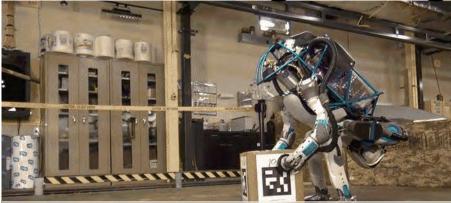


#### Human Interaction with Complex and Autonomous Systems and Vehicles Advanced Interaction Research Lab at Drexel

### Erin T. Solovey, Ph.D.

Assistant Professor of Computer Science College of Computing and Informatics School of Biomedical Engineering, Science & Health Systems Drexel University

### Increasing Usage of Automation



Search and Rescue Robots









### Human + Autonomy

#### Human Strengths:

- Inference
- Adaptation
- Intuition
- Judgment
- Morality

#### **Autonomy Strengths:**

- Fast
- Does not get bored
- Consistent
- Good for Predictable cases

#### Human Limits:

- Response Time
- Bandwidth
- Cognitive Capacity
- Inconsistency
- Endurance
- Training

#### **Autonomy Limits:**

- Adaptability
- Data requirements
- Interface with System
- Need Rules

# Using brain and body sensing for implicit interfaces

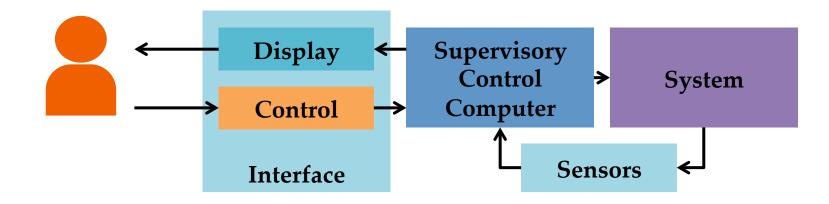
**Goal:** expand bandwidth between human & computer

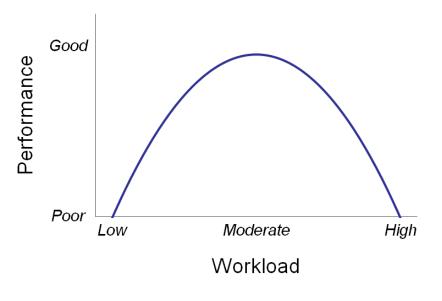
**Approach**: identify signals people naturally give off and adapt systems appropriately



When are these signals useful in human supervisory control? How do you use them effectively?

### Human Supervisory Control







#### The brain as explicit and primary input



BrainGate System at Brown University

#### Brain & body as implicit, supplementary input

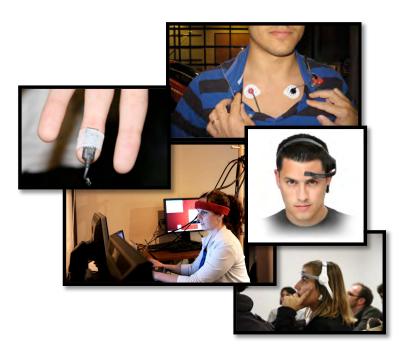


### Brain & body as implicit, supplementary input

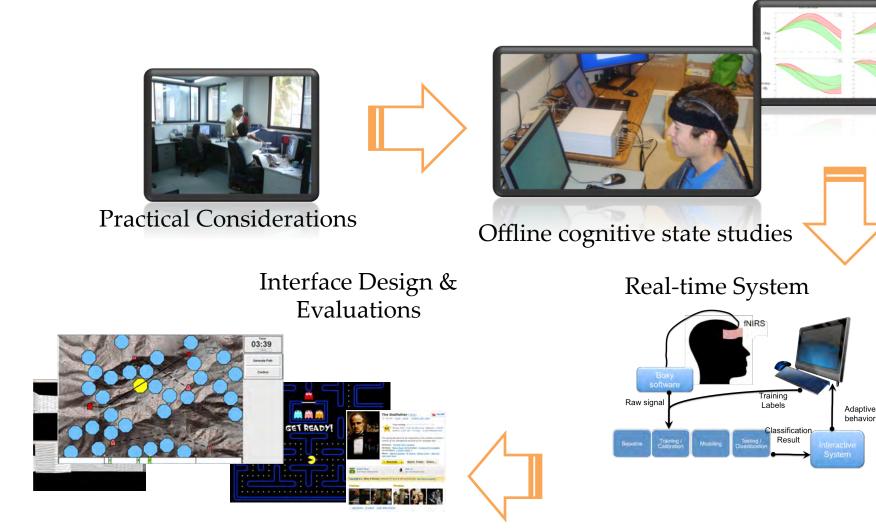
- Augment traditional input devices
- Wider group of users, beyond disabled
- Passive, implicit input channel
- Capture **subtle** cognitive state changes
- Input to **adaptive** interactive system
- Real-time, continuous data

#### Examples

- Adapting autonomy levels
- Modifying quantity of information
- Transform modality of info presentation
- Task allocation, manage task load, difficulty
- Offline evaluation of user interfaces, systems



# Brain & Body Signals as Input



**E.T. Solovey**, et al. Designing Implicit Interfaces for Physiological Computing: Guidelines and Lessons Learned using fNIRS. *ACM Transactions on Computer-Human Interaction*. Vol. 21, Iss. 6. 2015x.

# **Offline Feasibility Studies**

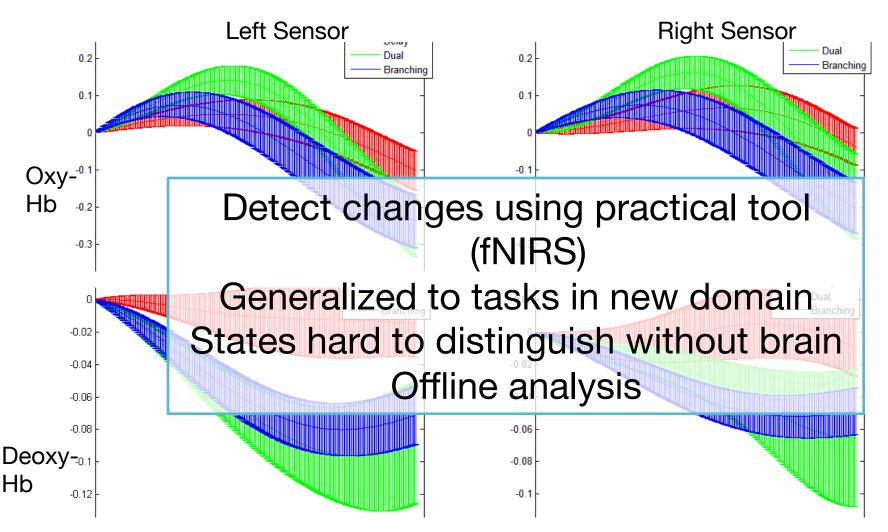
### **Questions:**

Can we detect relevant signals within brain and physiology that would be otherwise difficult to observe?
Are there generic brain processes that can be detected in multiple tasks and domains?

Photo by totalaldo

E.T. Solovey, K. Chauncey, F. Lalooses, M. Parasi, D. Weaver, M. Scheutz, P. Schermerhorn, A. Sassaroli, S. Fantini, A. Girouard, R.J.K. Jacob, "Sensing Cognitive Multitasking for a Brain-Based Adaptive User Interface," Proc. ACM Conference on Human Factors in 0 Computing Systems CHI'11, ACM Press (2011).

### **Different Activation Patterns**



### Feasibility Studies on the Road

#### 1) Within Individuals

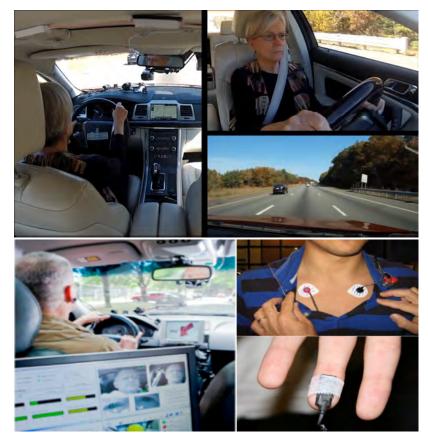
- Natural driving
- 2-back task
- Physiological and vehicle data
- 20 subjects

#### 2) Across Individuals

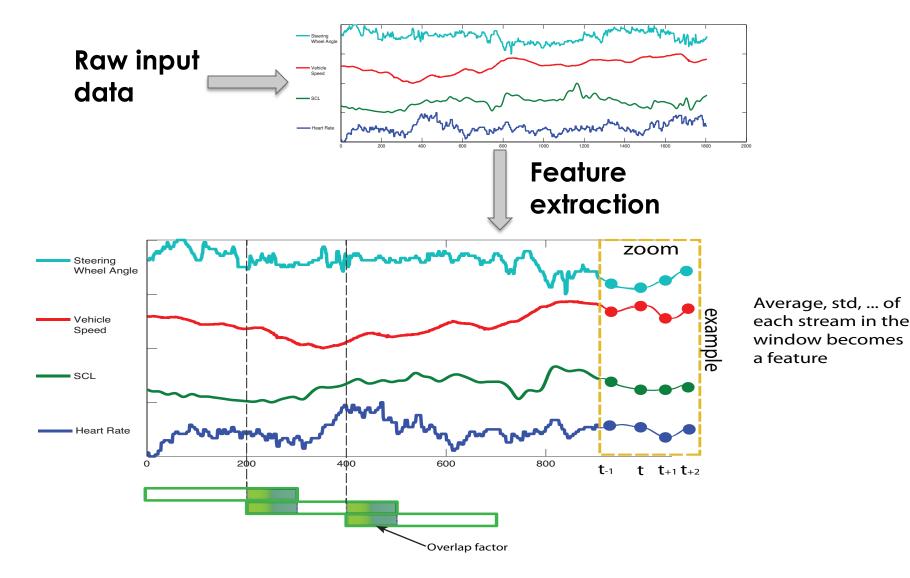
- Natural driving
- n-back tasks
- Physiological and vehicle data
- 99 subjects

#### 3) Experiment 3: Brain Sensing

- Simulator driving
- Simple driving, Blank-back, 0-back, 1-back, 2-back tasks
- 3 blocks of these tasks
- 19 subjects



### Feature extraction



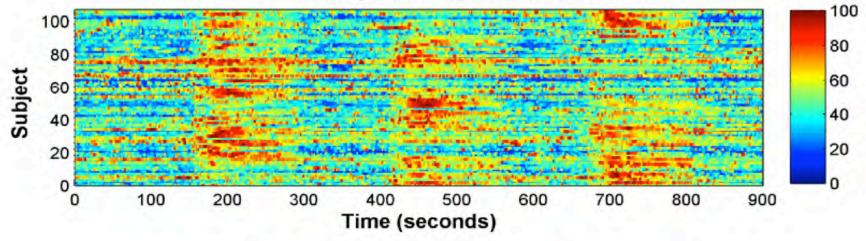
### **Experiment 1 results**

	All Features		Heart Rate	
	Mean	S.D.	Mean	S.D.
Decision Tree	75.0	10.8	72.8	12.8
Logistic Regression	75.5	10.9	73.9	11.3
Multilayer Perceptron	75.7	10.9	74.0	12.4
Naïve Bayes	75.0	12.5	74.1	11.8
Nearest Neighbor	69.4	11.6	71.5	10.3

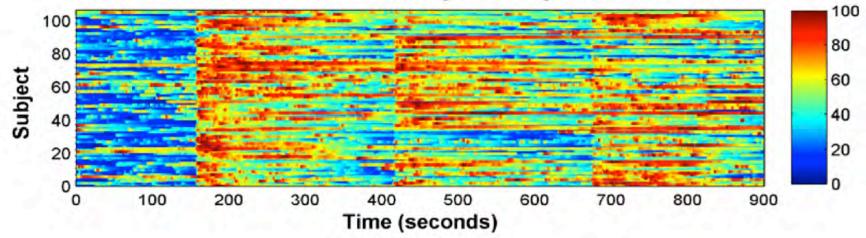
- Reasonable accuracy, using simple features and classification methods, HR alone even has promise
- 24 trials = ~48 minutes of data, training on 43 minutes
  - Okay for proof-of-concept, not ideal for real-world
  - Future: improved methods to shorten this
  - Classification across individuals may reduce/eliminate this training time (Exp 2)

### Experiment results

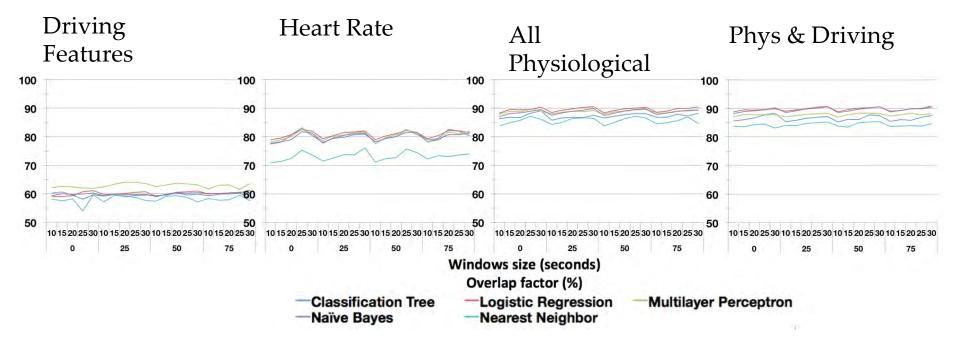
Heart rate change during experiment drive



#### Skin conductance level change during experiment drive

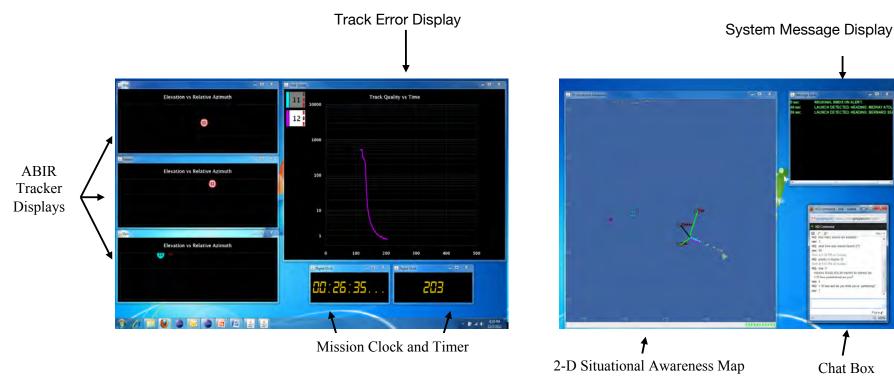


### **Experiment 2 Classification Results**

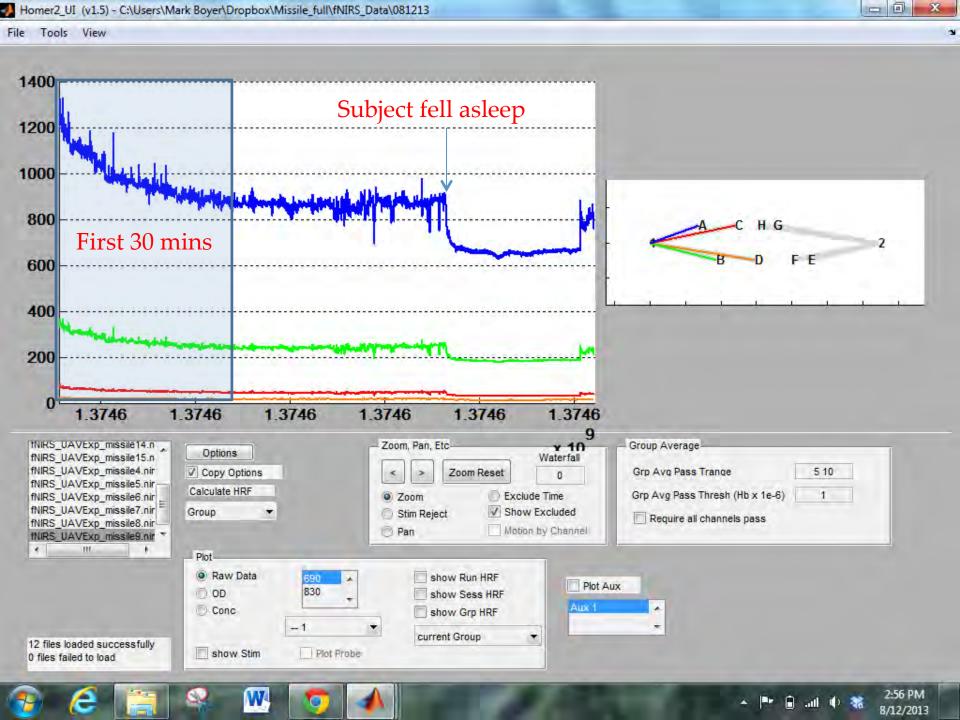


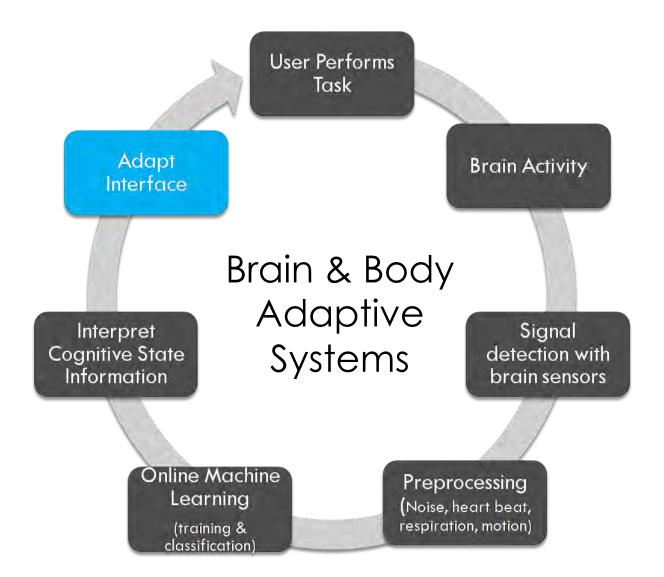
- Type of features had a clear effect on the classification results
  - HR had big improvement over driving only (64% -> 80%)
  - Adding SCL also improves

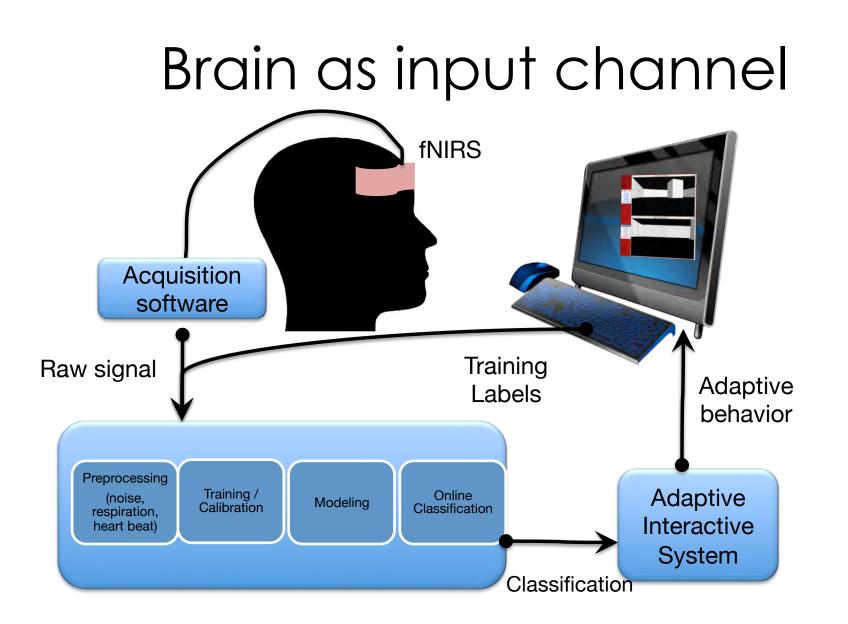
# Long Duration, Low Workload



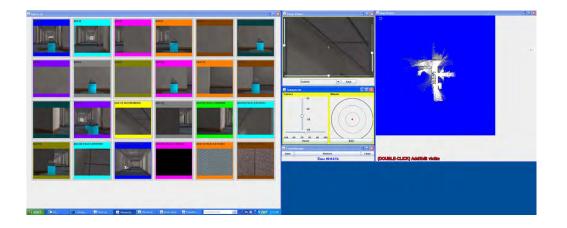
- 3.5 hour session
- controlling the sensors for 3 Unmanned Aerial Vehicles
- job is to direct which UAV will track which missile
- mission is to achieve sufficient track accuracy on every missile
- Targets begin to appear at 40, 100, or 160 minutes
- 3 or 6 targets at a time

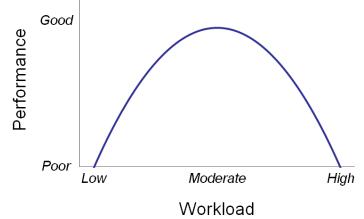




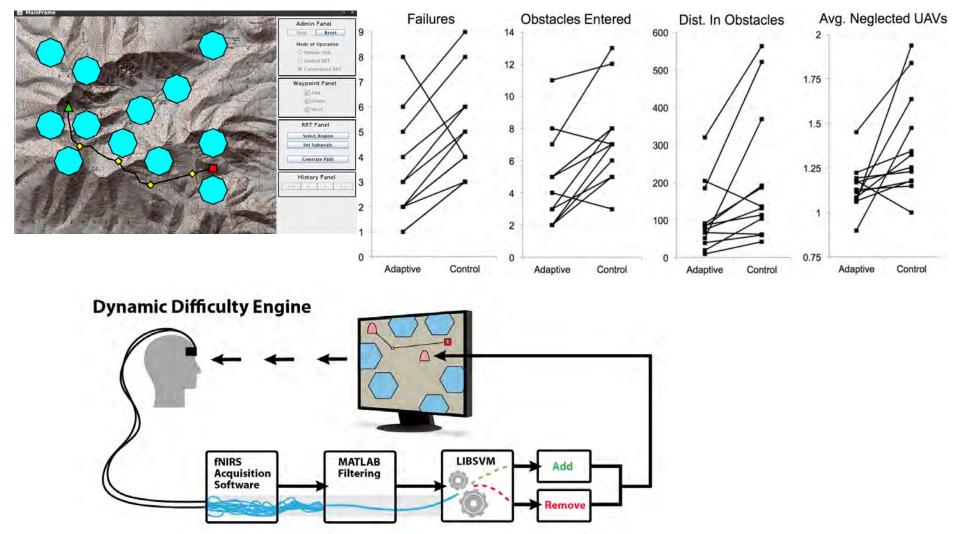


#### Case Study: Humans and Autonomy





#### Case Study: Dynamic Difficulty & Task Allocation



# User Interface Guidelines

- Augment other input devices
- Subtle, helpful changes to interface
- Not disruptive if signal is misinterpreted
  - Imperfect classification, noisy data
  - Avoid irreversible, mission-critical adaptations

#### Examples

- Adapting **autonomy** levels
- Modifying quantity of information
- Transform **modality** of information presentation
- Task allocation, manage task load, difficulty

### Tradeoffs in Teamwork

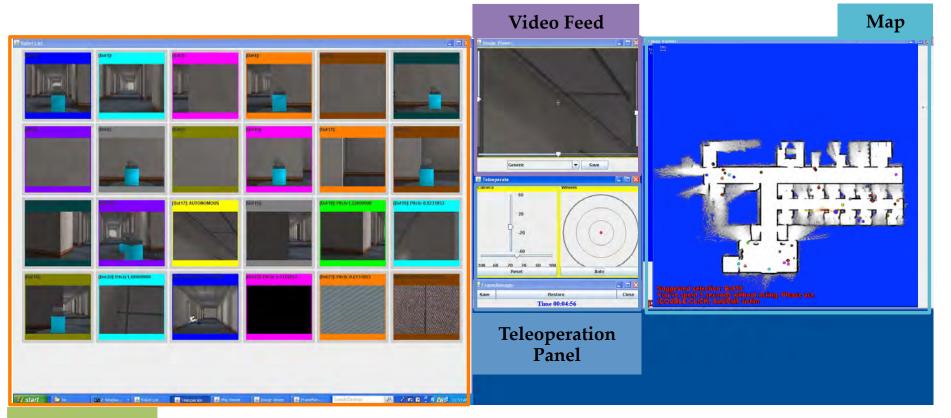
Process Gain Synergy Adaptability & Flexibility Productivity

Process loss Breakdown in internal team processes Collaboration overhead

Human-in-the-loop experiment: Effect of team structure and scheduling notification on operators' performance, subjective workload, work processes, and communication

#### Teamwork Experiments

Urban Search & Rescue Task: find as many victims as possible and mark their position on the map.

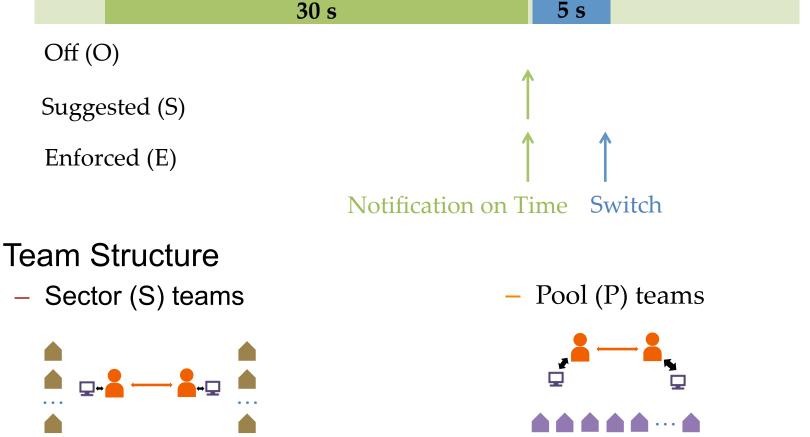


**Robot List** 

### Independent Variables

Robot Usage Notification

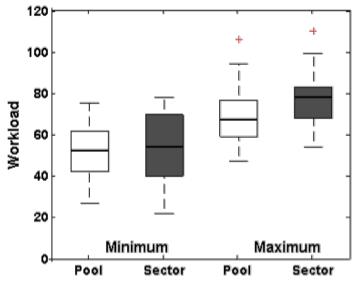
Robot selected



# Results

#### Teamwork

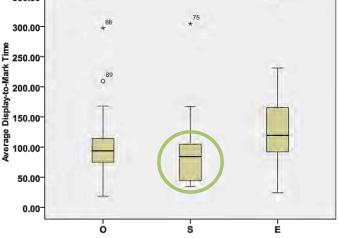
 Pool structure results in lower workload (NASA-TLX).



 Communication time was moderately negative correlated with errors in Pool teams (r = -0.309, p = 0.008).

#### 

Notification



In Sector Teams, those with

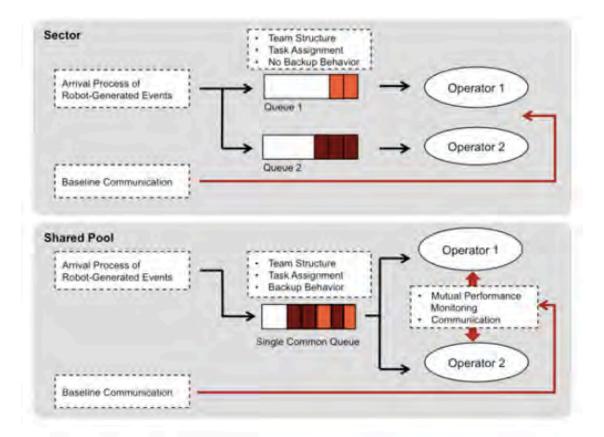
and mark victims faster as

Suggested notification identify

measured by display-to-mark

# Team Performance Modeling

#### **Discrete-Event Simulation (DES)**



# Team Structure Conclusions

- Lower workload reported with *Pool*
- Similar performance with both structures
- *Pool*: more communication, balanced workload from backup behavior
- DES model:
  - replicate experiment
  - Explore uncertainty & backup
    - *Pool* balanced workload, but more coordination
    - Backup meaningful only when the task load is unevenly distributed



#### Human Interaction with Complex and Autonomous Systems and Vehicles



## Acknowledgments

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- Robert J.K. Jacob, Audrey Girouard, Leanne Hirshfield, Michael Horn, Orit Shaer, Jamie Zigelbaum, Michael Poor
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