Adaptive Information Management Strategies in Mixed Human-Robot Teams

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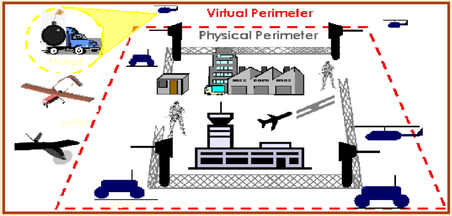
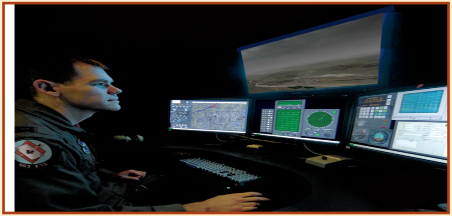
Big Picture: Human-robot decision dynamics

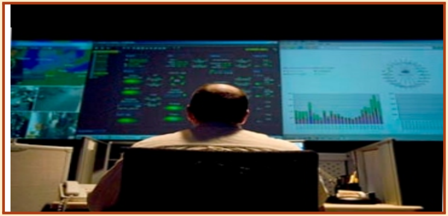


Uncertain environment surveyed by human-UAV team (Courtesy: Prof. Kristi Morgansen)



A Surveillance Operator (Courtesy: http://www.modsim.org/)

UCSB Camera Network



Data Center Operator

- How to handle information overload?
- What are optimal information management strategies?

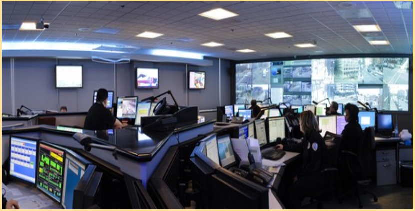
Two Critical Issues

Photo courtesy: The Wall Street Journal

Optimal information aggregation

- Which source to observe?
- Efficient search and detection
- Routing for evidence collection

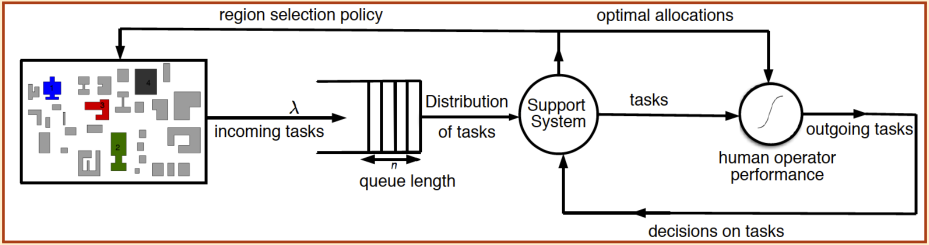
Optimal information processing



- Optimal time allocation?
- Optimal streaming rate?
- Optimal number of operators?

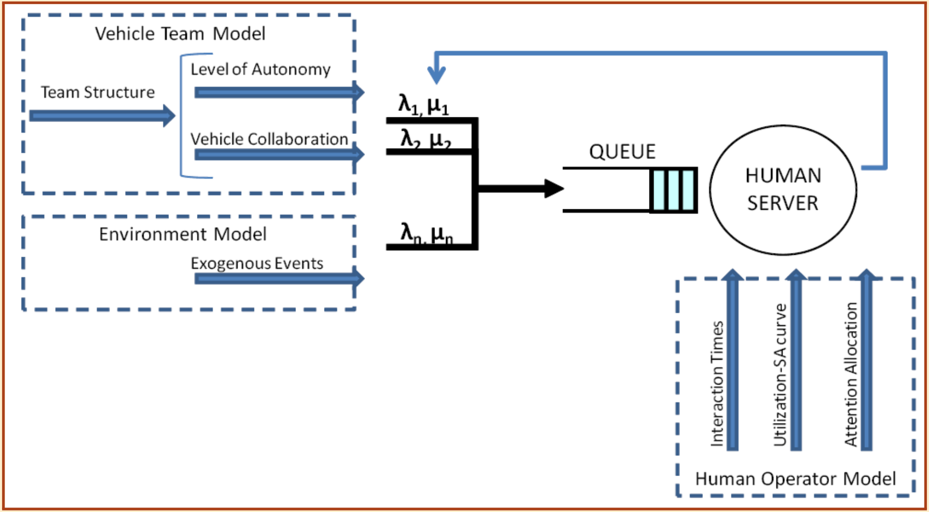
Decision support system to optimize human-robot team objective?

Problem Setup



- Support System (SS) collects information from the sensor network
- **Sensor Network $\equiv$ regions surveyed,**
  cold storages, different buildings, etc
- SS streams collected information to the human operator
- SS **specifies the time,** the operator should spend of each feed
- Based on the operator's decisions, the SS collects information
  from the **most pertinent source**

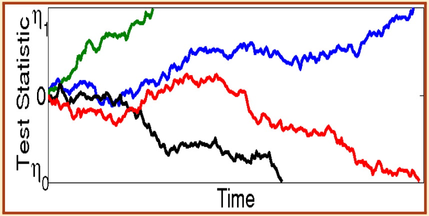
Operator Models I



General vehicle team and human operator interaction model

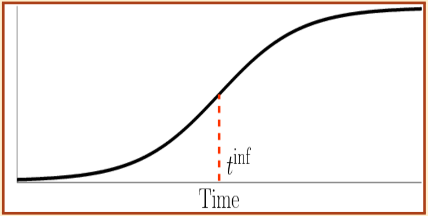
Nehme et al '08

Operator Models II



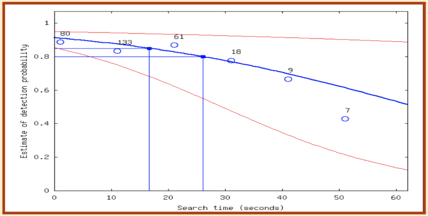
DDM for Human Decision Making

Bogacz et al '06



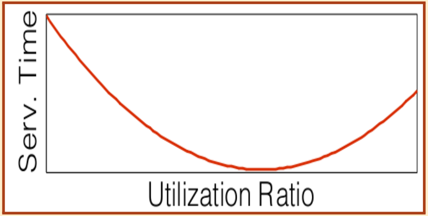
Evolution of probability of detection

Pew '68



Degradation of detection probability

Bertuccelli et al '10



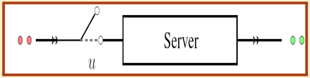
Yerkes Dodson effect

Yerkes-Dodson 1908

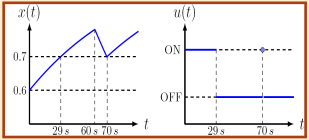
Literature Review I

Task Release Control

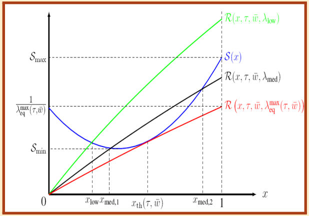
- The service time on a task is a function of utilization ratio (UR)
- Yerkes-Dodson(Y-D) law determines the expected service time
- Task release controller releases a task if UR is below a threshold
- The maximally stabilizing arrival rate depends on Y-D law and UR dynamics
- **Limitation:** Does not incorporate error rate in the policies



Task Release Setup



Task Release Controller



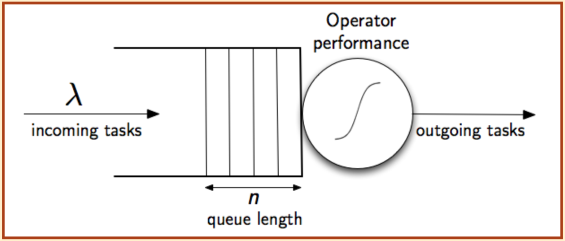
Max Arrival Rate

Savla et al '11

Literature Review II

Resource allocation for human operator

Problem: How to optimally allocate operator attention to a batch of tasks or to an incoming stream of tasks



– **Static queue:** serve N tasks in time T

– **Dynamic queue:** tasks arrive continuously at some known rate

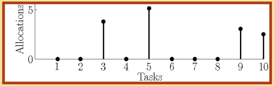
– **Optimal design of queue:** What is an optimal arrival rate

Srivastava et al '11

Literature Review III

Time Constrained Static Queue

$$\begin{aligned} \text{maximize} \quad & f_1(t_1) + \cdots + f_N(t_N) \\ \text{subject to} \quad & t_1 + \cdots + t_N = T \\ & t_\ell \geq 0, \quad \ell \in \{1, \ldots, N\} \end{aligned}$$



Optimal Allocations

Literature Review III

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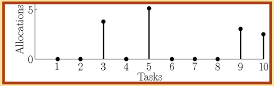
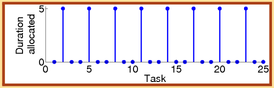


Optimal Allocations

Dynamic Queue with Latency Penalty

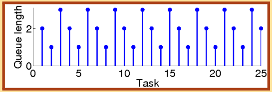
$$\max_{t_1, t_2, t_3 \ldots} \lim_{L \to \infty} \frac{1}{L} \sum_{\ell=1}^{L} \Big(f_{\gamma_\ell}(t_\ell) - \bar{c}\mathbb{E}[n_\ell] t_\ell - \frac{\bar{c}\lambda t_\ell^2}{2} \Big)$$



Optimal Allocations

where expected queue length

$$\mathbb{E}[n_\ell] = n_1 - \ell + 1 + \lambda \sum_{j=1}^{\ell-1} t_j$$



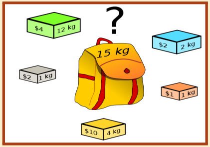
Expected Queue Length

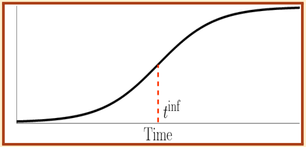
Limitation: Does not incorporate SA models in policies

Time Constrained Static Queue with Situational Awareness

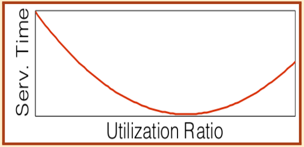
Objective:

- Serve N decision making tasks in time T
- Maximize expected number of correct decisions
- Keep utilization ratio optimal
- Each processed task should be allocated more time than the natural allocation





Probability of Detection



Yerkes Dodson effect

Dynamic Programming Formulation

Stage Cost

$$g_\ell = z_\ell(w_\ell f_\ell(t_\ell) + \beta(t_\ell - S(x_\ell))), \quad \ell \in \{1, \dots, N\},$$

System Dynamics

Allocation: $a_{\ell+1} = a_\ell + t_\ell + r_\ell, \quad a_1 = 0, \quad a_\ell \in [0, T]$

Utilization: $x_{\ell+1} = (1 - e^{-t_\ell z_\ell/\tau} + x(\ell)e^{-t_\ell z_\ell/\tau})e^{-r_\ell z_\ell/\tau}, \; x_\ell \in [x_{\min}, x_{\max}]$

$w_\ell =$ **weight,** $t_\ell =$ **allocation,** $r_\ell =$ **rest time**

$S =$ **Y-D curve** $\tau =$ **operator sensitivity** $\beta =$ **cost,**

$f_\ell =$ **performance func.** $z_\ell =$ **process / don't process**

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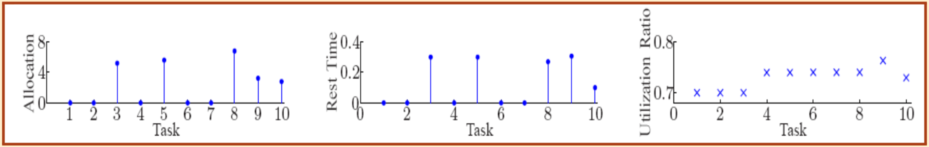

Optimal Solution

Dynamic Queue with Penalty and Situational Awareness

- Tasks arrive as a Poisson process with rate λ
- Tasks sampled from a distribution $p : \Gamma \to \mathbb{R}_{\geq 0}$
- Unit reward for each correct decision
- Latency penalty per unit-time c_γ, for task $\gamma \in \Gamma$, and $\bar{c} = \mathbb{E}_p[c_\gamma]$

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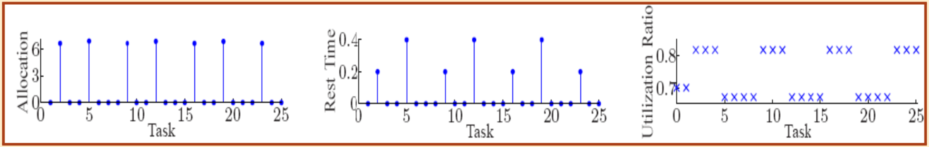
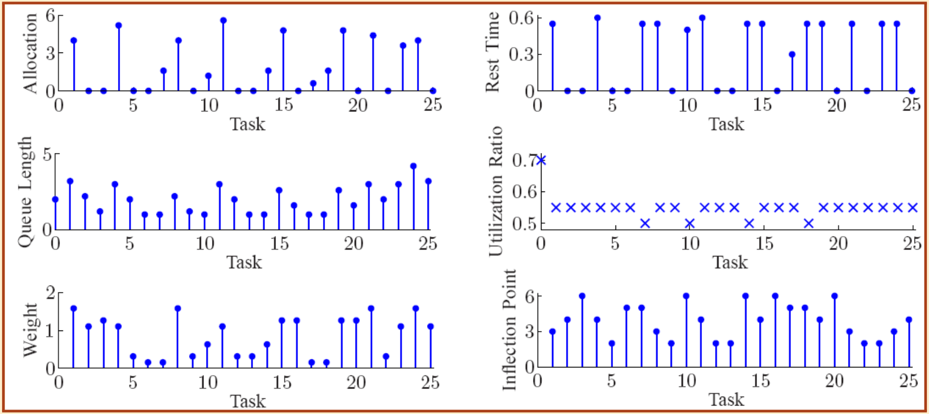


Certainty Equivalent Solution

Illustrative Example I

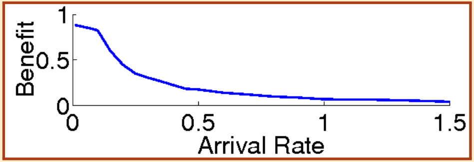
Optimal Allocations and Rest Time



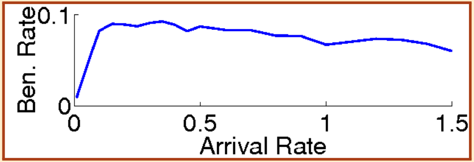
Receding Horizon Policy

Illustrative Example II

Reward versus Arrival Rate



Benefit per unit task



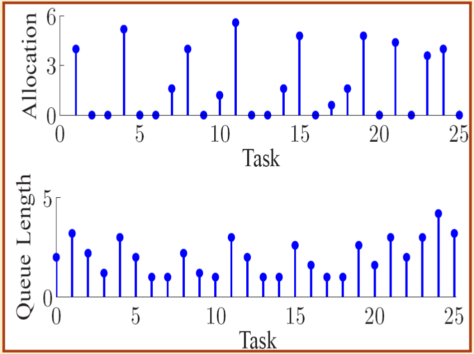
Benefit rate

Optimal arrival rate

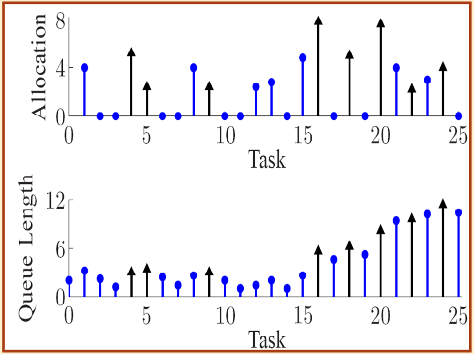
- Switching occurs when operator is expected to be always non-idle
- Designer may pick desired accuracy on each task to design arrival rate

Illustrative Example III

Handling Mandatory Tasks

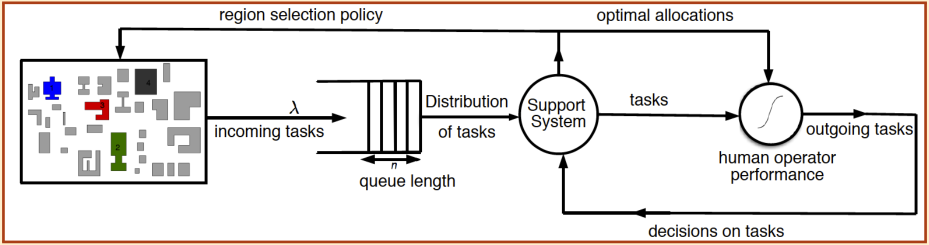


No Mandatory Tasks



Mandatory Tasks Present

Problem Setup



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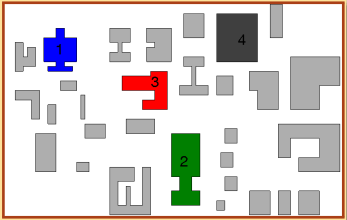
Quickest Spatial Detection

- N region to be surveyed
- any number of anomalous regions
- an ensemble of CUSUM algorithms
- collection+transmission+processing time at region ℓ is $T_\ell > 0$
- distance between region i and j: d_{ij}



UCSB Campus Map

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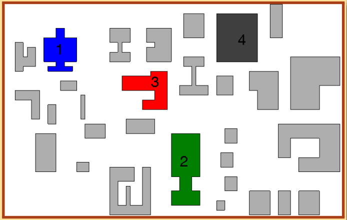

UCSB Campus Map

Spatial Quickest Detection (Srivastava & Bullo '11)

1. at iteration τ, pick a region ℓ from stationary distribution $\mathbf{q}$
2. go to region ℓ and collect evidence y_τ
3. update CUSUM statistic for region ℓ

$$\Lambda_\ell = (\Lambda_{\ell-1} + \log(f_\ell^1(y_\tau)/f_\ell^0(y_\tau))^+$$

4. declare an anomaly at region ℓ if $\Lambda_\ell > \eta$

Spatial Quickest Detection: Detection Delay

Expected detection delay at region ℓ

$$\mathbb{E}[T_d^{\ell}] = \frac{e^{-\eta} + \eta - 1}{q_\ell \mathcal{D}(f_\ell^1, f_\ell^0)}(\mathbf{q} \cdot \mathbf{T} + \mathbf{q} \cdot D\mathbf{q})$$

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Two stage quickest detection strategy

1. pick optimal $\mathbf{q}^* = \text{argmin} \sum_{\ell=1}^{N} \pi_\ell^1 \mathbb{E}[T_d^\ell]$
2. adapt $\mathbf{q}^*$ with the evidence collected at each stage

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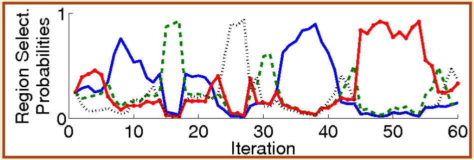
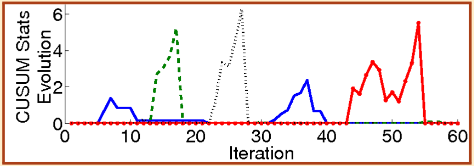


Region Selection Probability



Likelihood of Anamoly

Spatial Quickest Detection with Human Input

- human operator allocates time t to an evidence
  and decides on presence/absence of anomaly
- probability of correct decision at region ℓ evolves as sigmoid function

$$\begin{cases} f_\ell^1(t), & \text{if an anomaly is present,} \\ f_\ell^0(t), & \text{if no anomaly is present.} \end{cases}$$

- support system runs **spatial quickest detection** algorithm
  with the decisions of the operator

Critical Issue:

– human decisions are not i.i.d.

– detection delay expressions can not be used

Expected Detection Delay: Heuristic Approximation

For a drift diffusion model

Expected decision time $= \text{threshold}/\mathcal{D}(f^1, f^0) = t^{\text{inf}}$

Expected delay minimization

$$\underset{\mathbf{q} \in \Delta_{N-1}}{\text{minimize}} \quad \sum_{\ell=1}^{N} \frac{\pi_\ell^1 t_\ell^{\text{inf}}}{q_s} (\mathbf{q} \cdot \mathbf{T} + \mathbf{q} \cdot D\mathbf{q})$$

detection delay proportional to

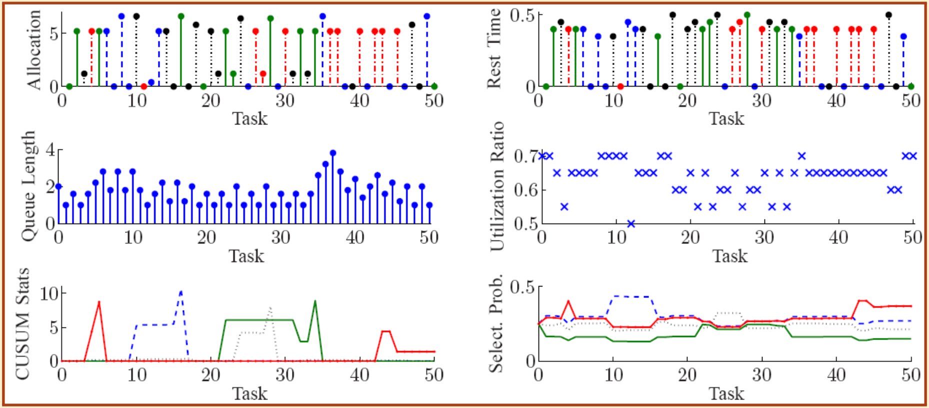
- likelihood of anomaly
- difficulty of task
- inverse of region selection probability
- processing time and average distance of the region from other regions

Simultaneous Information Aggregation and Processing I

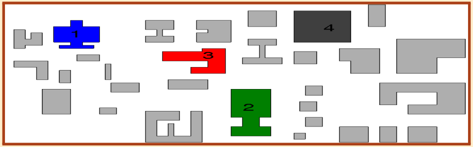
At each iteration

- the SS determines the optimal region selection policy
- the region selection policy determines
  the distribution of incoming tasks
- the performance on an incoming task
  from region ℓ is $\pi_\ell^1 f_\ell^1(t) + (1 - \pi_\ell^1) f_\ell^0(t)$
- the SS determines the optimal allocation to each task,
  based on current reward and penalty

Simultaneous Information Aggregation and Processing II



Optimal Policies



Conclusions & Future Directions

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- novel *simultaneous information aggregation and processing* framework
- incorporation of situational awareness models
- incorporation of human decisions in sensor management strategies
- an adaptive strategy that collects evidence from regions with high likelihood of anomalies and optimally processes it

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Future Directions

- re-queuing of tasks and preemptive queues
- validation with experiments
- dynamic anomalies