficiency in a given application. While many challenges still remain, continued collaboration among scientific disciplines will allow the maturation of future human supervisory control technology.

ACKNOWLEDGMENTS

This work has been supported by the Institute for Collaborative Biotechnologies through grant W911NF-09-0001 from the U.S. Army Research Office. The content of the information does not necessarily reflect the position or the policy of the Government, and no official endorsement should be inferred.

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