

Choice Modeling of Relook Tasks for UAV Search Missions

L. F. Bertuccelli, N. Pellegrino, and M. L. Cummings

Abstract—This paper addresses human decision-making in supervisory control of a team of unmanned vehicles performing search missions. Previous work has proposed the use of a two-alternative choice framework, in which operators declare the presence or absence of a target in an image. It has been suggested that relooking at a target at some later time can help operators improve the accuracy of their decisions but it is not well understood how – or how well – operators handle this relook task with multiple UAVs. This paper makes two novel contributions in developing a choice model for a search task with relooks. First, we extend a previously proposed queueing model of the human operator by developing a retrieval queue model that formally includes relooks. Since real models may deviate from some of the theoretical assumptions made in the queueing literature, we develop a Discrete Event Simulation (DES) that embeds operator models derived from previous experimental data and present new results in the predicted performance of multi-UAV visual search tasks with relook. Our simulation results suggest that while relooks can in fact improve detection accuracy and decrease mean search times per target, the overall fraction found correctly is extremely sensitive to increased relooks.

I. INTRODUCTION

One of the core applications in human supervisory control research [1] revolves around futuristic Unmanned Aerial Vehicle (UAV) operations, where the human operators act as mission managers overseeing high level aspects of the mission (such as resource planning, scheduling, and generating new strategies), rather than manually flying the remotely piloted vehicles [2], [3]. In an attempt to understand the complex interactions between the human and the different layers of high-level control, it is of paramount importance to model the human operator, and in particular, gain understanding into human decision making processes so as to develop more appropriate decision support systems.

Mathematical models for human operators interacting with UAVs have been developed using a queueing framework [3], [4], where external tasks/events arrive according to an underlying stochastic process, and the human supervisor, modeled as a server, has to service this stream of tasks/events. These queueing-based mathematical models lend themselves to both elegant analysis that can then be used to infer limits of performance on the human operators [5], as well as used for a thorough sensitivity analysis to parameters (such as

variation of the task arrival rate) via the use of Discrete Event Simulation [3]. In visual search task applications, these queueing models can be used to determine theoretical operator capacity limits and verify them through human experimentation. In addition, human experimentation can be used for parameter estimation of important variables in the visual search task, such as accuracy and mean search times. These parameters also arise in the context of commonly-used 2-alternative choice models [6]–[10], where the operator needs to select between choosing that a target is present or not.

An important aspect of UAV missions is the visual search task, where the operators are responsible for finding a target in an image or a video feed. The military already finds it difficult to analyze all incoming UAV imagery (both full motion video and static images), and given the future DoD vision of one operator supervising multiple UAVs, the amount of incoming imagery to analyze in real-time will grow dramatically. Moreover, with recently announced wide area airborne sensors such as Gorgon Stare and Argus which generate up to 64 images per a single UAV camera, there is an urgent need to develop more efficient approaches for human analysis of UAV-generated imagery [11], [12].

In their current formulations however, the previously mentioned queueing models fall short in addressing an important feature of UAV search missions: the ability for operators to conclude that there is insufficient information to make a good decision, and require an additional visit to look at the target. These so-called *relooks* are of obvious operational importance in minimizing collateral damage and reducing errors, and have been studied in the context of optimal stopping problems [13] and inspection problems [14]. Single UAV relook problems in the presence of fuel constraints have been presented in [14] and [15]. However, the operator is primarily modeled with a stationary confusion matrix, while the true error rates may depend on the actual search time, as anticipated in the human factors literature. Furthermore, multi-video stream visual search tasks with the possibility of relook can be much more complex than single-UAV counterparts since the multi-UAV aspect requires a fine balance between planning for the other vehicles and understanding how to re-allocate the vehicles to gain additional information, all the while under intensive time pressure.

This paper makes two novel contributions in presenting a choice model for a search task with relooks. First, we develop a queueing model for the visual relook task in the spirit of Refs [16]–[19] that formally includes relooks. Since real models may deviate from some of the theoretical assumptions made in the queueing literature, we next

Manuscript received on XX XXXX, 2010. This work was supported by the Michigan/AFRL Collaborative Center in Control Science and under ONR Grant N00014-07-1-0230. L. F. Bertuccelli is a Postdoctoral Associate at the Massachusetts Institute of Technology, Dept of Aeronautics and Astronautics lucab@mit.edu. N. Pellegrino is an undergraduate student at the Massachusetts Institute of Technology, Dept of Electrical Engineering, nickpell@mit.edu. M. L. Cummings is an Associate Professor at the Massachusetts Institute of Technology, Dept of Aeronautics and Astronautics, missyc@mit.edu

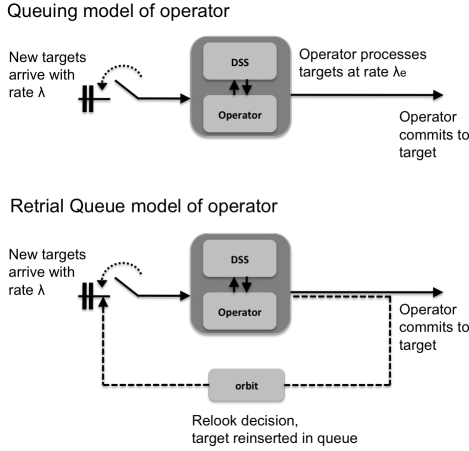


Fig. 1. A queuing model for the human operator (top) and a retrial queue (bottom) to model a relook strategy

develop a Discrete Event Simulation (DES) that embeds operator models derived from previous experimental data and present new results in the predicted performance of multi-UAV visual search tasks with relook.

This paper is outlined as follows. Descriptions of queueing models and choice models for human operators are presented in Section II, and the retrial queueing model is presented in Section III. The simulation study is presented in Section IV and we conclude with future work in Section V.

II. OPERATOR MODELING

A. Queueing model for Operator Behavior

Queueing models for human operators have been originally proposed in the context of air traffic control [4], where the human operator was treated as a serial controller, capable of handling one complex task at a time. Operator models were further developed and extended in the context of human supervisory control of multiple UAVs [3], to account for operator workload and situational awareness.

A simplified queueing model in the spirit of [3] can be described as follows (see Figure 1). The tasks/events are generated by a Poisson process with rate λ , and the human operator (with possible help from the decision support system, DSS) services the tasks at a rate λ_e (e.g., searches for targets in the images). In complex tasks, operators may dedicate themselves only to a single task, allowing the incoming tasks to accumulate in the queue. For the purposes of this paper, the randomly generated tasks are assumed to be visual search tasks that are generated uniformly across the environment. After a new target is generated (on average, every $1/\lambda$ seconds), and after a UAV visits that target, the operators is presented with an image containing the target. The visual search task initiates when the operator begins examining the image feed to the target, and concludes with a decision on whether the target was found or not.

B. Decision models

A key concern in supervisory control is the role of vigilance-like effects, whereby operator performance (in

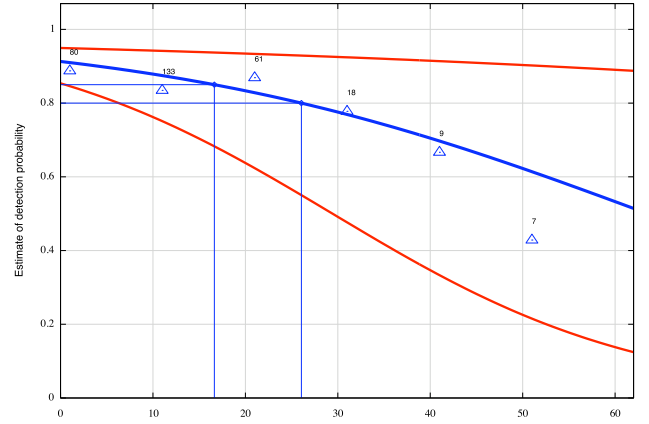


Fig. 2. Detection probability decreases as a function of time: best estimate is solid line, $3\text{-}\sigma$ regions shown in lighter lines, Maximum Likelihood estimate in triangles. Vertical lines show corresponding search times for detection probabilities of $P_d = 0.85$ and $P_d = 0.80$

terms of accuracy) degrade with time [20], and this is a critical consideration for human supervisors of UAV missions. Data collected in previous human-in-the-loop experiments (including visual search tasks [3]) has shown that detection probability in the search task can degrade with increased search time dedicated to the task. Figure 2 shows the maximum likelihood estimate of the probability of detection (solid line) as a function of search time for a visual search task run from previous experimental data in multi-UAV simulated missions [3]. In this case, the estimate of detection probability \hat{P}_d was modeled using a logistic regression of the form

$$\hat{P}_d = \frac{1}{1 + \exp(\hat{\beta}^T \mathbf{t})} \quad (1)$$

with $\mathbf{t} = [1, t_s]$; t_s is the total search time; and $\hat{\beta} = [\beta_0, \beta_1]$ is the vector of parameters of the logistic regression. Using this insight, there are certain thresholds beyond which the operator performance degrades, and it may be beneficial to temporarily abandon the current search task and possibly relooking at it later. Note that unlike 2-AC models, the relationship between detection probability is with respect to the overall search time t_s , not the average search time \bar{T} .

III. RETRIAL QUEUEING MODEL

In order to account for relook in the queueing model, this section formulates this problem as a retrial (in the spirit of Refs. [16], [17]). A retrial queue model of the human operator treats the human as a server [3] and if the server is available (i.e., operator free to initiate a visual search task), the task can be serviced immediately. If the server is not available, the task is inserted in a so-called *orbit* pool (see Figure 3) to be serviced at a later time. In this setting, the orbit pool could represent the list of requeued targets but also targets waiting to be processed. The following retrial queue formulations of [18], [19] describe the model.

Detailed retrieval queue model of operator

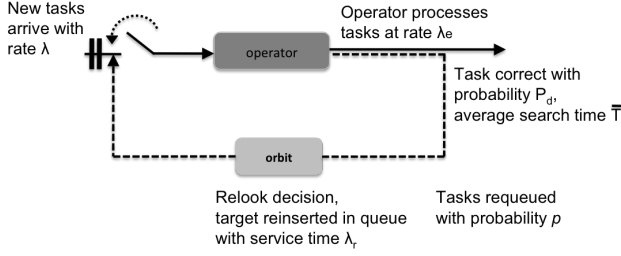


Fig. 3. Detailed retrieval queue model with parameters to be estimated

A. Arrivals and servicing rates

This model assumes that new tasks arrive in the system as a Poisson arrival with rate λ . The model further assumes that new tasks are serviced by the operator at a rate λ_e . Note that for queueing models of visual search tasks performed with UAVs, λ_e has a strong dependence on numerous factors, but the two principal drivers are operator search time and vehicle routing policy. Thus, if an operator is not efficient in the search task (e.g., spends too much time searching) and does not route the vehicles along efficient paths, the service rate can be potentially much lower than the arrival rate $\lambda_e \ll \lambda$, leading to queue instability, where the number of outstanding targets will grow unbounded over time.

B. Requeueing policy

The requeueing policy is one of the most important features of the relook task, and yet remains to be completely identified from experimental data. However, we can gain insight from requeueing models with Bernoulli feedback [18], where the operators perform relooks (i.e., requeues the targets) with some probability p . In general, this probability may depend on the total amount of time searched in the targets, but can also have a functional relationship with the total number of outstanding targets, target arrival rates, etc. As a first approximation, this paper assumes that the relook probability depends on the search time, with additional details provided in the next section. In addition we make the following assumptions:

- requeued tasks are serviced with probability q , and
- requeued tasks are serviced at a rate λ_r .

These preliminary assumptions are made as a reasonable way to capture the uncertainty in the operator choice models, but also to allow correspondence to some retrieval queueing models with known analytical results [18], [19].

C. Choice model

The choice model is the underlying decision-making mechanism under which the operator makes a decision on the target in the image. Building upon previous experimental data from [3] and using guidance from the 2-AC model literature, we abstract the operator choice model in a detection probability and search time distributions.

For the detection probability, we have identified operator visual search task accuracy via the logistic regression of Eq. (1). The operator is assumed to make correct detections with probability $P_d(t_s) = \frac{1}{1 + \exp(\hat{\beta} T t)}$ with $t = [1, t_s]$ and where t_s denotes the search time. In distinction to the work in [15], the detection probability is a non-stationary quantity, and is dependent on the search time t_s . From previous experimental data [3], we have determined that $\hat{\beta} = [-2.300, -0.037]$.

In addition, previous experimental data regarding the visual search task in multi-UAV experiments has shown that the log-normal distribution (Eq. 2) well approximates the search time distribution (where $t_s > 0$)

$$f(t_s; \mu, \sigma^2) = \frac{1}{\sqrt{(2\pi\sigma^2 t_s^2)}} \exp\left(\frac{-(\log(t_s) - \mu)^2}{2\sigma^2}\right) \quad (2)$$

For the search time distributions, we have found that $\mu = 3.1$ and $\sigma^2 = 0.6$.

D. Discussion and some results in retrieval queues

The queueing model of Figure 3 is an initial attempt at understanding how a repeated visual search task with a relook option can be properly formalized in queueing theory. As such, the requeueing policy of Section III-B is a simplified model of the actual policy that should be developed. For example, human operators could generate a relook policy based on the current number of outstanding targets, the estimated arrival rate of targets, as well as the total number of search vehicles. The goal of the ongoing experiment will be to identify the unknown model parameters (λ_e , p , q and λ_r), as well as understand human performance in the relook task.

Retrieval queueing theory has a rich history that makes available numerous results that can be applied to this work. For example, one could be interested in the total average number of outstanding targets in the queue, and could apply the following retrieval queue in a retrieval framework, given information on requeueing probability p

Theorem 1: (Nominal queue size) [18] The mean queue length of the normal queue is given by

$$N_{nom} = \frac{(1-p)\lambda^2 E(S^2)}{2(1-(1-p)\rho)} \quad (3)$$

where $\rho = \lambda \bar{T}$ is the utilization, \bar{T} is the mean service rate, $E(S^2)$ is the second moment of the service time, and p is the probability that a target will be requeued. ■

This type of result is useful in that, assuming that the probability of relooking is known and stationary, given the arrival rate λ and knowledge of the second moment of the service time, then the queue size could in principle be determined.

However UAV operator models for retrieval queues may deviate from some of the common assumptions necessary for analytical tractability. For example the work of Choi [18] assumes that a task in the orbit queue can only be serviced if the nominal (or *priority*) queue is empty. This is not a suitable representation of the UAV relook problem, since a target can be relooked whether or not there are any remaining

outstanding visual search tasks. In addition, the work of Choi [18] (and in queueing theory in general) assumes that the queue is stable, in the sense that the number of tasks does not grow unbounded over time. Realistic mission requirements may however not satisfy these restrictions. While it will be the topic of future work to investigate whether the analytical methods from retrial queueing theory may be applicable, a method for admitting less restrictive assumptions can be addressed by using Discrete Event Simulation (DES).

IV. DISCRETE EVENT SIMULATION OF RETRIAL QUEUE

This section discusses the use of a simulation environment to understand the behavior of the retrial queue approach to the visual search relook problem.

A. Simulation description

The goal of the simulation environment is to replicate the simulation environment in which the experiment is conducted without needing actual human operators. Targets are generated according to a Poisson process with arrival rate λ [sec/target], and UAV allocation is governed by a routing policy that is generated by the operator. The mission objective is to maximize the total number of targets correctly found (N_F) out of the total number possible in the environment (N_T). Clearly, N_F is a function of numerous operator-specific parameters (such as target difficulty and associated search time, detection probability and relook policy), but it also clearly has a strong dependency on the routing policy that the operators choose. For example, operators who do not carefully implement a routing policy will increase their travel time by assigning a vehicle to visit a distant target, rather than allocating vehicles to service nearer tasks.

B. Routing Policy

Operators may not be effective planners in routing problems. As a reasonable compromise (and area of future work), for these simulations, we assume that operators allocate UAVs to targets according to a greedy policy, routing UAVs to the targets that are nearest geographically. This is found at each time step of the simulation by updating the distance matrix $D(x_i, x_j)$ between all points in space $x = [x_T, x_U]$, where x_T (respectively, x_U) denote the (x,y)-position of the targets and UAV. Targets are assumed stationary.

Upon reaching the targets, the UAVs are assumed to loiter around the target (as in the simulation environment), and initiate a visual search task only when the operator has chosen an available UAV. For the simulation, UAVs initiate a visual search task according to a First Come First Served (FCFS) policy, in which the first UAV to reach the target initiates the search task first. The search times are modeled with the search time distributions from previous experiments. A new search time (t_s^i) is realized by generating a new random number generated from the log-normal distribution with mean μ and variance σ^2 ,

$$t_s^i \sim f(t_s \mid \mu, \sigma^2) \quad (4)$$

In turn the search outcome (target found $\delta = 1$ or not found, $\delta = 0$) is determined by generating a random number sampled from the uniform distribution, and verifying whether this number is greater than $P_d(t_s^i)$. That is,

- Generate $r \sim U[0, 1]$ and return

$$\delta = \begin{cases} 1 & \text{If } r < P_d(t_s^i) \\ 0 & \text{If } r \geq P_d(t_s^i) \end{cases} \quad (5)$$

Search outcomes and search times are recorded at each point in the mission.

C. Relook model

The actual human-in-the-loop experiment will present the operator with a relook option, and the data collected will help identify the operator relook policy. However, there is the (realistic) possibility that even when confronted with the possibility of taking a second or third look at an image, operators choose to simply not relook. Thus, the experiment will contain three different modes

- **No relook (NR):** Operators do not have the ability to relook
- **Relook with Consent (RWC):** Operators had the option of relooking at any time, but after T_{rl} seconds the operator is prompted to relook
- **Relook without Consent (RWOC):** Operators had the option of initiating a relook at any time, but after T_{rl} seconds, the target will be automatically requeued

Since one of the main objectives of the experiment is to identify the likelihood of relooking (to estimate the probability p in the model for **RWC**) the simulation therefore focused on comparing the **RWOC** model with the **NR** model. The critical relook time was varied as a simulation parameter and discretized in the interval $T_{rl} \in \{20, 25, 30, \dots, 60\}$. For each randomly generated search time t_s^i , if this time exceeded the critical time T_{rl} for that simulation, the target was automatically requeued in the **RWOC** model.

Note that the theoretical relook probability \bar{p} for each of the critical times T_{rl} can be found with the following integral

$$\bar{p}(T_{rl}) = \Pr(t \geq T_{rl}) = 1 - \int_0^{T_{rl}} f(t_s \mid \mu, \sigma^2) dt_s \quad (6)$$

and numerical routines can be used to evaluate the CDF of the log-normal distribution. The algorithmic flow for the Discrete Event Simulation model (DES) can be visualized in Algorithm 1.

D. Performance prediction

The goal of the human-in-the-loop experiment will be to determine the effect of the relook on the overall performance of the mission. As described in Section IV-A, since the primary objective is to maximize the number of targets found correctly, a small but revealing analysis on the performance prediction with the relook policy can provide insight into the predicted results. Consider the quotient of the expected value of the number found correctly ($E(N_F)$) and the expected number of total target ($E(N_T)$). Then, it can be shown that

$$J_F \doteq \frac{E(N_F)}{E(N_T)} = \frac{\lambda_e \bar{P}_d}{\lambda} \quad (7)$$

Algorithm 1 DES Model

```

Initialize UAV/target states  $x_U, x_T$ 
Initialize timer  $t = 0$ 
while  $t < T$  do
  Sample from exponential distribution with rate  $\lambda$ 
  Advance timer and update UAV position
  if reached a target then
    Start searching, sample search time  $t_s^i$  (Eq. 4)
    Outcome  $\delta$  (Eq. 5)
    Continue
  end if
end while
  
```

where \bar{P}_d denotes the average detection probability of the operator during the experiment, and λ_e denotes the service rate of new targets.

Given that we expected \bar{P}_d to improve with relooks, the real question is how the service rate λ_e (and in turn J'_F) will be affected the use of relooks (since fewer targets may be processed because of the requeueing). This is investigated in the following simulation results.

E. Simulation results

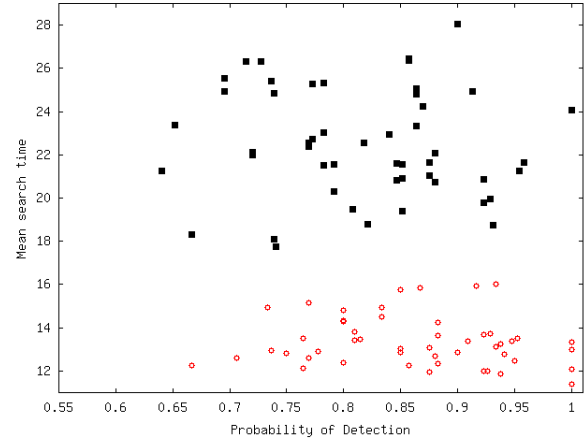
This section presents simulation results of the performance using the operator choice models analyzing 50, 10-minute long simulated UAV missions. In this setting we analyzed the following principal figures of merit

- **Operator mean search time (\bar{T}), detection probability (P_d):** The mean search time and error probabilities are averaged across all targets found by the operator
- **Fraction found correctly (J'_F):** This is the ratio of total targets found correctly divided by the total possible number of targets during the course of the simulation

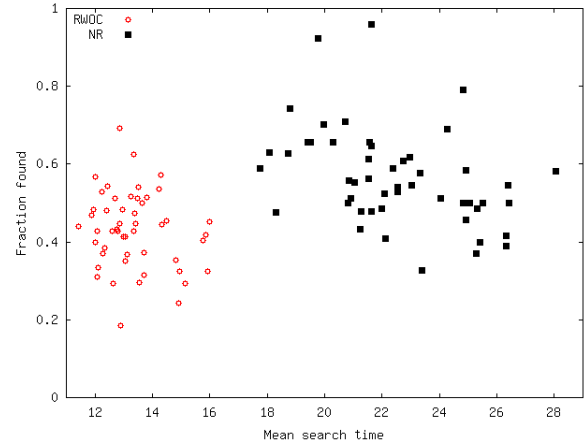
Targets were modeled as being generated with 3 distinct average arrival rates $\lambda \in \{20, 30, 40\}$ [sec/targ]. The first results of the Monte Carlo simulations are shown in Figure 4(a), where the x-axis shows the detection probability for each operator (averaged over the total targets found) and the mean search time.¹ Figure 4(b) shows the fraction found correctly (J'_F) plotted as a function of mean search time (\bar{T}). The data for the **RWOC** is shown in empty red squares, while the data for **NR** is shown in black filled squares. Predictably, both probability of detection and mean search time improve under the relook mode (**RWOC**) but there is evidence to suggest that there is a slight decrease in the fraction of targets found correctly (presumably because operators requeue targets).

Figure 5 shows the agreement between the theoretical prediction relating the relook probability with the search time T_{rl} . Recall from Eq. 6 that as the search time T_{rl} threshold increases, we intuitively expect the probability of relook to decrease since operators will actually be making decisions on

¹For these numerical results, the relook time T_{rl} was chosen by finding the time at which the detection probability decreased below 80%. This number, T_{rl} was determined to be 25 seconds (see Figure 2). The search time included multiple visits to the targets in the **RWOC** mode to ensure a fair comparison.



(a) Mean search time vs. detection probability



(b) Fraction found vs. mean search time

Fig. 4. Monte Carlo simulations for **RWOC** (in red open square) and **NR** (in black filled square) show improvements in overall detection rate and search time

the presence or absence of the target. The empirical estimates of the relook probabilities are found as

$$\hat{p}(T_{rl}) = \frac{1}{N} \sum_{k=1}^N \hat{p}_k(T_{rl}) \quad (8)$$

where this is average over the $N = 50$ simulations (and hence may exhibit some variation from the theoretical results of Eq. 6).

Figure 6 shows the impact of varying the probability of relook on the detection probability (top) and fraction correctly found J'_F (bottom), averaged over the 50 Monte Carlo simulations. Predictably, the increase in relook probability (which is increased by reducing the search time threshold T_{rl}) improves the detection probability, since the search models predict that operator detection probability decreases with increased search time.

However, Figure 6 also shows the sensitivity to increase of relook probability for the fraction of targets found J'_F as the probability of relook increases. Note for lower target arrival rate $\lambda = 40$ [sec/targ] and no relook ($\bar{p}(T_{rl}) = 0$), the simulation predicts that $J'_F \approx 0.62$ of the total targets

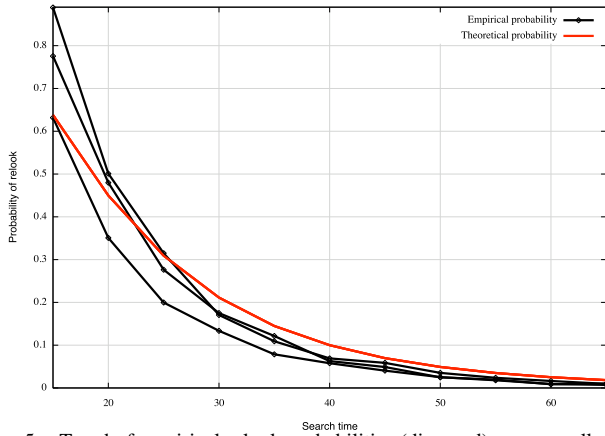


Fig. 5. Trend of empirical relook probabilities (diamond) agrees well with theoretical relook probability (solid line) for 3 different arrival rates

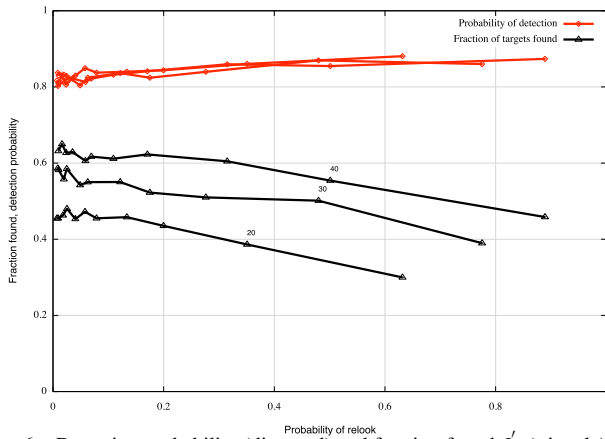


Fig. 6. Detection probability (diamond) and fraction found J'_F (triangle) vs. relook probability for 3 different arrival rates. Lower arrival rate decreases J'_F from 0.62 to 0.42 as relook probability increases to 0.8, but detection probability increases from 0.8 to 0.9

will be identified correctly, and as the relook probability increases to 0.3, there is only a slight decrease to $J'_F = 0.60$ while the detection probability increase to $P_d = 0.85$. For lower arrival rates ($\lambda = 20$ [sec/targ]), the fraction found J'_F is much more sensitive to increased relook probability, decreasing from $J'_F = 0.45 - 0.47$ to $J'_F = 0.35$. While this decrease comes at the added gain of increased detection probability, the decrease indicates that relook strategies can have a profound impact on overall mission performance. Predictably, relooks will result in longer average travel times to targets, and in turn imply a lower fraction of targets found. These simulation results show that there is an important tradeoff between maximizing this performance metric, and ensuring a high overall accuracy in target classification. It remains to be seen whether these results are also observed in the actual experiment with human subjects.

V. CONCLUSION AND FUTURE WORK

This paper has developed a queueing model that includes relooks by formulating this task as a retrial queue. We have formulated a new retrial queue framework that parametrizes the relook policy of the operator, and have investigated a Discrete Event Simulation (DES) that uses operator data from

previous experiments. While improving error probability and mean search time, relook policies seem to be extremely sensitive to relook probabilities and the results suggest that decision support systems must be developed to aid operators in appropriate use of the relooks.

Current work includes a human-in-the-loop experiment that will generate the necessary data for estimating model parameters and evaluate the impact of relook policy on human subjects performance. The experiment will be performed under different relook conditions. This future work will attempt to develop “optimal” relook policies, understanding that in practicality, generating satisficing parameters [21] is more realistic since true optimality may be difficult to quantify in dynamic, uncertain command and control settings.

REFERENCES

- [1] T. Sheridan, *Telerobotics, automation, and human supervisory control*. MIT Press.
- [2] M. L. Cummings and P. J. Mitchell, “Predicting Controller Capacity in Remote Supervision of Multiple Unmanned Vehicles,” in *IEEE Systems, Man, and Cybernetics, Part A: Systems and Humans*, vol. 38, pp. 451–460, 2008.
- [3] C. Nehme, *Modeling Human Supervisory Control In Heterogeneous Unmanned Vehicle Systems*. PhD thesis, MIT, 2008.
- [4] D. K. Schmidt, “A queuing analysis of the air traffic controller’s workload,” in *IEEE Systems, Man, and Cybernetics*, vol. 8, pp. 492–498, 1978.
- [5] K. Savla, T. Temple, and E. Frazzoli, “Human-in-the-loop vehicle routing policies for dynamic environments,” in *IEEE Conference on Decision and Control*, 2008.
- [6] R. Bogacz, E. Brown, J. Moehlis, P. Holmes, and J. D. Cohen, “The Physics of Optimal Decision making: A Formal Analysis of Models of Performance in Two-Alternative Forced Choice Tasks,” in *Psychological Review*, vol. 113, pp. 700–765, 2006.
- [7] J. R. Busemeyer and A. Diederich, “Survey of Decision Field Theory,” in *Mathematical Social Sciences*, vol. 43, pp. 345–370, 2002.
- [8] J. R. Busemeyer and J. T. Townsend, “Fundamental Derivations From Decision Field Theory,” in *Mathematical Social Sciences*, vol. 23, pp. 255–282, 2000.
- [9] A. Diederich and J. R. Busemeyer, “Simple Matrix Methods for Analyzing Diffusion models of Choice Probability, Choice Response Time, and Simple Response Time,” in *Journal of Mathematical Psychology*, vol. 47, pp. 304–322, 2003.
- [10] R. J. Herrnstein, “Rational Choice Theory: Necessary but Not Sufficient,” in *American Psychologist*, vol. 45, pp. 356–357, 1990.
- [11] C. Drew, “Military Is Awash in Data From Drones,” <http://www.nytimes.com/2010/01/11/business/11drone.html>.
- [12] M. Hoffman, “New Reaper sensors offer a bigger picture,” http://www.airforcetimes.com/news/2009/02/airforce_WAAS_021609/.
- [13] D. Bertsekas, *Dynamic Programming and Optimal Control*. Athena Scientific, 2005.
- [14] M. Pachter, P. R. Chandler, and S. Darbha, “Optimal sequential inspection,” in *IEEE Conference on Decision and Control*, 2006.
- [15] A. Girard, S. Darbha, M. Pachter, and P. R. Chandler, “Stochastic Dynamic Programming for Uncertainty Handling in UAV Operations,” in *IEEE American Control Conference*, 2007.
- [16] G. I. Falin and J. G. C. Templeton, *Retrial Queues*. Chapman and Hall, 1990.
- [17] J. Artalejo and A. Gomez-Corral, *Retrial Queueing Systems*. Springer, 2008.
- [18] B. D. Choi and K. K. Park, “The M/G/1 Retrial Queue with Bernoulli Schedule,” in *Queueing Systems*, vol. 7, pp. 219–228, 1990.
- [19] N. Sherman and J. Kharoufeh, “An M/M/1 Retrial Queue with Unreliable Server,” in *Operations Research Letters*, vol. 34, pp. 697–705, 2006.
- [20] M. Mouloua and R. Parasuraman, *Automation and Human Performance: Theory and Applications (Ch. 9)*. Lawrence Erlbaum Associates, 1996.
- [21] W. C. Stirling, *Satisficing Games and Decision Making: With Applications to Engineering and Computer Science*. New York, NY, USA: Cambridge University Press, 2003.