Exploring the integration of BDI agents in games and virtual environments

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Agenda

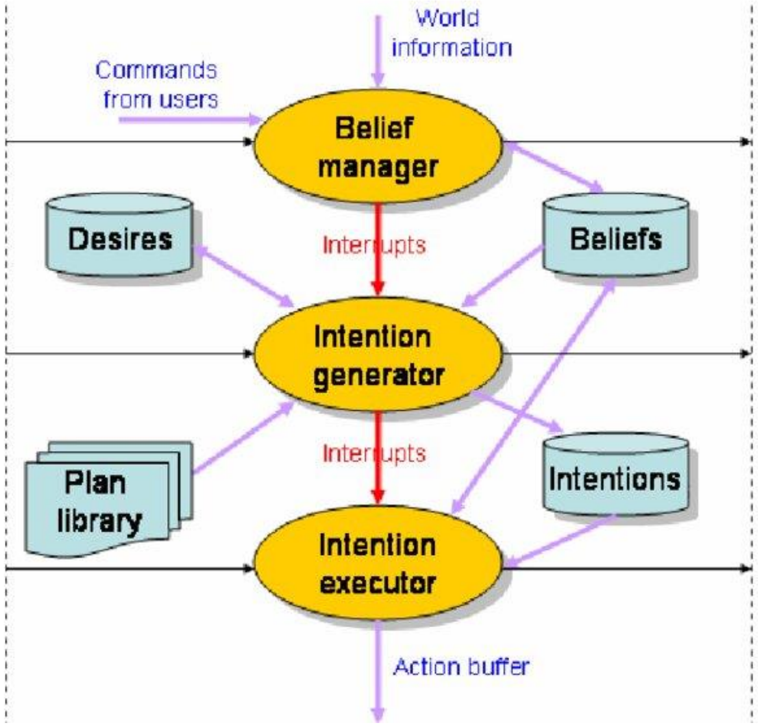
- Introduction
- Belief-Desire-Intention (BDI) framework
- Agents design & architecture in
  - ViP-Jogoman (turn-based RPG)
  - Unreal Tournament Agent (FPS)
  - Orphibs II (A-Life simulator)
  - 0 A.D. (RTS)
- Discussion
- Conclusion

Introduction

- **MAS Applications**: Used successfully in communication, industry, administration, and increasingly in entertainment (e.g., AI bots in video games)
- **Problem**: Traditional game AIs lack human-like behavior, reducing player immersion
- **BDI Model**: Mimics human problem-solving via beliefs, desires, and intentions; improves realism in AI behavior
- **Games & Simulation:** can represent a simplified model of a real-world aspect
  - Help understand the phenomenon
  - Consequences can extend to other fields (e.g. robotics & automation)

The BDI framework

- **Belief Desire Intention (BDI):** Adapted from Bratman's theory of practical reasoning
  - **Belief**: Agent's understanding of the environment
  - **Desire**: Goals the agent aims to achieve
  - **Intention**: Selected action plan to fulfill desires
- **Functionality**: Enables agents to make autonomous, deliberativ take context-aware decisions
- **Efficiency**: Filters irrelevant info, reducing computational cost
- **Human-Like Reasoning**: Mimics human decision-making processes
- **Adoption in Game AI**: Widely used for creating responsive, realistic virtual characters



ViP-Jogoman

Adamatti, D.F., Sichman, J.S., Coelho, H., 2009. An analysis of the insertion of virtual players in gmabs methodology using the vip-jogomanprototype. Journal of Artificial Societies and Social Simulation 12, 7.

- **Overview**
  - digital RPG simulating water resource management in Brazil
  - Players (human or virtual agents) assume roles (e.g., mayor, water company admin) and make decisions, negotiate, and strategize
- **BDI Agent Architecture**
  - Belief: game state (land plots), roles, actions
  - Desire: role-dependent
    - Improve water quality, financial goals, administration etc.
  - Intention
    - step-by-step plans to achieve what they want
    - Strategies can be changed depending on context
  - Agents were designed with expert opinions in mind
- **Communication:**
  - SACI + KQML – direct message passing between agents
  - SOAP (agent-environment)

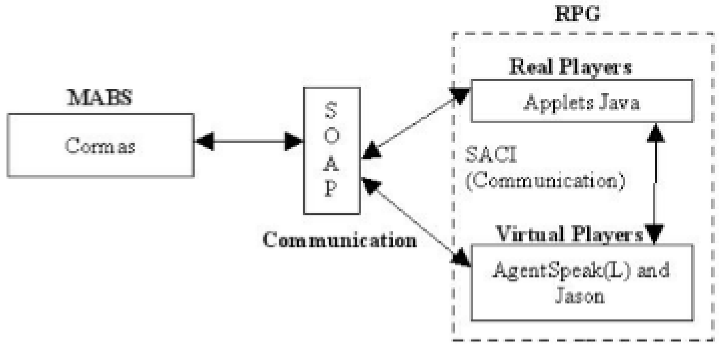


Fig. 1: Architectural design of VIP-Jogoman [1]

```
+plot(L,R): not forest(L)[source(percept)] &
     not settlement(L)[source(percept)] &
     not agriculture(L)[source(percept)] &
     .myName(M) & owner(M,L,P)[source(percept)]
        <- changelanduse(l,agriculture);
           !nextposition(l,r).
```

Fig. 2: Example of strategy in a behavioral profile [1]

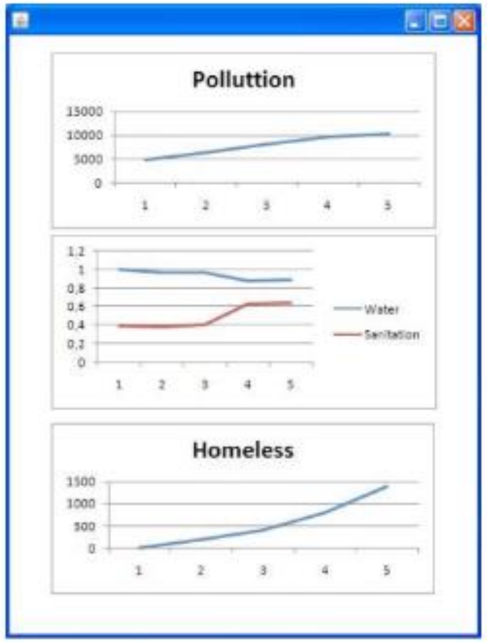
ViP-Jogoman

Adamatti, D.F., Sichman, J.S., Coelho, H., 2009. An analysis of the insertion of virtual players in gmabs methodology using the vip-jogomanprototype. Journal of Artificial Societies and Social Simulation 12, 7.

- **Evaluation**
  - Behavioral profile
  - Questionnaires
  - Turing-style tests confirmed realism and strategic depth
- **Results**
  - BDI agents effectively mimicked human behavior
  - Some players couldn't distinguish agents from humans
  - Agents are proactive
    - Initiate negotiations (but have low acceptance rate compared to human intentions)
  - Exceled at fulfilling their role-dictated goal

Table 3: Cash box values of Land Owners in a **ViP-JogoMan** VP game with 4 rounds

Player	Round 1	Round 2	Round 4	Round 5
Land Owner 1 – Ecologic	2.000,00	-49.452,00	-53.104,00	-51.756,00
Land Owner 2 – Economic	2.000,00	5.300,00	8.600,00	11.900,00
Land Owner 3 – Ecologic	2.000,00	-70.300,00	-56.100,00	-53.900,00
Land Owner 4 – Economic	2.000,00	6.500,00	11.200,00	15.900,00
Land Owner 5 – Ecologic	2.000,00	-89.500,00	-68.600,00	-63.700,00
Land Owner 6 – Economic	2.000,00	7.000,00	12.000,00	17.000,00
Land Owner 7 – Ecology	2.000,00	-71.500,00	-15.700,00	-12.900,00
Land Owner 8 – Economic	2.000,00	5.387,00	8.774,00	12.161,00
Land Owner 9 – Ecologic	2.000,00	-82.139,00	-52.965,00	-50.791,00



Unreal Tournament

Davies, N., Mehdi, Q., Gough, N., 2006. A framework for implementing deliberative agents in computer games, in: Proceedings 20th European Conference on Modeling and Simulation Wolfgang Borutzky, Alessandra Orsoni, Richard Zobel I'ECMS

- **Problem addressed**
  - Traditional game AI is rigid and lacks human-like behavior, affecting player experience
- **Game overview**
  - Unreal Tournament used as testbed—ideal for its fast-paced, unpredictable gameplay
- **BDI agent framework** simulates human decision-making in dynamic FPS environments
  - **Belief**: World knowledge (e.g., enemy locations)
  - **Desire**: Capture the flag, stay healthy, explore, etc
  - **Intention**: Context-sensitive actions like taking cover under fire, find healing packs
- **Communication**
  - **Java Bot Client**: Interfaces between agent and game server
  - **Sensory Input Only**: Agent operates with limited, player-like perceptions (no omniscient info)
  - **Mind-Body Separation**: Agent logic runs externally; actions simulate human delays

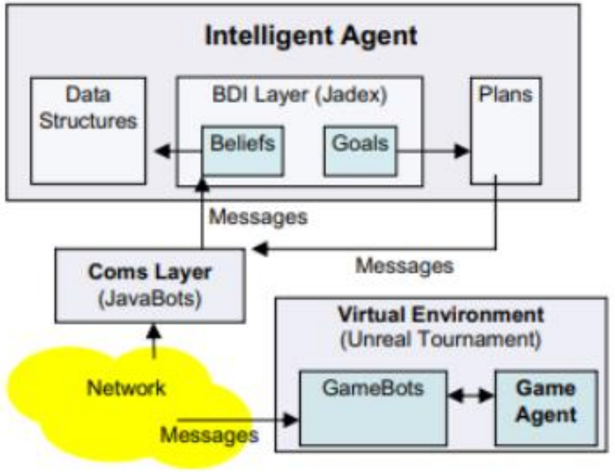


Fig. 4: System design architecture [5]

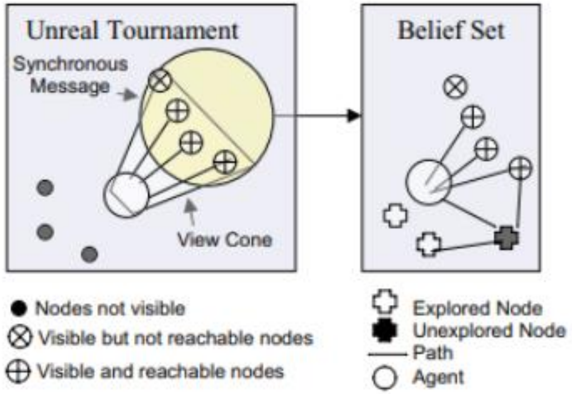


Fig. 5: Message system for navigation purposes [5]

Figure 2: Screen shot of Unreal Tournament

Unreal Tournament

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- **Evaluation**
  - Demonstrated with simple behaviors (e.g., pathfinding, basic combat)
- **Highlights**
  - Modular design supports advanced strategy, team AI, and negotiation extensions

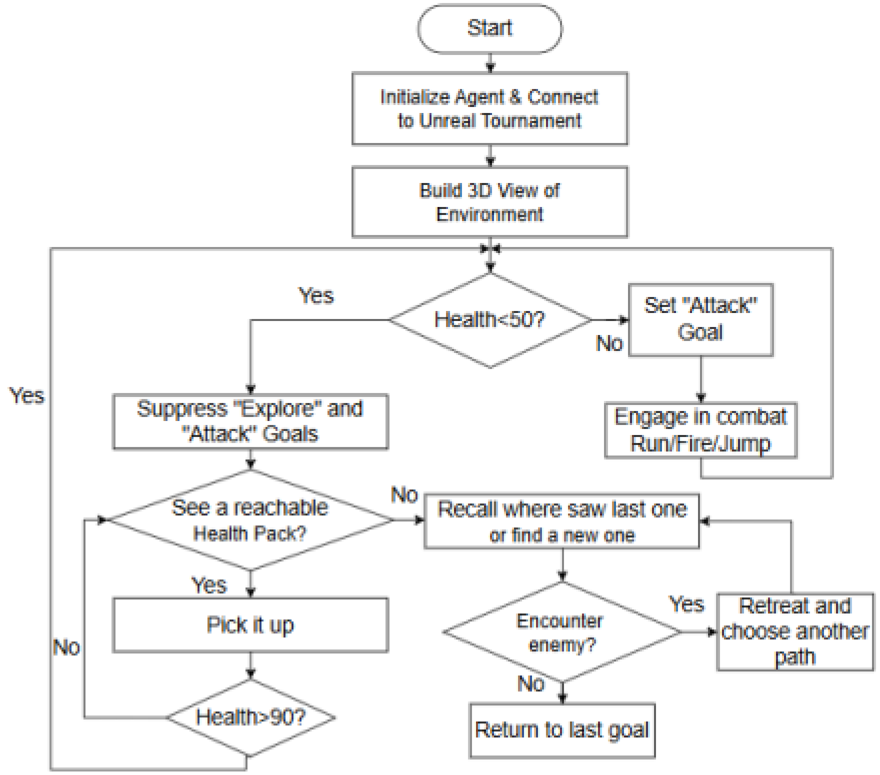


Fig. 6: Unreal Tournament Agent reasoning highlighting prioritizing goals under certain circumstances

Orphibs II

Barreto, N., Macedo, L., Roque, L., 2014. Multiagent system architecture in orphibs ii, in: Artificial Life Conference Proceedings, Citeseer.pp. 588–595.

- **Overview**
  - Artificial Life (A-Life) game with alien-like agents (Orphibs) exhibiting emergent behavior
  - MAS with genetically inherited “personalities”
  - Bottom-up, agent-centric design focused on individual needs and autonomous decisions
- **Architecture**
  - Unity3D using a modular, component-based architecture
  - Perception via sensors
  - Internal needs: hunger, energy, fun, socials w/ decay rates
  - Actions chosen by satisfaction scores based on needs
  - Introduces Goal-Based Behavior (GBB)
    - hunger → seek food
  - Genome encodes traits like color and behavior preferences for heredity
    - Enhances The Sims-like systems with evolutionary dynamics

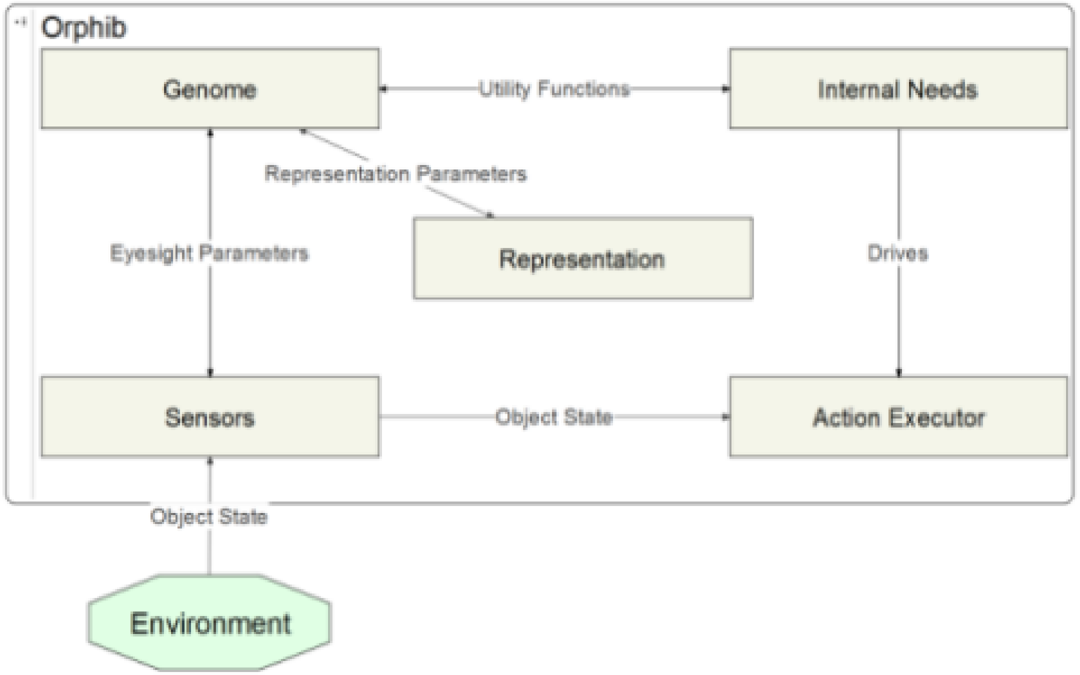


Fig. 7: Architecture of an Orphib's agent [3]

$$\text{score}(\text{action}) = \\ = \sum^{needs} [U_{need}(current) - U_{need}(future)]$$

Orphibs II

Barreto, N., Macedo, L., Roque, L., 2014. Multiagent system architecture in orphibs ii, in: Artificial Life Conference Proceedings, Citeseer.pp. 588–595.

- **Indirect communication** via environmental and social behaviors
  - Social drives promote group interactions and reproduction via genetic crossover
  - Non-verbal object interactions affect environment and other agents
- **Evaluation**
  - 14 minute simulation with 15 initial random Orphibs
  - Metrics: population stability and age distribution
- **Results**
  - Simulations show population growth and diverse age without premature deaths
  - Emergent behaviors (e.g., resource competition, clustering) validate MAS design
  - Demonstrates scalable, lifelike ecosystems with goal-driven autonomy and genetic diversity
  - Suggested improvements: population control, integrating emotions via memory (CBDTE)

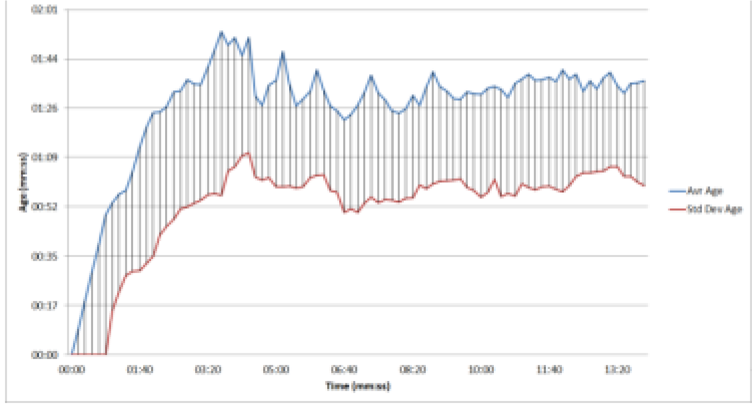


Fig. 7. The population's average age and respective standard deviation, expressed in minutes, during the test run.

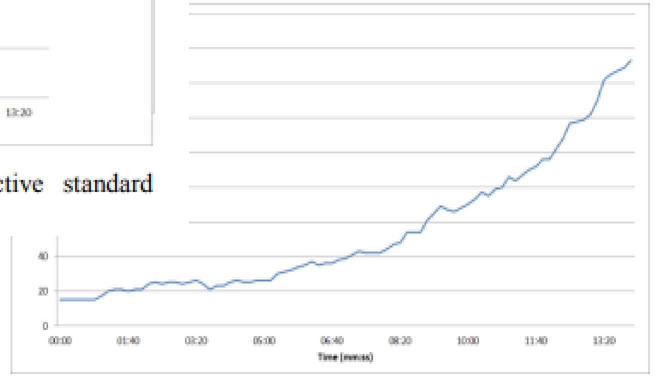


Fig. 6. Orphibs' population evolution over time during the test run.

0 A.D. - ABot

Dallatana, A., 2012. BDI agents for Real Time Strategy games. Ph.D. thesis. University of Bologna.

- **Overview**
  - ABot: A multiagent, BDI-based AI for 0 A.D., replacing centralized architectures
  - Enables adaptive, human-like decision-making in dynamic RTS environments
  - Balances realism and computational efficiency
- **Architecture**
  - Agent-centric BDI architecture: each unit/building is an autonomous agent
  - **BDI**
    - **Beliefs**: Game perceptions (e.g., enemy locations)
    - **Desires**: Role-specific goals (e.g., gather, train)
    - **Intentions**: Action plans (e.g., build, move)
  - Modular roles (Worker, Soldier, TrainingBuilding) enable reuse and hierarchy
  - **Botalk**: Custom agent-oriented language abstracts JavaScript logic
  - Immaterial agents (e.g., Job Market Agent) coordinate tasks without game-entity ties

Fig. 9: Agent reasoning loop [4]

0 A.D. - ABot

Dallatana, A., 2012. BDI agents for Real Time Strategy games. Ph.D. thesis. University of Bologna.

- **Communication System**
  - Indirect, asynchronous messaging via turn-delayed **mailbox**
  - Avoids synchronization issues
  - supports autonomous yet coordinated behavior
- **Evaluation**
  - ABot is compared to QBot (centralized AI) over 5-minute RTS scenarios and with human game plays
- **Results**
  - Human-like strategies (e.g., early treasure collection, tower defense)
  - Scalable performance with linear efficiency
  - Better in resource management and exploration
  - 30% runtime spent on perception handling
  - Late-game suboptimal tuning (e.g., low food priority)
  - Tactical rigidity in military formations
  - Demonstrates MAS **viability** in RTS games and community

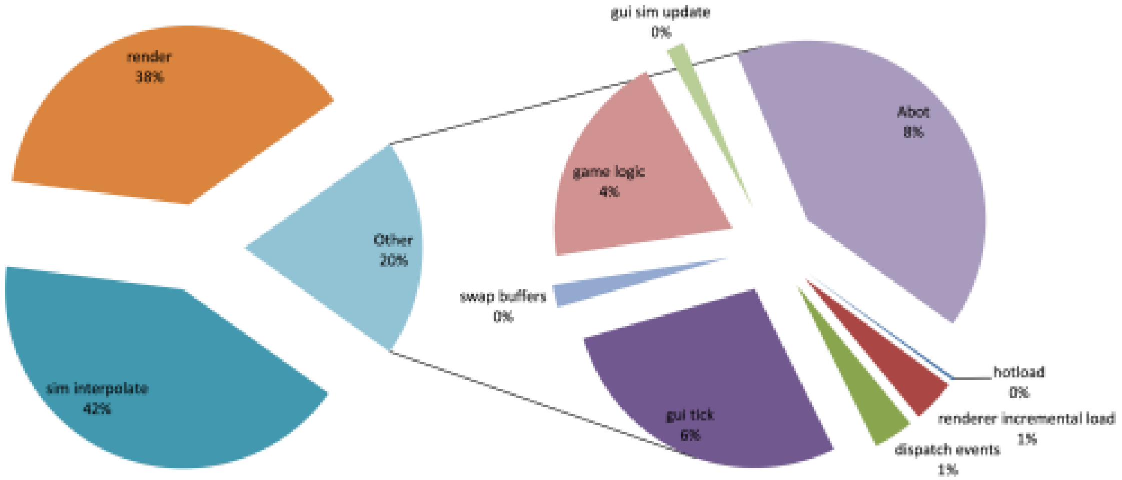
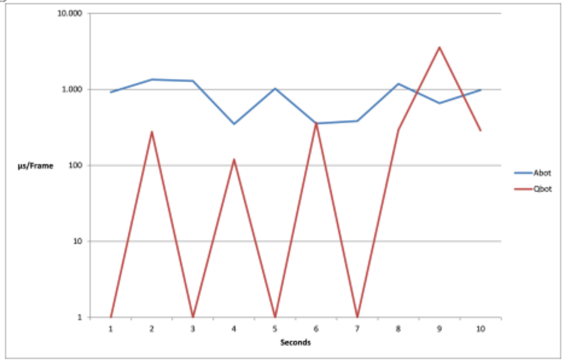
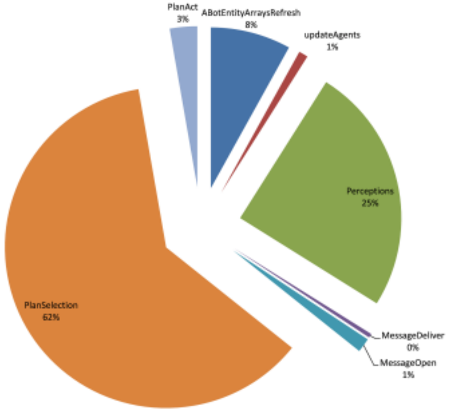


Figure 12.2.21: Load division between different sections of ABot

Figure 12.2.19: Results taken after 5 minutes from the start of the match





Discussion (1)

Author(s)	Domain / Application	BDI Integration	Granularity	Extensions
Adamatti et al.	RPG simulation for natural resource management	Full BDI architecture	Virtual players with specific roles in human-driven simulation	Behavioral profiles based on human players
Davies et al.	First-person shooter (FPS) game	Full BDI architecture	AI controlling individual non-player characters (NPCs)	Focus on human-like behavior
Barreto et al.	Orphibs II – life simulation	Simplified BDI (Goal-Based Behavior)	Individual creature agents (Orphibs)	Genetically driven personalities
Dallatana	Real-time strategy (RTS) game	Full BDI for all entities	Highly granular – every game element is a BDI agent	Custom MAS platform; Botalk domain-specific language for agent programming

Discussion (2)

Paper	Agent Platform/ Framework	Programming Language(s)	Game/ Simulation Environment	Communication Technology
Adamatti et al. (2009)	Jason	Java, AgentSpeak(L), Smalltalk	Cormas (MABS)	SACI (KQML), SOAP
Davies et al. (2006)	Jadex	Java	Unreal Tournament	JavaBots/GameBots
Barreto et al. (2014)	Unity3D	*Not mentioned (C# or C++)*	Orphibs II	*Indirectly via environment interactions*
Dallatana (2012)	ABot	Custom agent language (Botalk), Javascript, Prolog	0 a.d.	Mailbox system

Table 1: Technologies employed by the discussed approaches

Environment	Accessibility	Deterministic	Dinamicity	Discrete/Continuous	Episodic/Sequential	Known/Unknown
Adamatti	Accessible	Deterministic	Dynamic	Discrete	Sequential	Known
Davies	Inaccessible	Non-deterministic	Dynamic	Continuous	Sequential	Unknown
Barreto	Accessible	Non-deterministic	Dynamic	Continuous	Sequential	Unknown
Dallatana	Inaccessible	Non-deterministic	Dynamic	Continuous	Sequential	Unknown

Table 2: Properties of the studied environments

Discussion (3)

Author(s)	**Focus of Evaluation**	**Key Findings**
Adamatti et al.	Impact of virtual BDI players in simulation	Virtual agents influenced game outcomes meaningfully in resource management
Davies et al.	Believability of AI in FPS	BDI agents made AI opponents/teammates more believable and challenging
Barreto et al.	Personality and reasoning in artificial life	Genetic personalities & needs-based logic led to varied and engaging behaviors
Dallatana	Agent realism and performance in RTS	BDI agents showed strong strategy, realism, and effective performance

Conclusion

- **Overall Insight**
  - Integrating BDI agents enhances game realism, strategic depth, and agent diversity
    - more believable
    - adaptive,
    - engaging player experiences
  - BDI-based approaches increase sophistication and adaptiveness of game agents across simulations, FPS, life sims, and RTS games
  - Contribute to more immersive and believable player experiences

Thank you for your attention!

Bibliography & Resources

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