

AGENT: A testbed for developing & evaluating AI pilots

COMAN PEDFORMA

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Charles River Analytics CHI Systems Discovery Machine Fduworks SoarTech Stottler Henke Assoc. **TiER1** Performance Solutions



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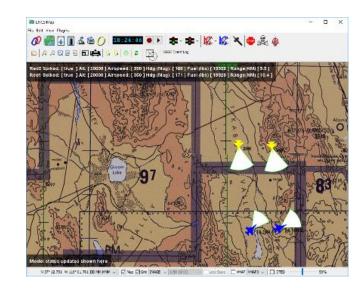


Challenge: Accelerate Development & Assessment of AI Agents in Training Sims

- Benefits of current CGFs
 - Increase complexity of training environments
 - Reduce costs of human operator control of opposing forces

• Limitations of current CGFs

- Small tactical repertoire
- Unrealistic responses (or no responses) to "surprising" trainee actions







Challenge: Accelerate Development & Assessment of AI Agents in Training Sims

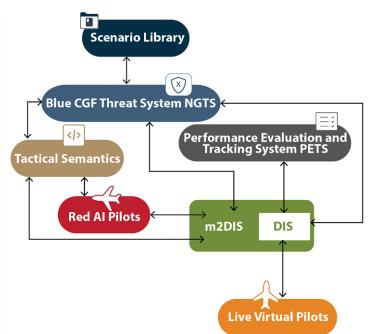
- Smart, resilient, AI agents are needed
- CGFs are built slowly, by hand from and for impoverished data environments
 - <u>Data of sufficient quality, quantity, & variability</u> would enable efficient machine-learning, hand-tuning of agents
- CGFs are generally evaluated by expert judgment
 - <u>Automated performance measurement</u> would enable rapid assessment





AGENT: An Agent Generation & Evaluation Networked Testbed

- Data Quality
 - Standard entity state and interaction data (DIS)
 - Tactically meaningful information over a special purpose interface (m2DIS)
 - Measures of performance and effects (PETS)
- Data Variability
 - Advanced blue CGF
 - Parameterized scenarios
- Data Quantity
 - Library of scenarios
 - Large batch runs







Data Quality

Challenge

- Developers invest time coding transformations of data into tactically meaningful information
- Developers have less time to design, program, and test advanced, adaptive agents



Solution

- Deliver raw data to agents
- Deliver semantically rich summaries of the tactical state to speed development
 - TOA describes the adversary formation and location, much as an AWACS operator would do for pilots in flight.
 - FC-TAC responds to tactical requests: "Am I in the adversary's weapons engagement zone? Where is my wingman in relation to me?"





Data Quantity

Challenge

Agent

Developers

- Developers design agent
 behaviors from tactical
 documentation and expert
 guidance
- Developers rarely have sufficient flight data with which to machine-learn tactical states and behaviors

Scenario Run 1

Scenario Run ...

Scenario Run n

Solution

Common

Data

Store

- Increase data quantity with batch scenario runs at executed at high speed
- Store all data from all runs for all developers in a common data store

Agent

Developers





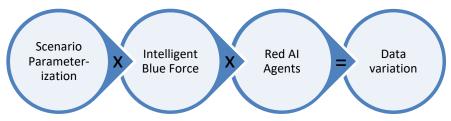
Data Variability

Challenge

- Developers currently test agents against few, invariant scenarios.
- Test scenarios rarely sample the range of trainee behaviors, so agents can't respond to trainee failures and inventions
- Statistical and machine learning require variance in data concerning states, behaviors, & effects

Solution

- Developers can parameterize batch runs re: weapon load, fuel load, and starting position
- Developers fight unusually intelligent, responsive CGFs from the Next Generation Threat System
- Developers' agents are themselves highly adaptive







Measurement

Challenge

Fffect

- Developers currently observe agents to discover, diagnose, and repair failures
- Developers are unreliable observers because they are not domain experts

Maneuvers

Visibility

 Observation is slow, incomplete, and inaccurate

Solution

Weaponsuse

- Automated measurement of agent performance identifies and quantifies the tactical states, behavior, & effects
- Measurements provide feedback at speed, in volume to accelerate development

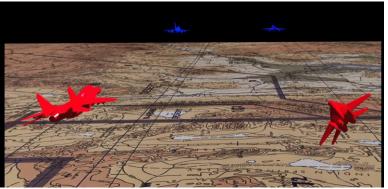
Zones/Threat Ranges





Future Directions

- Refine data output requirements for future Air Force simulators operational systems
- Assess the use, usability, and utility of key testbed features:
 - parameterized batch control of scenarios
 - automated performance measurement
 - responsive blue CGFs
 - shared data store
- Develop an AI librarian for a library of adaptive, robust AI pilot agents





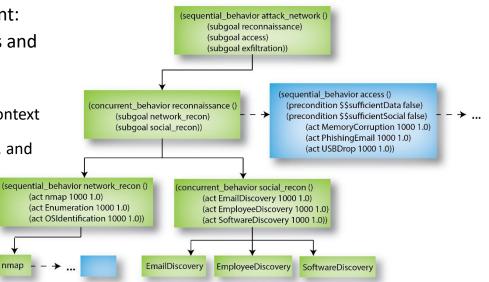


charles river analytics

Hap Agent Architecture

Reactive Cognitive Architecture for Agent Development:

- Characterizes agents with organized, dynamic Goals and the Behaviors it employs to achieve them
 - Goals specify what needs to be accomplished, with conditions for success
 - Behaviors specify how to fulfill goals/subgoals, with context in which they operate
 - Hap adaptively chooses tactics based on the situation, and shifts tactics as the situation warrants
- Goals, subgoals, and behaviors are activated during executed based on observations
 - Conflicts are addressed by Hap during execution
 - Active behavior tree maintains currently executing goals and behaviors
 - Supports intermixing of deliberate and reactive reasoning
 - Hap management of processing guarantees rapid response
- Task-specific sensors collect observations tailored to goals and behaviors
 - World-as-its-own model principles, with task-specific reasoning for tactical agility



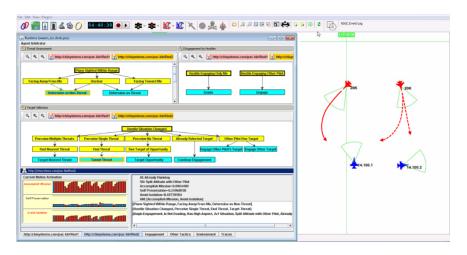
Current applications include:

- Multi-agent swarms
- Multi-agent soldier control
- Air-to-air combat teams
- Cyber adversaries
- Medical teams
- Physiological assessments
- Believable game behavior

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- Theoretical Approach
 - Agent episodic/interactional knowledge is represented as narrative structures or 'story-spaces'
 - Like humans, PAC agents use story spaces to understand others, discern threats & opportunities, activate & interpret their motives, execute strategies, encode & retain shared knowledge
- Practical Approach
 - PAC visual authoring tool allows for rapid creation and modification of narrative stories
 - Stories are composed of sub-stories that can be reused and easily aggregated
 - High variability of agent behavior within stories is achieved through changing motivations and goals, within context
- Benefits
 - Transparency human-interpretable agent decision process
 - Realistic behavioral variability across agents
 - Reduced cost intuitive, rapid construction/modification through visual narrative authoring to address changing application (e.g., training) requirements
- Applications
 - Adversary or own-team agents for training in virtual environments (AFRL)
 - UAV control experimentation (ONR)
 - Decision support protoype (ONR)





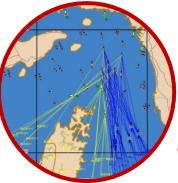
- DMInd Cognitive Architecture
 - Visual hierarchical modeling
 - Concurrent strategy processing
 - Situational Awareness Processing
 - Working memory of reactive behaviors
- Leverages mental model representations that are:
 - Accessible to Subject Matter Experts,
 - Visually traceable during execution,
 - Contain intrinsic explanation capability, and
 - Support blame/credit assignment for rapid adaptation.
- DMInd agents have been deployed in training showing 10x reductions in white cell operator workloads.



Intelligent Agents for Patterns of Life in Marine Intelligence Training



Virtual Instructor Pilot Exercise Referee (VIPER™) for Pilot Training Next (PTN)





Intelligent Agents for Air Support Operations Center (ASOC) Training in JTAGSS



Intelligent Agents for Natural Gas Well Site Operator Training

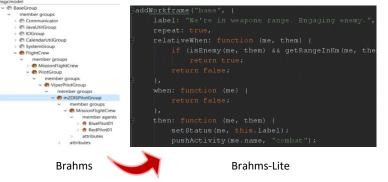
Intelligent Agents for Anti-Submarine Warfare Training

eduworks

Activity-Based Modeling for NSGC

Activity-Based Air-to-Air Modeling

- Agent-based Modeling of Human Teams, Activities and Systems
- Adopts socio-technical paradigm from Brahms
- Can simulate communication, interaction w/automated systems
- Can model normal & degraded coordination, comm, systems
- Uses activity-based theoretical construct





Implemented in Brahms-Lite

- Java-script development & run-time
- Implements Brahms workframes, thoughtframes & activities
- Applies Brahms process model (Pandora-inspired)
- Integration-ready
 - Agents can be run as web page/ service, command line option, API

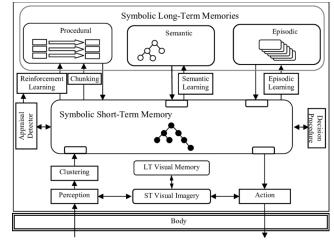
SOARTECH

Soar-based State Inference Cognitive Architecture With MADDPG Reinforcement Learning by Aptima and Soar Technology, Inc.

For our WNSGC agent, Aptima and SoarTech combine the principles of the Soar Cognitive Architecture with a state-of-the-art reinforcement learning method for behavior modeling called Multi-Agent Actor-Critic for Mixed Cooperative-Competitive Environments (MADDPG). Soar is a production system that searches a problem space and dynamically revises agent knowledge and actions to accomplish goals. If programmed at sufficiently fine level of granularity, a production system can effectively generate novel tactical inferences and actions. Soar agents are particularly capable of variable behavior within scenarios, and potentially of evolution over them. We paired this technology with MADDPG, which generated a state-action model based on observed simulation behaviors. This state-action model serves as the basis of our Soar-based agent's production rule set.

Soar-based agents have also been developed for the following domains:

- DoD simulation and training
 - Fixed-wing and rotary-wing piloting
 - Assistive role-playing agents
 - Cultural trainers
 - Cyberwarfare
- Medical diagnosis
- Autonomous platform control

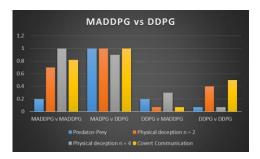


Soar 9 architecture (Laird, 2017)



Aptima's Reinforcement Learning Policy Learning

- AI/Reinforcement Learning approach called Multi Agent Deep Deterministic Policy Gradient (MADDPG) handles competitive, cooperative, and mixed multi-agent situations gracefully.
- Goal: Use MADDPG to train Red Air RL agents in NSGC environment.
 - Policy (best actions to take given the current state) automatically learned in NSGC environment.
 - Policy conveyed as advisory to SoarTech's agents using Policy Description Language (PDL).
- *Status:* MADDPG prototype developed, NSGC states and actions identified, PDL defined.



From Lowe, Wu, Tamar, Harb, Abbeel, & Mordach (2017). Multi-Agent Actor Critic for Mixed Cooperative-Competitive Environments. *Neural Information Processing Systems*.

Stottler Henke

Smarter Software Solutions



Visual IDE: Specify and review behavior

models via parallel, hierarchical flow charts.

Log SternIntercept SternIntercept

Learning: Use Dynamic Scripting nodes in behavior models to learn from experience.

SimBionic Behavior models: Used to control agents and recognize complex events in

- Autonomous Systems
- Intelligent Tutoring Systems
- Simulations
- Virtual Assistants

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Status: Available on GitHub <u>StottlerHenkeAssociates/SimBionic</u>

POC: Jeremy Ludwig <u>ludwig@stottlerhenke.com</u>



DREAMIT by TiER1 Performance

- DREAMIT is a software platform that allows different human performance modeling tools to be combined to produce coherent behaviors
 - The goal is to allow the human performance modeler to choose "the right tool for the job"
 - Allows fidelity requirements to drive choice in modeling architectures
 - Promote encapsulation and model reuse
 - A Big Tent approach to HBR development
 - We've used DREAMIT to develop complex human behavior representations for both prediction and training

