

Human Supervisory Control

The diagram illustrates the Human Supervisory Control loop. On the left is the Human Supervisor, represented by a brain icon. In the center is Automation, represented by a computer monitor and keyboard. On the right are Tasks, represented by three interlocking gears. The flow is: Human Supervisor sends **Controls** to Automation, which sends **Actuators** to Tasks. Tasks provide **Sensors** to Automation, which sends **Displays** back to the Human Supervisor.

- **Complex, time-pressured, high risk domains**
- **Humans on the loop vs. in the loop**
- **Supporting knowledge-based versus skill-based tasks**
- **Individuals and Teams**
- **Decision-Support Systems**

The graph shows Performance on the y-axis (ranging from Poor to Good) and Workload on the x-axis (ranging from Low to High). The curve starts at a low performance level at low workload, rises to a peak of 'Good' performance at 'Moderate' workload, and then declines to a low performance level at 'High' workload.

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
3


Human Supervisory Control

The diagram illustrates the Human Supervisory Control loop, similar to slide 3, but with an added design and simulation cycle. The Design and Evaluate (Experiments) boxes are connected by a blue double-headed arrow. A red box labeled Simulation is positioned below them, with red arrows pointing from Simulation to both Design and Evaluate, indicating that simulation informs the design and evaluation processes.

- **Complex, time-pressured, high risk domains**
- **Humans on the loop vs. in the loop**
- **Supporting knowledge-based versus skill-based tasks**
- **Individuals and Teams**
- **Decision-Support Systems**

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
4


Overview




Interface Design




HSC and Mission Planning







Predictive Models of Operator, Team,
and System Behaviors





MASSACHUSETTS INSTITUTE OF TECHNOLOGY

5



INTERFACE DESIGN





MASSACHUSETTS INSTITUTE OF TECHNOLOGY

6

Human Control of Small UAVs with an iPhone

- Miniature Aerial Vehicle-Visualization of Unexplored Environments (MAV-VUE)
 - Using an iPhone to explore unknown territory with a Micro Aerial Vehicle
 - High level goal – develop a mobile interface for interacting with an autonomous MAV
 - Create collision detection and avoidance displays for navigating crowded environments



Map Display and General Interface of MAV-VUE for high level control



Overview of Nudge Control Interface for low level control



Flying the vehicle using the MAV-VUE interface on the iPhone

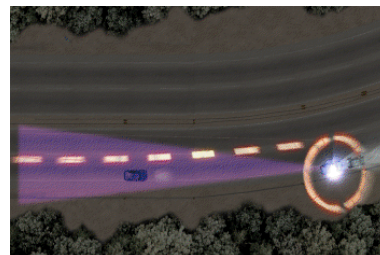


NIJ Divert and Alert Project

To prevent vehicle collisions and injury of officers during roadside stops

Proposed Effort: three thrusts

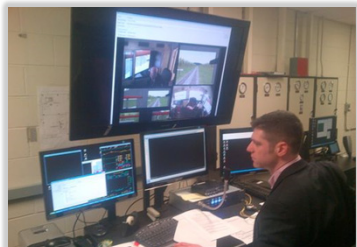
- Motorist Diverting Mechanism (MDM)
 - Project laser light onto roadway to guide oncoming vehicles around stop site
- Officer Alerting Mechanism (OAM)
 - Monitor oncoming traffic with machine vision, asses threat level, and generate timely warning alerts
- Human Factors
 - Easy to activate, configure, and use
 - Effective in diverting traffic and alerting officers
 - Appropriate and feasible economically and technically



FRA – MIT High Speed Passenger Rail Project



Cab Technology Integration Laboratory (CTIL)



CTIL Control Room/Observation Area

- Project focuses on the use of displays to aid locomotive engineers while operating trains
- FRA sponsored project provides access to the Cab Technology integration Laboratory (CTIL)
 - Located at the Volpe Center in Kendall Square (Cambridge, MA)



HSC AND MISSION PLANNING



Collaborative Human-Computer Decision-Making

- Both humans and computers bring different strengths and limitation to problems solving in large problems spaces with many variables, some changing dynamically
- Determine how humans and computer optimization algorithms can complement each other
 - Decision Support for Multi-UAVs Mission Replanning
 - Scheduling algorithms for UAV and Carrier Operations

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
11

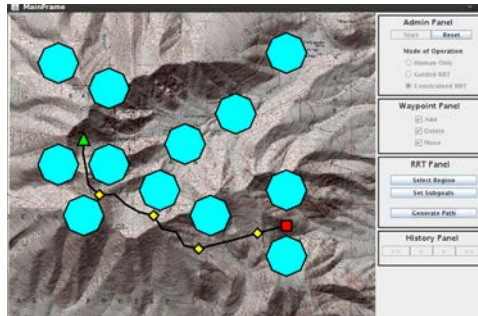
Collaborative Human-Computer Decision-Making

- Both humans and computers bring different strengths and limitation to problems solving in large problems spaces with many variables, some changing dynamically
- Determine how humans and computer optimization algorithms can complement each other
 - Decision Support for Multi-UAVs Mission Replanning
 - Scheduling algorithms for UAV and Carrier Operations

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
12

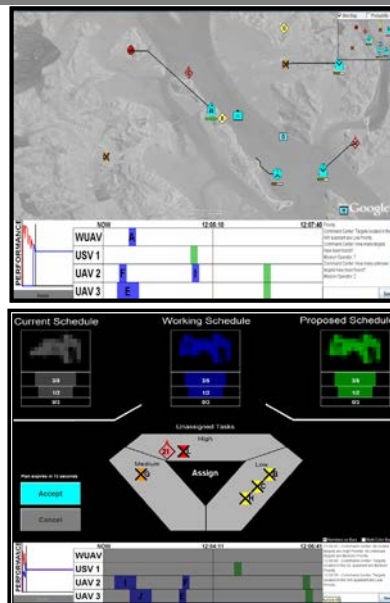
Supervision of Mission Path Planning

- **Rapidly-Exploring Random Trees (RRT) for UAV Mission Path Planning**
 - RRTs are a continuous-space path planner that produces random, but feasible, solutions
 - Goal – reduce path planning workload for human supervisors during UAV mission planning
 - Assess the sustainability of the RRT algorithm for human-automation path planning



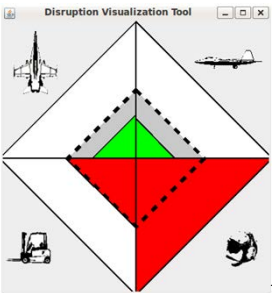
Supervisory Control of UAVs in a Search and Track Task

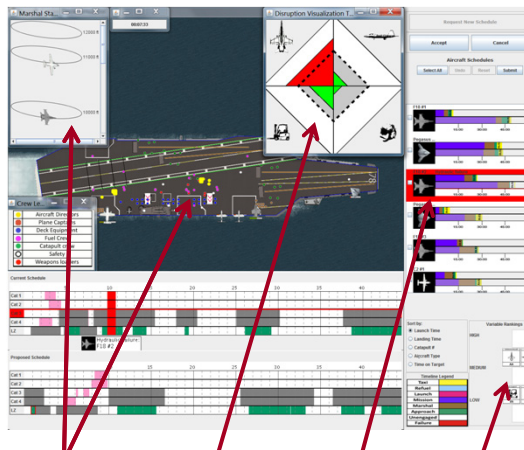
- **OPS-USERS**
 - Operator can now control multiple heterogeneous UVs
 - Optimization algorithms are notoriously “brittle”
 - Combine computational ability of optimization algorithms combined with the judgment and adaptability of human supervisors
- **HAL has developed and tested such systems**
 - Simulation-based experiments, indoor flight tests, and outdoor flight tests
 - Human-computer collaborative system can best handle a realistic scenario with unknown variables, possibly inaccurate information, and dynamic environments





Supervision and Replanning of Complex Operating Schedules




- **Deck operations Course of Action Planner (DCAP)**
 - Motivation – the integration of UAVs into complex, heterogeneous operating environments
 - Objective – develop a decision support tool that enables real-time planning of aircraft carrier deck operations







Situational Awareness components	Schedule fitness representation	Local Constraint modifier	Global priorities modifier
----------------------------------	---------------------------------	---------------------------	----------------------------



MASSACHUSETTS INSTITUTE OF TECHNOLOGY
15

PREDICTIVE MODELS OF OPERATOR, TEAM, AND SYSTEM BEHAVIORS



MASSACHUSETTS INSTITUTE OF TECHNOLOGY
16

Modeling Human-Automation Collaborative Scheduling of Multiple UVs

- Major challenges of collaborative multi-UV scheduling include:
 - Undertrust or overtrust in the automation
 - High cognitive workload
 - Poor goal alignment of the human and automation
- Goal: Develop a predictive simulation model of real-time human-automation collaborative scheduling of multiple UVs
 - Test the impact of changes in system design and operator training on human and system performance without costly and time-consuming human-in-the-loop testing and design iteration
- Utilizing System Dynamics modeling techniques
 - Capture non-linear human behavior and performance patterns
 - Model the impact of latencies and feedback interactions on the system
 - Utilize qualitative variables such as human trust

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
17

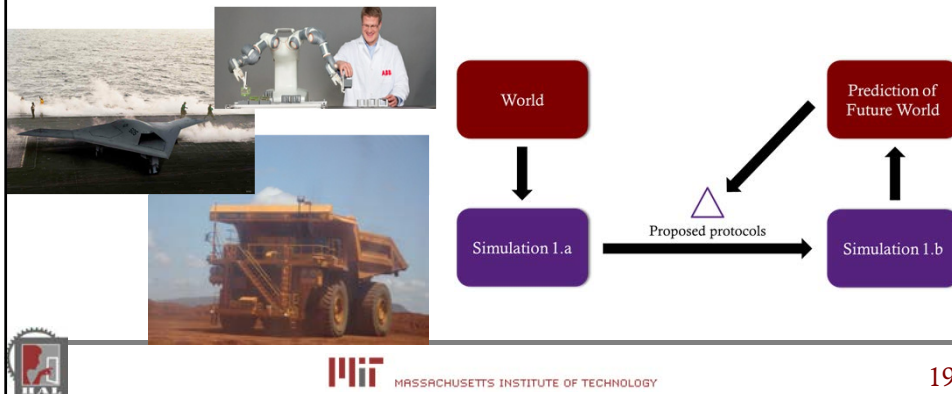
Team Models

- Modeling Teamwork of Human-Agent Teams
 - Future systems of increase size and complexity, even with enhanced automation, will still require several operators
 - Communication and teamwork in this group is paramount in achieving safe and productive system operations
 - Develop discrete event models of human performance in these domains to capture effectiveness of different strategies

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
18

Simulation of Unmanned Systems for Safety and Productivity

- **Multi-Agent Safety and Control Simulation (MASCS)**
 - Develop agent-based simulation of Human-Unmanned Systems environments to evaluate effects of control architectures and safety protocols on performance.
 - Control architecture defines the capabilities of unmanned vehicles; safety protocols constrain their behavior to promote safety. There exists a tension between the two that leads to potentially problematic interactions. Often, testing is only done through field trials – not possible for larger-scale systems (e.g., National Airspace System)
 - Use simulation as testbed to examine the tradeoffs between the two.



Current and Former Projects

- **Former projects:**
 - Tracking operators' cognitive strategies in mission (re)planning (TRACS)
 - Assisting interruption recovery in collaborative time-sensitive targeting
 - Remote collaboration for urban search and rescue
 - Decision support for lunar and planetary exploration
 - Multimodal Interface Toolkit for UAV Systems (MITUS)
 - Design of an error resolution checklist for shared manned-unmanned environments (GUIDER)
 - Human-Automation Collaborative Taxonomy (HACT)
 - Configural Decision Support for Schedule Management of UAV Operations (StarVis)
 - Decision Support for Systems Acquisition (FanVis)
 - Investigating the effects of low workload in supervisory control of unmanned vehicles
 - Replan understanding for heterogeneous Unmanned Vehicle Teams
- **Current Projects**
 - Mobile Advanced Command and Control Station (MACCS)
 - Deck operations Course of Action Planner (DCAP)
 - Effects of vigilance on nuclear control operator performance
 - Examination of real versus perceived complexity in the nuclear control room environment
 - Minimum Information Interface for Locomotive Operation (MILO)
 - Scheduling air for human operator surveillance tasks (HOSS)
 - Human-Automation Collaborative RRT for UAV Mission Path Planning
 - Micro Aerial Vehicle Visualization of Unexplored Environments (MAV-VUE)
 - Effects of workload transition on brain activity in ballistic missile defense operators

All publications are available at halab.mit.edu/publications

Videos at youtube.com/halabatmit

April 23-24th 2014

A Machine Learning Approach To Training Evaluation

Alexander Stimpson
ajstimps@mit.edu



MIT MASSACHUSETTS INSTITUTE OF TECHNOLOGY

Why Train?

- Yield knowledge and skills that are useful, durable, and flexible, with the intention of improving the performance of the trainee (Bjork and Bjork 2006)

Goals of Training

Organizational

- Safety
- Productivity
- Efficiency
- Minimize time/cost

Individual

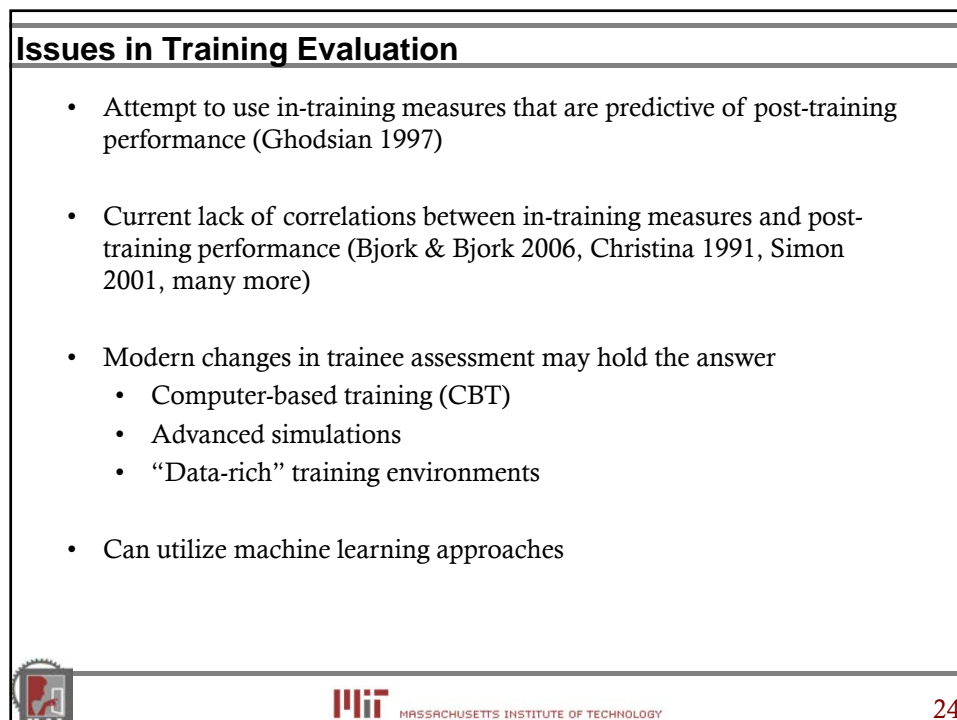
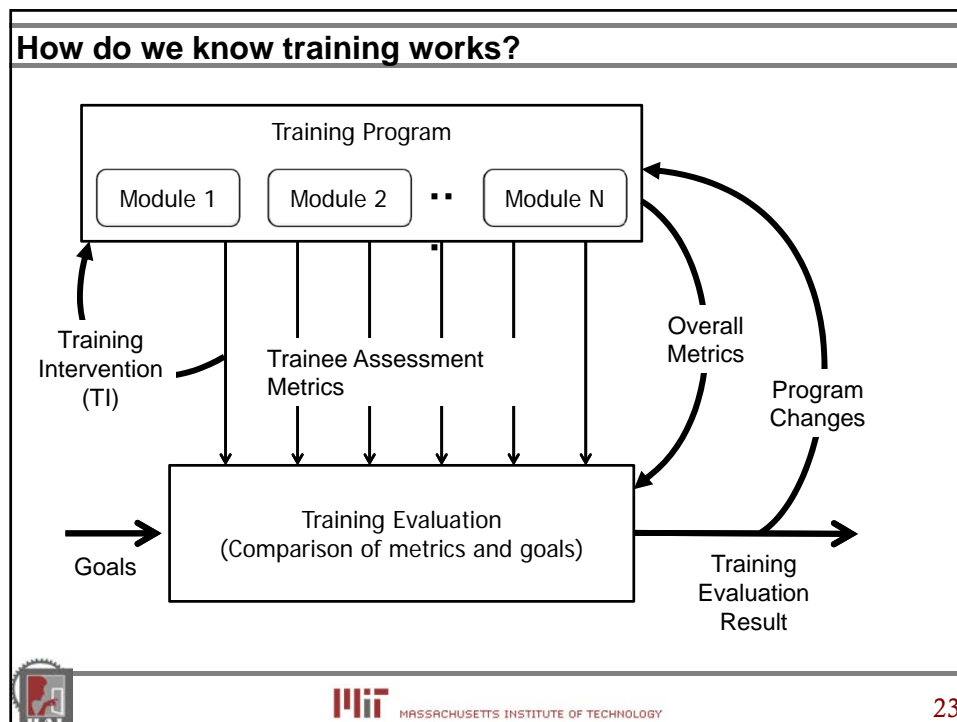
- Learning
- Job Security
- Safety

- Need to assess whether goals are met (Kraiger et al. 1993, Bjork and Bjork 2006, Eseryel 2002, Alvarez et al. 2004, Blanchard et al. 2000, Ghodisan et al. 1997, ...)



MIT MASSACHUSETTS INSTITUTE OF TECHNOLOGY

22



Modern Training Data

- Changes in Data Specificity

Discrete
Continuous

Classroom

Exams, Projects, Quizzes,
Homework Assignments

Aggregate Measures

CBT

Simulations, walkthroughs,
interactive modules

Process-level Measures

- Issues compared to traditional ML domains
- Number of data points
- Number of features
- Noise

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
25

General Approach

- Develop descriptive and predictive models of trainee performance
- Utilize machine learning algorithms as the basis for these models
 - Unsupervised (descriptive)
 - Supervised (predictive)

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
26



Case Study – Knowledge-based Environment

- Data collected from MIT undergrad/grad course (N=35)
- 19 Quizzes
- 3 Projects
- 2 Problem Sets
- 2 Exams

} **Features**

- Final Grade ← **Target**

- Topics included
 - Controls
 - Displays
 - Experimental Design
 - Memory



MASSACHUSETTS INSTITUTE OF TECHNOLOGY

27

Temporal Regression Analysis

- Training intervention relies upon early predictions of performance

The graph plots Sum of Squared Errors (SSE) on the y-axis (ranging from 0 to 1800) against Class Number on the x-axis (ranging from 0 to 25). Three data series are shown: 'Without Quiz Data' (red line), 'High-error Quiz Data' (black line), and 'All Quiz Data' (blue line). All series show a decreasing trend in SSE over time. The 'All Quiz Data' series consistently shows the lowest SSE, while 'Without Quiz Data' shows the highest. Vertical dashed lines indicate the timing of various assignments: Pset 1 (class 6), Project 1 (class 10), Test 1 (class 12), Project 2 (class 13), Project 3 (class 17), Pset 2 (class 20), and Test 2 (class 23).

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

28

Conclusions from Knowledge-based Environment

- Process-level information does not contribute to post-hoc prediction accuracy
- Process-level information made major contribution to the timing of accurate predictions – implications for trainee intervention
- Simple ML techniques provide similar prediction accuracy to more complex models
- Need subject matter experts or additional information to clarify machine learning results
- ML can act as a tool
 - Provide objective metrics for trainee assessment
 - Does not replace instructor/supervisor



Questions?



All publications are available at
halab.mit.edu/publications
Videos at youtube.com/halabatmit

